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Doctor of Philosophy

Effectiveness of Artificial Intelligence Adoption in Recruitment and Selection

by

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DECLARATION

I certify that this thesis:

Does not incorporate, without acknowledgment, any material previously submitted for a degree or diploma at any university.

The research within will not be submitted for any other future degree or diploma without the permission of Flinders University.

To the best of my knowledge and belief, does not contain any material previously published or written by another person, except where due reference is made in the text.

Anusha Hewage

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Hewage, 2023, Applicability of Artificial Intelligence in Interview Phase of Recruitment and Selection Processes, Human-Computer Interaction, Paper submitted for publication.

ABBREVIATIONS

AI	Artificial intelligence
AI-RS model	Artificial Intelligence in recruitment and section model
ANZ	Australia and New Zealand
AU	Australia
BE	Benefit Expectations
BI	Behavioral Intentions
BPO	Business process outsourcing.
COH	Cost of Hire
EE	Effort Expectations
FC	Facilitating Conditions
GDPR	General Data Protection Regulations
HM	Hiring Manager
HRE	Human Resource Executive
HRM	Human resource management
ILO	International Labor Organization
ML	Machine Learning
NLP	Neuro Language Processing
OC	Outcomes

PE	Performance Expectancy
PEOPLE	Performance, Environment, Organizational design, People, Learning, Education
QOH	Quality of Hire
RP	Recruitment Phases
RPA	Robotic Process Automation
RR	Retention Rates
RS	Recruitment and Selection
RS processes	Recruitment and selection processes
RS process	Recruitment and selection process
RS professionals	Recruitment and selection professionals- Recruiters, hiring managers, Human Resource Executives
SI	Social Influence
SME	Subject Matter Experts
TAM	Technology Acceptance Model
TOE	Technology, Organization, Environment
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TTH	Time To Hire
UTAUT	United Theory of Acceptance and Use of Technology
UTAUT-OM	United Theory of Acceptance and Use of Technology- Operations Management
WEP	World Economic Forum

DEFINITIONS

Industry 4.0:

This refers to integrating advanced digital technologies and automation in the manufacturing and production processes. This includes the use of technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning, robotics, and big data analytics to create a smart, interconnected, and flexible manufacturing system (Lasi, et al., 2014)

AI Literacy:

The knowledge and skills required to comprehend the overall usage of AI, interpret its capabilities and functioning, and apply it effectively in the daily work of RS while also mitigating its negative effects to reap its benefits and improve the RS.

SME :

Subject Matter experts in the context of this research are the recruiters, hiring managers and Human Resource Executives

ABSTRACT

This doctoral thesis investigates the factors that drive the integration of artificial intelligence (AI) in recruitment and selection (RS) processes in the context of Human Resource Management (HRM). Furthermore, this study explores the impact of AI adoption on achieving strategic human resource (HR) goals through RS.

In doing so, the study addresses critical problems HR professionals face: what factors influence AI adoption in RS, how AI can contribute to achieving HR outcomes, and under what conditions AI contributes to HR outcomes. The research questions guiding this study are (1) What factors drive AI adoption in RS, and what do recruitment professionals perceive are the potential benefits and drawbacks of AI? (2) Under what conditions are the adoption drivers applicable in adopting AI in RS? and (3) How and under what circumstances does using AI in RS affect strategic HR outcomes?

This study contributes to the HRM literature by developing the AI-RS model for the effective use of AI in RS and the complexities associated with AI adoption in RS. Thus, the theoretical contribution of this study is three-fold. Firstly, this multidisciplinary study integrates the AI technology adoption and HRM literatures and extends the Unified Theory of Acceptance and Use of Technology (UTAUT)-Operational Management (OM) by including key RS processes into the model. By doing so, it explores the circumstances when AI use is most effective in RS, especially in achieving HR outcomes. Secondly, the study provides a perspective from recruitment professionals such as recruiters, hiring managers, and HR executives, who are the primary actors in RS functions. Prior research largely ignored this critical perspective; therefore, this study provides a valuable viewpoint that directly impacts the effective use of AI. Thirdly, the study establishes a link between

AI adoption in RS and the achievement of HR outcomes, which is found to be a gap in the literature. Thus, the proposed model would help other researchers and HRM executives use it for other emerging technologies to understand their effectiveness in achieving HR outcomes.

The study uses a mixed method of qualitative and quantitative research to develop, test, and validate the AI-RS model and answer the research questions. The qualitative phase includes 17 interviews with RS professionals, and the quantitative phase involves a survey of 215 recruiters, hiring managers, and HR executives from different industries. Structural equation modeling is used to test the model statistically.

The study found that AI is rapidly being adopted in RS, with the main driving factors being expected benefits, facilitating conditions, AI behavioral intentions, and specific recruitment phases. The anticipated benefits of AI adoption include achieving work-life balance, increasing the quality of the recruitment process, and enhancing the career progression of professionals associated with the recruitment process. Facilitating conditions for AI adoption include AI systems integration with other HR systems, tracking how AI makes decisions in the recruitment process, and protecting candidate data privacy. The study also highlights the influence of modern emerging technologies, media, and customer expectations upon RS professionals in promoting AI adoption.

The findings reveal that AI can achieve HR outcomes, including improving hiring quality through standardized processes and reducing the time and cost of hiring. The conditions necessary for achieving these outcomes include meeting facilitating conditions and using AI only in specific recruitment phases. The study also indicates experience of RS professionals moderates this relationship in such a way that less experienced professionals are more inclined to adopt/use AI compared to experienced professionals, and these outcomes depend on different hiring volumes.

The study provides recommendations for RS professionals. These suggestions advocate for a collaborative approach to AI adoption involving a hybrid AI-human recruitment and selection process. The aim is to address concerns raised by professionals about AI's limitations in establishing a human-like connection with candidates and its potential negative impact on candidate experience.

The study provides practical managerial implications into the applicable aspects of RS where AI can be effectively applied, and the facilitating conditions required to achieve the expected outcomes. The study’s findings also have implications by identifying channels that can be used to motivate RS professionals to use and adopt AI. The proposed AI-RS model provides a guide for using AI to contribute to achieving HR outcomes. Overall, this study provides insights to guide managerial interventions for the effective adoption of AI.

CHAPTER 1

RESEARCH INTRODUCTION

1.1 Introduction

This chapter provides a background to the research, scope, topic, questions, and significance of this research. Furthermore, this chapter presents the intended contribution of this study to both the theoretical body of knowledge and the practical application of this knowledge in recruitment and selection (RS) in Human Resource Management (HRM).

1.2 Overview

This proposed research study aims to examine the utilization of artificial intelligence (AI) in RS within the domain of human resource management (HRM). Specifically, this study will further provide a basis to understand AI adoption in RS and its consequences and impact on HR outcomes. The HR outcomes to be evaluated in this research study are time to hire, cost of hire, quality of hire, and retention rates, which are considered crucial key performance indicators (KPIs) in HRM (Suen et al., 2019).

The study aims to investigate the perspectives of professionals associated with RS processes. Thus, the main actors in the research are recruiters, hiring managers, and HR executives, who play a pivotal role in the RS process. The research suggests the RS professionals' perspective is understudied compared to the perspectives of candidates (Phillips & Gully, 2015).

The primary theoretical framework adopted for this research is the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been widely employed in studies exploring technology adoption (Venkatesh et al., 2003). The study will also consider emerging theories, such as the extended UTAUT for operations management (OM), to further examine the adoption of AI tools in the RS context. This theory is based on UTAUT and specifically addresses the adoption of AI tools (Venkatesh, 2021). This study will identify any existing gaps by evaluating the applicability of these theories to AI adoption in RS. Subsequently, the study will contribute theoretically by developing a conceptual model, the Artificial Intelligence for Recruitment and Selection Process (AI-RS) model. In doing so, this model extends the UTAUT and UTAUT-OM to address the specific phenomenon of AI adoption in RS.

1.3 Background to the research

The utilization of AI is widely regarded as a significant driver of economic growth(Lu, 2021). According to the Australian Government (2021), integrating AI into various industries can create jobs, enhance business operations, and ultimately improve the quality of life for humans. It is estimated that AI could contribute over AUD$20 trillion to the global economy by 2030 (Australian Government, 2021). Moreover, integrating AI technology into business processes will revolutionize how businesses operate by facilitating collaboration between humans and AI (Daugherty & Wilson, 2018).

Consequently, business leaders, strategists, government institutions, and regulatory bodies are increasingly investing in strategies, policies, and regulations to leverage the power of AI at various levels.

To achieve the full potential of AI, governments are actively prioritizing the development of AI capability and strategy. For example, the Australian Government has established its AI action plan to transform Australian businesses (Australian Government, 2021). Similarly, other countries like China, USA, UK are also adopting AI, and this focus is reflected in their research agendas (George et al., 2021). For instance, the United States reports the highest number of AI-based research publications, researchers investigating AI, and developing AI-based patents (Artificial Intelligence Index Report Introduction to the AI Index Report 2023, 2023, pp. 20-30). China and the UK follow as the second and third countries, respectively, recognizing that AI will transform the way people work by automating manual and repetitive tasks.

AI technology is expected to create significant job opportunities in the coming years. AI is predicted to create 1.2 million new technology jobs in Australia by 2034 (Australian Government, 2021). The World Economic Forum (WEF) predicts that these changes will be global, as the future of work is transforming due to Industry 4.0 and the COVID-19 pandemic (World Economic Forum, 2020). These changes are intended to address the constant cost-saving measures and improve employees' work life. However, integrating AI-based automation is also expected to lead to job displacement in many sectors. For example, 43% of companies plan to reduce their workforce with AI-based automation (World Economic Forum, 2020).

Furthermore, by 2025, it is anticipated that humans and machines will share an equal division of labor in the workplace. The WEF predicts that 85 million jobs will be displaced by technology, while 97 million new jobs will be created by 2025 (World Economic Forum, 2020). However, there are also implications for the workplace. In the future workplace, 40% of the workforce will require re-skilling due to the integrating of emerging technologies such as AI, robotic process automation (RPA), and similar technologies (World Economic Forum, 2020).

More recently, ChatGPT, an emerging AI technology developed by OpenAI, has brought about revolutionary changes in various business contexts, indicating that AI will become an integral part of every job (Aljanabi et al., 2023)That review evaluates the impact of ChatGPT AI on several business sectors and suggests that it has the potential to automate routine tasks, create new job categories, and change organizational structures, reshaping the nature of work(Korzynski et al., 2023). Adopting AI tools such as ChatGPT has also created a need for upskilling in other businesses to remain competitive in the market. In addition, the underline algorithmic technologies of ChatGPT has profound implications for HRM, enabling organizations to automate HR tasks, improve talent management practices, and provide data-driven insights for HR decision-making (Korzynski et al., 2023).

Thus, workplace transformation will require a significant role from HRM-related professionals as HRM-related professionals are responsible for developing strategies around human capital in an organization, such as attracting and retaining human capital (Dessler et al., 2021).

Hence, the function of HRM itself may require transformation, as traditional methods of operation may not help compete or even survive the uncertainties brought by disruptive technologies and economic downturns. HRM must adapt to changing workforce needs and integrate new technologies, such as AI, to ensure the success of organizations in the future. Thus, it is vital that HRM is ready and equipped to undergo such a transformation (Suseno et al., 2022).

The transformation of the workplace and the demands of modernization pose several challenges to human resource management (HRM). Factors such as globalization, remote working, the gig economy, and technological disruptions require rapid changes in HRM operations, including workforce planning, recruitment strategies, capability development, and retention (Melchor, 2013). Recruitment and selection are particularly critical, as they are the central processes that bring new human capital to an organization.

Despite the introduction of e-recruitment, which uses the Internet and world-wide-web-based technologies, recruitment and selection processes have undergone very few changes since their original manual models (Kramar, 2014). This has resulted in operational inefficiencies and deficiencies (Kim et al., 2021). Most recruitment and selection operations remain manual, semi-automated, time-consuming, costly, and sub-optimal, leading to challenges in attracting and retaining top talent (Fong & Ng, 2018).

HRM faces challenges associated with a continuously evolving modern workplace (Suseno et al., 2022). To stay relevant, HRM needs to adopt new technologies such as AI and automation to improve RS, attract and retain talent, and gain a competitive edge.

1.4 Recruitment and selection process

HRM departments perform various functions, including talent management, recruitment, and selection, employee development, performance management, compensation and benefits, and labor relations (Noe et al., 2020). However, recruitment and selection (or talent acquisition) are among the most important functions of the HR department as they directly impact the organization's success (Combs et al., 2006). RS involves attracting, screening, and hiring qualified candidates for job positions in an organization (Gennard & Judge, 2019), ensuring that the organization has the right people with the required skills and abilities to achieve its objectives (Collings et al., 2020).In recent years, RS has started integrating AI technologies to increase its effectiveness, as explained next.

1.5 AI use in RS

Recent studies have shown that AI-based recruitment systems can enhance the efficiency and effectiveness of RS. For instance, AI can automate resume screening and candidate matching processes, reducing time-to-hire and improving the quality of hire (Kambur, 2021). Furthermore, AI-based recruitment systems can lower the administrative costs associated with recruitment activities, such as advertisement and candidate communication (Kambur, 2021). AI-based recruitment systems can also reduce bias in the selection process by removing human judgment and subjectivity, leading to more diverse and inclusive hiring outcomes (Black & van Esch, 2020).

AI technologies can eliminate conscious and unconscious bias during the selection process by identifying the most suitable candidates based on their qualifications and experience (Black & van Esch, 2021a). For example, AI can analyze candidates' skills, education, work experience, and other relevant information to identify the best fit for a particular role, regardless of their demographic characteristics, when there is no bias in training data (Black & van Esch, 2021a).

AI-based automation of RS tasks can result in significant cost savings for organizations and enable HR managers to focus on other important tasks. Thus, the integration of AI into RS is an emerging trend that holds tremendous potential to transform RS (Black &

van Esch, 2021). By enhancing the efficiency, effectiveness, and fairness of the RS process, AI can lead to improved business outcomes (Black & van Esch, 2021; Kambur, 2021).

Recently, there is a growing trend toward incorporating AI-based technologies, such as chatbots, robots, and interviewing tools, in various RS functions, including candidate assessments, sourcing, pre-screening, and candidate engagements and communications (Jia et al., 2020). Several prominent organizations, including Hilton, Johnson & Johnson, and Walt Disney, have reported that these technologies have enhanced performance and effectiveness, as reflected by the reduced time-to-hire and cost-of-hire (Cascio, 2018).

In addition to the efficiency gains, AI-based technologies are also expected to enhance the work-life balance of recruitment professionals by automating time-consuming and repetitive tasks, thereby freeing up more time for meaningful activities (Jepsen et al., 2019). The anticipated benefits have motivated strategic leaders, such as CEOs, to invest in AI-injected RS (Liao & Wong, 2021). Consequently, there is a growing interest in incorporating AI-based technologies in RS, which is expected to continue in the foreseeable future (Wang & Wanberg, 2017).

However, integrating AI into the RS poses challenges, such as the risk of perpetuating biased algorithms and the potential negative impact on candidate experience (Black & van Esch, 2021). Thus, HR managers may have specific implications on themselves, especially related to uncertainties and anxiety caused by AI (Suseno et al., 2022). Therefore, HR managers need to carefully evaluate the risks and benefits of AI-based recruitment systems and implement appropriate policies and procedures to ensure fairness, transparency, and accountability in RS.

However, despite the widespread adoption of these technologies, the motivations of RS professionals who are responsible for utilizing AI have been largely overlooked (Hemalatha et al., 2021). RS professionals are considered subject matter experts (SMEs) possessing in-depth knowledge about the RS process through their daily interactions with various stakeholders, such as business leaders, customers, and candidates Collings et al. (2020).

It is, therefore, essential to investigate how AI can achieve optimal outcomes for candidates, business leaders, and RS professionals (Hemalatha et al., 2021). This area of research is still underexplored, even amidst the ongoing industry 4.0 transformation process, and requires further investigation to fully comprehend the potential impact of AI on RS professionals (Keaney, 2021).

To address this first research gap, it is crucial to unpack the phenomena from the RS professional's perspective by adopting an SME-centered approach, thus, this study will generate valuable insights into how AI can be effectively integrated into the RS to benefit all stakeholders involved in the RS process.

1.6 Research Topic

AI has been identified as a potentially transformative technology for RS in HRM. Large organizations, including Amazon, Hilton Hotels, Unilever, and GE, have reported significant benefits resulting from the integration of AI in their RS, such as reduced time and cost of hiring (Davenport & Kirby, 2015). However, research on the potential impact of AI adoption in small or medium-sized organizations is lacking, especially from the perspectives of RS professionals.

Additionally, the technology adoption literature highlights the importance of considering end-users' perspectives, as their acceptance or rejection of new technologies can significantly impact their implementation and subsequent socio-economic benefits (Karahanna et al., 1999). Factors such as end-users perceived benefits, psychological and behavioral phenomena, infrastructure concerns, and other related issues influence technology adoption at the end-user level needs understanding (Venkatesh et al., 2003). Therefore, examining end-users perspectives regarding the use of AI in RS can provide valuable insights into the feasibility of using AI in RS and the necessary managerial interventions required to address underlying issues to achieve strategic HR objectives. Thus, this research aims to address the following research questions:

1) What factors drive AI adoption in RS, and what do recruitment professionals perceive are AI's potential benefits and drawbacks?

2) Under what conditions are the drivers applicable in adopting AI in RS?
3) How and under what circumstances does the use of AI in RS affect strategic HR outcomes?

By addressing these research questions, this study aims to provide strategic insights for the HR sector and strategic leaders, enhancing the adoption and implementation of AI in RS to achieve strategic HR goals.

1.7 Scope of the Study

The scope of this research has been demarcated within boundaries associated with the research areas, research participants, and the theoretical framework, as explained in sub-sections 1.7.1-1.7.4.

1.7.1 Demarcation of the research area

This study falls within the human resource management (HRM) discipline, which encompasses functions such as recruitment and selection, onboarding, performance management, learning and development, rewards management, etc. This research focuses on the recruitment and selection process (RS). RS involves a range of functions, including recruitment planning, candidate sourcing, pre-selection, interviews, and candidate engagement through communication channels. The scope demarcation of this study is visually represented in Figure 1.

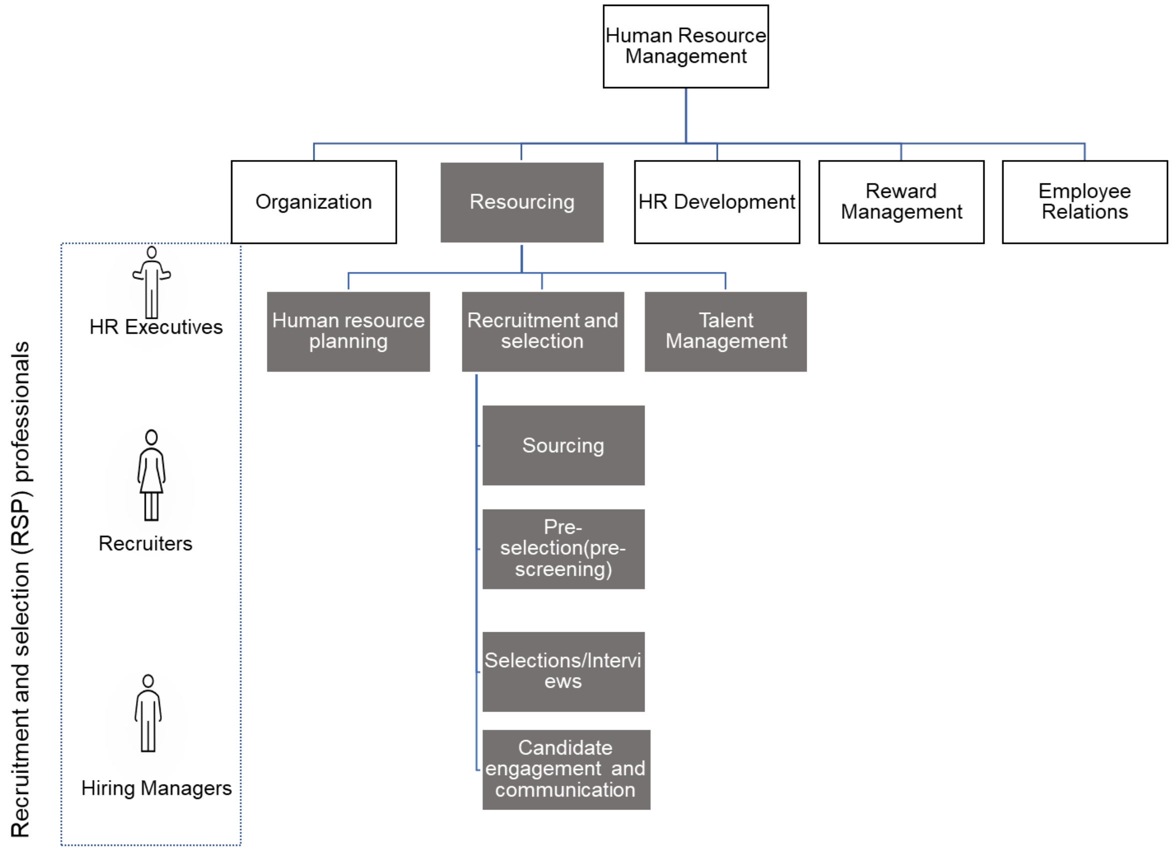

Figure 1: Research scope in RS (highlighted in grey)

1.7.2 Out of scope areas

Given the breadth of HRM functions, the present study is limited to R&S and excludes other functions such as employee onboarding, learning & development, performance management, rewards management, and employee relations. While AI may have potential applications in these other areas of HRM, this research will not address those areas, as they are typically relevant to existing employees of the organization compared to candidates who become employees once the hiring is completed. In contrast, RS is a distinct area of HRM that focuses on identifying and evaluating external or internal potential candidates, making it a unique domain with different stakeholders. Therefore, this research aims to examine the potential impact of AI on RS exclusively.

1.7.3 Demarcation of the research participants

Recruiters, HR managers, and hiring managers play critical roles in RS, and understanding their perspectives on the potential impact of AI on RS is essential. Although the roles in RS vary from organization to organization, recruiters are generally responsible for identifying and attracting potential candidates. In contrast, HR managers oversee the overall recruitment process and manage the organization's HR policies (Azeem & Yasmin, 2016). Hiring managers are often responsible for making final hiring decisions, providing job descriptions, and setting selection criteria (Chen et al., 2020).

In organizations with a centralized HR department, HR managers may take specific roles, including those of recruiters and hiring managers (Budhwar & Debrah, 2013). Conversely, in smaller organizations, especially in organizations where HR departments seldom exist or do not exist at all, hiring managers may typically take on more HR responsibilities, such as sourcing and preselection activities (Lepak & Gowan, 2010). In such cases, the roles of HR managers and recruiters overlap (KPMG, 2016).

To gain insight into the potential impact of AI on RS, it is essential to understand the roles and activities of these three stakeholders during RS processes. This understanding will enable researchers to identify how AI can be used to improve the RS while addressing the needs and concerns of each stakeholder group.

1.7.4 Demarcation of the Literature

While there are many studies that have focused on AI adoption for employees (Leicht-Deobald, U., et al., 2019), the present research is centered on the HRM discipline, with a specific focus on the sub-function of recruitment and selection. Thus, the study aims to explore various aspects related to RS, including its functions, tasks, challenges, opportunities, and evolution, by reviewing the relevant literature. Moreover, the study intends to investigate the use of AI in RS and its implications for HRM. This will critically evaluate empirical studies and predictions related to AI and its impact on RS. Different AI technologies, such as AI chatbots, AI-based interview tools, and AI-based sourcing tools, will be examined in this context.

Furthermore, the study will draw upon technology adoption theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), to understand the adoption of AI in business functions. Emerging theories related to technology adoption will also be studied.

1.8 Contribution of the research

This research addresses the growing need to adapt to emerging technologies and disruptions in the business environment, specifically in the context of AI. By focusing on HRM as a critical business function responsible for managing human capital, this research aims to contribute to various stakeholders in HRM.

Firstly, the qualitative and quantitative research findings will contribute to the academic community by providing new knowledge and understanding of the impact of AI on HRM and recruitment and selection processes. The same knowledge will contribute to the HR leaders' understanding of the phenomena of AI adoption in RS.

Secondly, the research will contribute by developing an adoption framework for AI-RS, which could be used as a theoretical foundation to study and understand AI and similar emerging technologies in the RS area.

Thirdly, it will provide empirical evidence to business functions and strategic leaders on the potential impact of AI on RS, helping them to make informed decisions about their future HR strategies.

Fourthly, it will guide government and regulatory bodies in developing policies and regulations related to AI in HRM, ensuring that ethical and legal concerns are addressed.

Fifthly, it will offer practical insights to AI technology developers and entrepreneurs, enabling them to create more effective AI-based recruitment tools that can better meet the needs of organizations.

Lastly, it will offer guidance and insights to HR professionals on effectively integrating AI into their recruitment and selection processes, improving efficiency and accuracy while maintaining a positive candidate experience.

1.8.1 Theoretical contribution

This research develops and tests a conceptual model (AI-RS) to investigate the adoption of AI in the RS process of human resource management (HRM). Although prior studies have developed theoretical models to explore technology adoption in HRM, the potential disruption of AI in the era of Industry 4.0 necessitates a multifaceted examination of the phenomenon, incorporating organizational, process, and human behavior perspectives (Schramm-Klein & Morschett, 2019). Consequently, the proposed conceptual framework adopts an end-user perspective, specifically the RS professional, which has not been previously adequately explored (Ryan et al., 2019).

The proposed conceptual model synthesizes constructs from UTAUT and AI operations models with new constructs applicable to RS. These new constructs comprise trust in AI and the recruitment phase and the HR outcomes specific to the AI and RS function of HRM (Ejaz, 2015; George et al., 2021; Gumbs et al., 2022; Jirawuttinunt, 2015).

The conceptual model also incorporates the viewpoint of various job functions, including recruiters, hiring managers, and HR executives. More importantly, it analyses under what circumstances will AI be most effectively applied, such as the experience of the RS professionals and the hiring volumes. These conditions will predict when HR outcomes are achievable and not, providing valuable managerial implications.

Moreover, the proposed framework assesses the influence of AI usage on HR outcomes, such as time-to-hire, cost-of-hire, quality-of-hire, and retention rates, which may be crucial to accomplishing strategic HR goals (Sharma, 2021). Therefore, the proposed conceptual model may provide an understanding of AI adoption in RS and its effects on HR outcomes.

1.8.2 Contribution to RS and AI

RS is a crucial aspect of HRM as they enable organizations to attract and acquire the necessary human capital to achieve their strategic goals. With the advent of AI, RS is rapidly evolving with the incorporation of AI to create a "*smart recruitment*" process. According to Noe et al. (2020) including AI in RS can potentially bring about significant changes. Additionally, AI is predicted to automate several recruitment functions, such as candidate sourcing and screening, within the next five years (Bullhorn, 2018)

The potential impact of AI on the RS has led to an interest in understanding the phenomenon. To address this interest, researchers have investigated how AI is changing

RS and the implications of such changes for HRM. For example, in a study on AI and recruitment, Kuhn et al., (2021) explored the impact of AI on recruitment processes and identified several challenges organizations might face in adopting AI. This triggers the requirement of exploring and understanding these challenges so that mitigation action can be identified if challenges are understood. Similarly, Hong et al. (2020) examined the effect of AI on the fairness of recruitment processes and found that while AI could increase objectivity, it could also perpetuate bias. Such insights trigger the questions of how AI contributes to unfairness and bias and how it should be addressed. Thus, more research is needed to take a nuanced approach by examining under what circumstances AI can be effectively applied.

This research will identify the potential benefits and limitations of AI in RS, highlighting areas where it can be most effective and where it may not be applicable. It will also explore the implications and barriers to AI adoption in RS. Additionally, this study addresses a gap in the existing literature by examining the conditions that facilitate successful AI adoption and benefit realization in RS.

Insights gained from this research on the potential benefits and limitations of AI in the RS will be essential in integrating Industry 4.0 into business processes (Ghadi et al., 2019). These insights will aid in determining the roles that AI and humans can play in developing new business processes together that produce optimal outcomes.

Additionally, this study's findings can be extended in future research to explore the social and ethical implications of AI adoption in RS, including the impact on the workforce, government regulation of AI, and the need for accountability and transparency (Yaghoubi et al., 2021).

The findings of this study may also be relevant to other industries and business sectors, as AI adoption is becoming increasingly ubiquitous across various domains. The insights and recommendations generated from this research can be valuable for policymakers, industry leaders, and organizations seeking to leverage AI to enhance their business processes and drive innovation.

1.9 Significance of the Research

This study is significant in developing an AI-RS model to drive the effective use of AI and RS in achieving HR outcomes. It does so by examining the perspectives of HR professionals and by taking a nuanced approach to uncover circumstances when AI will be most applicable. Prior research conducted by Nawaz (2019) identified limited empirical literature on the use, adoption, barriers, and drivers of artificial intelligence (AI) in the recruitment and selection process. Therefore, the current study represents a significant contribution to the academic field of HRM.

Additionally, this study contributes to the existing knowledge on technology adoption by extending the Unified Theory of Use and Acceptance of Technology (UTUAT) theory by integrating RS factors and HR outcomes.

Therefore, this research develops and contributes a theoretical model (AI-RS) which can be used to understand AI adoption in HRM. The research findings also fill a gap in the existing literature on HRM and AI by providing a model explaining how AI adoption in the RS can be measured and attributed to HR outcomes.

1.10 Thesis structure

This thesis is organized into several chapters. The first chapter introduces the research, including background, motivation, and key research questions. It also outlines the scope, intended contribution, and significance of the research.

The second chapter focuses on the literature review investigating previous empirical research on RS, AI, and its application in RS. The literature review aims to identify gaps in the existing literature relevant to the research topic.

The third chapter is focused on technology adoption in RS, relevant theoretical frameworks and previous studies, and the insights generated from those studies relevant to AI adoption in RS.

The fourth chapter provides an overview of the proposed theoretical framework developed (AI-RS) to study AI in RS, which is the objectivity of this research.

The fifth chapter presents the qualitative research design in detail, including the chosen method of semi-structured interviews, the approach to data collection, data sources, and data analysis methods.

The sixth chapter presents the qualitative research results, including the demographic data in detail, including emerging themes. The sixth chapter also provides the results related to the main constructs and moderating factors influencing the relationships between main constructs and the user behaviors and outcomes of AI use in RS. The qualitative results obtained will be used in the quantitative research design, as presented in Chapter 7.

The seventh chapter presents the design considerations of the quantitative research, including the chosen research method of survey, the data sources identified, the data collection approach, and the data analysis approach.

Chapter eight provides a detailed presentation of the quantitative research results, including the statistical analysis approach of structured equation modeling. The chapter details the model fit to the data and the hypothesis testing results.

The final chapter, 9, discusses the overall research results and answers the research questions. The chapter also outlines the theoretical contributions and managerial implications. Additionally, the chapter provides limitations of the research and suggestions for future research. This structure is illustrated in Figure 2 below.

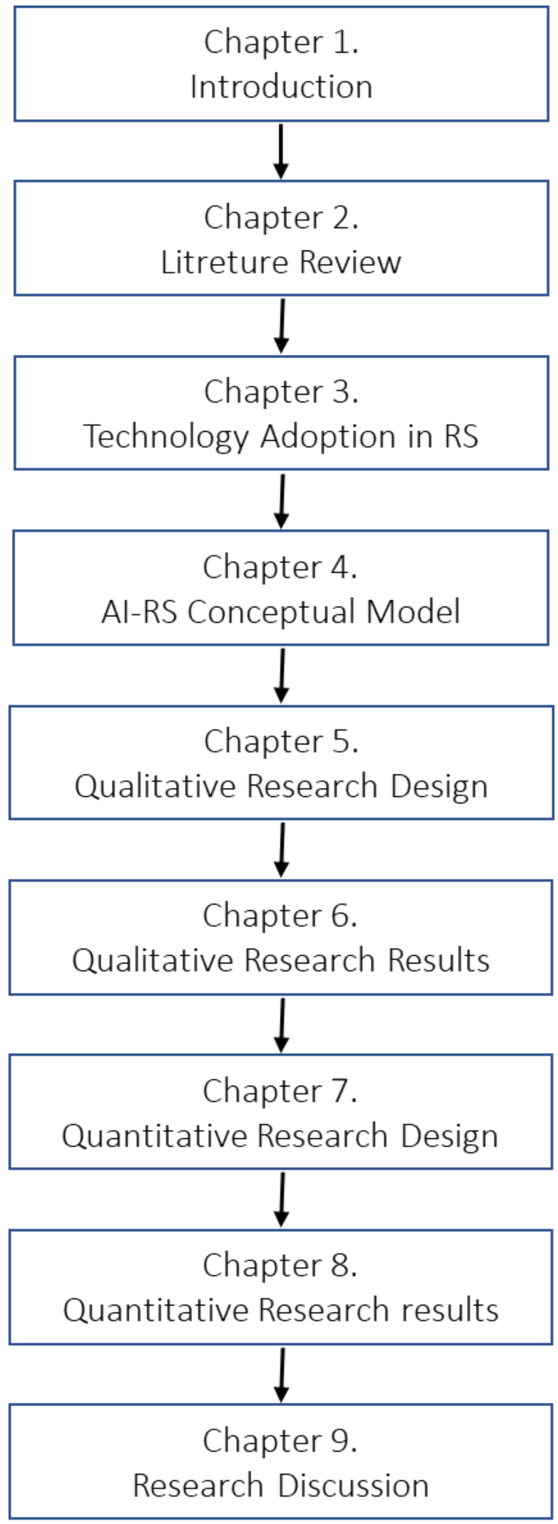

Figure 2: The structure of the chapters

1.11 Summary

This study examines the adoption of AI in RS of HRM. The research focuses on the perspectives of recruiters, hiring managers, and HR executives as key stakeholders in RS. The study aims to identify drivers and barriers to AI adoption in RS and its impact on HR outcomes. A conceptual model of AI-RS, an extension of UTAUT-OM, is used to comprehend the factors influencing AI adoption. Three research questions: 1). What factors drive AI in RS, and what do recruitment professionals perceive are AI's potential benefits and drawbacks? 2). Under what conditions are the drivers applicable in adopting AI in RS? 3). How and under what circumstances does the use of AI in RS affect strategic HR outcomes? are formulated to understand the drivers, conditions, and circumstances of AI adoption in the RS and its impact on strategic HR outcomes. A mixed-methods approach was used, including interviews and a survey of RS professionals. The study contributes to developing a theoretical model to drive effective AI adoption in RS.

CHAPTER 2

Recruitment Selection & AI

2.1 Introduction

This chapter aims to analyze literature at the intersection of RS and emerging technology in HRM, focusing on AI. The chapter is structured into four sections, beginning with a review of the literature on RS, including its evolution, traditional methods, and challenges. The concept of AI in the context of RS is explored in the second section, including its definition, characteristics, and potential benefits for HRM. The third section examines the applications of AI in RS, such as automated resume screening, chatbots for candidate communication, and predictive analytics for candidate selection. The implications of AI use in RS, including ethical and legal issues related to bias and privacy, are discussed in the fourth section. Finally, research gaps are identified, and areas for future study are summarized. Therefore, this chapter provides insights into how AI is shaping the future of RS and its impact on HRM.

2.2 Recruitment and selection processes

RS processes are vital in identifying the best candidates to meet an organization's human capital needs (Ameen et al., 2021). Thus, RS significantly impacts organizational growth and performance (Dhameeth et al., 2021). Therefore, most organizations prioritize implementing strategies to attract and identify the most suitable candidates for their organizations (van Esch et al., 2019a).

RS includes various functions: recruitment planning, sourcing, pre-selection, selection, communication, and engagement with candidates and other stakeholders.

Armstrong (2015) describe 10 RS stages, including defining requirements, attracting candidates, screening applicants, interviewing, testing, assessing candidates, obtaining references, offering employment, and follow-up. RS can be complex and multifaceted, as Armstrong (2015) 's comprehensive list of RS stages implies. Figure 3 illustrates some of the key stages of RS.

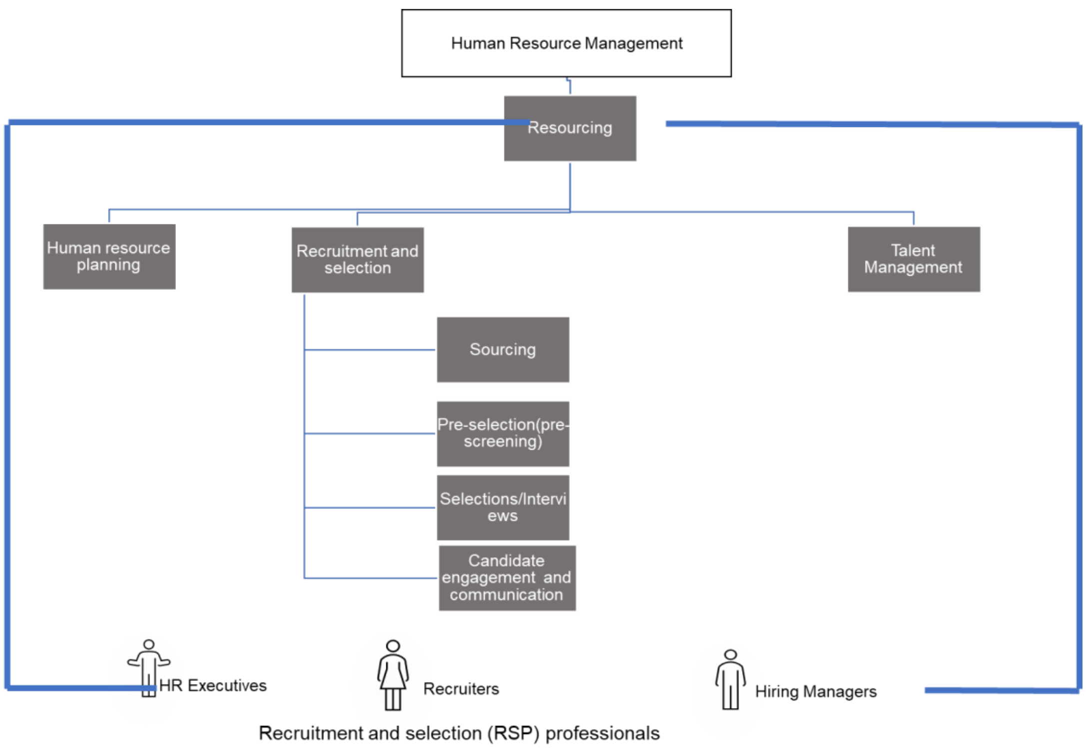

Figure 3: Recruitment and Selection Process

Each function consists of sub-functions and associated tasks, as explained in the next sub-section.

2.2.1 Recruitment planning

Recruitment planning constitutes an integral facet of RS, which plays a pivotal role in laying the groundwork for the efficient recruitment of candidates (Kanagavalli et al., 2019). It involves several activities, such as specifying recruitment prerequisites, ascertaining sourcing strategies, outlining job descriptions, and determining financial benefits (Kanagavalli et al., 2019; Hallam, 2009). During the pre-planning phase, there is a relationship between the recruitment process and the organization's strategic objectives. This relationship ensures that appropriate candidates are selected for suitable roles within the specified timeline (Thebe, 2014). Additionally, recruitment pre-planning enables identifying skill deficiencies, analyzing turnover and retention rates, and evaluating the efficacy of sourcing channels, facilitating informed recruitment-related decisions (Kanagavalli et al., 2019). Salima et al., (2020) suggest that pre-planning allows organizations to analyze their historical data on employee turnover and retention rates. This information can help recruiters identify any patterns or trends affecting the organization's ability to retain talent and adjust their recruitment strategies accordingly. According to Ghazali et al., (2021), recruitment pre-planning helps to identify the skills and competencies required for specific roles within the organization. By doing so, recruiters can develop targeted recruitment strategies aligned with the organization's strategic objectives. Thus, recruitment pre-planning represents a fundamental step in RS, facilitating the effective and efficient accomplishment of organizational objectives through recruitment activities.

2.2.2 Sourcing

Sourcing represents a crucial step in RS, which involves identifying potential candidates and attracting them to apply for open positions within the organization (Dahshan et al., 2018). The effectiveness of RS is highly dependent on the recruitment or sourcing channels utilized, which can significantly impact the number and quality of candidates who apply for the job (Orlitzky, 2007). Although traditional channels such as newspapers, magazines, and radio or television advertisements have proven effective in the past, web-based job advertisements (such as Seek) and platforms such as LinkedIn and Facebook have emerged as dominant recruitment channels in recent years (Koch et al., 2018).

With over 774 million users in over 200 countries as of 2021, LinkedIn has become a prevalent choice for recruiters, with its usage in recruitment increasing steadily (Brown (2021). According to statistics, 81 job applications are submitted every second, 210 million job applications are submitted every month, and 4 people are hired every minute on LinkedIn (LinkedIn, 2021; Becton et al., 2019; Suen, 2018; Hassan et al., 2019).

Other sourcing channels, such as referrals, recruitment agencies, recruitment events, and hiring through colleges, also exist and can be effective depending on the type of job (MUSCALU, 2015). The choice of sourcing channel(s) is thus critical in ensuring that the recruitment process is aligned with the organization's objectives and goals. Consequently, sourcing is an indispensable element of the RS as it lays the foundation for identifying and selecting the most suitable candidates to fulfill the organization's human capital requirements.

2.2.3 Pre-screening (or shortlisting)

The pre-selection or pre-screening process is an essential step in RS that involves reducing the number of applicants to fewer candidates for further evaluation. This process is often tedious and time-consuming due to the large number of applications received by recruiters for a particular job vacancy (Chapman & Webster, 2003; Grundner & Neuhofer, 2021; Koo et al., 2020); Sheehan et al., 1998). Black and van Esch (2020a) note that it can take an average of 40 minutes to review a single resume and determine if the candidate should be selected for the next stage.

Traditionally, the pre-selection process involves screening, ranking, and searching for supporting information (Esawi & Ashby, 2003)However, the manual and repetitive work involved in this process often results in tiredness or mistakes associated with deselecting the right candidates, which is not the desired outcome as it eliminates the best candidate being selected, selecting the wrong candidate (Esawi & Ashby, 2003). Various techniques like e-recruitment-based filtering criteria have been used to overcome these challenges as an alternative to manual screening processes. However, these e-filtering-based screening processes have limited effectiveness due to inconsistent CV formats and structures and a lack of contextual information in resumes (Esawi & Ashby, 2003).

Despite the limitations of e-recruitment-based screening processes, the use of automated techniques like natural language processing (NLP) and machine learning (ML) algorithms have shown promise in improving the efficiency and effectiveness of pre-screening processes (Li et al., 2021). These techniques can be more efficiently analyze resumes and identify relevant information, such as skills and experience, and rank candidates based on their suitability for the job.

2.2.4 Interviews

While RS varies from organization to organization, the next step in the RS is typically to interview to select the right candidate/s from the shortlisted pool of potential candidates (Barclay, 2001). This step is taken after the shortlisting of candidates. The interviews aim to evaluate the job-related and person-organizational fit of the candidates by assessing their knowledge of the job-related subject, communication skills, ability to convey information concisely, teamwork skills, and more (Esawi & Ashby, 2003).

The interview process often includes multiple tests and various rounds of interviews, which may differ based on the job type and selection criteria (Bernthal, Wellins, and Noe et al. (2020). Dearnley (2005) found that some companies use cognitive ability tests and personality assessments to predict job performance, while others prefer situational judgment tests and behavioral interviews. Furthermore, the selection process for different positions may require different tests and interviews, which can be multiphase-like situations or behavioral (Blumer, 2012; Metcalf et al., 2019).

The situational questions ask the candidates to provide examples from their past experiences, while behavioral questions assess how they would react in future situations (Esawi & Ashby, 2003). This interviewing process is evolving, and various types of interviews are emerging. Another emerging test is coding tests for software engineers, where candidates are asked to write a piece of code or a complete program within a given time frame (Wyrich et al., 2019). Such tests evaluate criteria like the candidate's depth of knowledge of specific programming languages like C++ or Java and software engineering standards. This suggests that assessment criteria and how the assessments are conducted are subject to the job being hired and various other factors like the interviewers. Thus, the ability to utilize AI is subject to AI being able to conduct these tests.

Also, the interview process involves different stakeholders in addition to the candidate, such as subject matter experts, hiring managers, business unit leaders, recruiters, HR managers, and senior executives like the chief executive officer or chief technology officer, depending on the role (Blom et al., 2015). As a result, this process requires coordination amongst interview panel members and candidates and can take a long time to complete, potentially even several months. Thus, benefits accrue to the organization and the candidate if AI can replace some of these tests.

2.2.5 Candidate engagement and communication

Candidate engagement and communication are crucial elements in RS as they can significantly impact talent acquisition rates (Ameen et al., 2021; Ross & Beath, 2002). Recruiters' language and warmth displayed during the engagement process can influence candidates' perceptions of the organization (Keaney, 2021; Suen, 2018). Consequently, organizations are making efforts to enhance communication and engagement with candidates (Athanur et al., 2021). However, providing the appropriate information to candidates at different stages of the recruitment process can be challenging, as candidates expect different types of information, such as organizational details, job descriptions, interview process, assessment criteria, and interview updates on the progress, among others (Palenius, 2021).

Lack of proper candidate engagement and communication can lead to negative effects, including reputation damage, a low number of candidates in the pool of applicants, and a lengthier recruitment cycle (Miles & McCamey, 2018). Thus, despite the critical role of candidate engagement and communication in attracting new candidates, it presents several challenges that must be addressed to ensure successful RS.

2.2.6 Issues in RS

Recruitment pre-planning is a crucial but challenging phase in RS, and organizations often neglect it due to its complexity and cross-industry challenges (Zoller, 2018). According to Hallam (2009), the lack of workforce planning can significantly impact ongoing and future projects, making it difficult for organizations to operationalize their strategies effectively.

The sourcing and pre-screening phases of recruitment also pose several challenges. A shortage of HR professionals to handle demanding recruitment needs can result in an overwhelming volume of applications that recruiters must process in a limited time frame (Felzmann et al., 2019; Torres, 2017). This situation can lead to human bias or errors, more generally in candidate pre-screening and selection, resulting in the wrong hire and/or negative candidate experience (Lim et al., 2015).

Furthermore, recruiters often face challenges in accurately assessing candidates, leading to the selection of the wrong candidate. Some recruitment tests, such as psychometric tests, lack validity and reliability (Armstrong, 2015; Baraniuk, 2015). Additionally, candidates may provide false information on their resumes, leading to the wrong hire and increasing the cost of hiring (Combs et al., 2006; Melchor, 2013).

While technological advancements have significantly impacted the recruitment process (see Chapter 1, section 3), the effectiveness of these technologies remains debatable, as explained by Lochner et al. (2021), where different channels and technologies used in recruitment have no impact on the recruitment and organizational growth. Some organizations have adopted artificial intelligence (AI) and machine learning (ML) to automate recruitment processes, such as candidate pre-screening, and reduce the burden on HR professionals (Aljanabi et al., 2023). However, these technologies can still be biased, and their use requires careful consideration to ensure accuracy and fairness in the selection process (Lim et al., 2015).

2.3 The RS evolution – with technology and AI

RS has undergone significant evolution over time. Historically, RS was primarily manual, involving paper-based methods such as newspaper advertisements and resume submission to recruiters (Armstrong, 2015). However, such methods were time-consuming and inefficient, leading to the emergence of e-recruitment that utilized computer-assisted technologies such as Applicant Tracking Systems (ATS), online job platforms, and online assessments (Mohammad, 2020; Abia & Brown, 2020; Furnham, 2008). Digital technologies have improved the productivity and efficiency of the recruitment and selection process for both candidates and organizations (Narin et al., 2022).

More recently, a new phase of RS has emerged, with the introduction of AI technologies into various phases of RS (Wangthong & Suksanchananun, n.d.). AI-based chatbots, candidate recommendation tools, communication tools, and interviews have been introduced, with specific AI technologies such as machine learning, chatbots, and predictive technologies improving the efficiency and productivity of RS (Hunter et al., 2017). This phase is often referred to as "smart recruitment" (Wangthong & Suksanchananun, 2023). It is also known as virtual recruitment or v-recruitment due to the fully automated RS functions with AI (Mhadgut et al., 2022). This technology leverages facial recognition algorithms to authenticate candidate identity and natural language processing techniques for conducting interviews, and V-recruitment has demonstrated a high level of accuracy, with facial recognition-based candidate identification achieving a 96% accuracy rate, suggesting that in-person interviews may become unnecessary (Mhadgut et al., 2022). As such, the following sub-section explores a general study on AI that aligns with this study.

2.4 Artificial Intelligence (AI)

AI is a set of technological components that can process and act on data to simulate human intelligence (Tabassum et al., 2023). Unlike other computer-based technologies, AI can develop its own knowledge, like human cognitive ability. This is achieved through various technologies, including machine learning, natural language processing, neural networks, and computer vision (Kaplan & Haenlein, 2019b).

Neural networks map human neurons and their functions into computer systems using fuzzy logic and case-based reasoning (Mackie, 2018). This technology enables computers to learn from data and predict the relationships between inputs and outputs. On the other hand, natural language processing allows computers to analyze human language and react appropriately. This has been likened to building human ears and the brain inside the computer(Kietzmann & Pitt, 2020).

Computer vision is another technology used in AI, akin to building human eyes and the brain inside computers. It enables computers to recognize still, video, or live images and make meaningful connections to generate appropriate reactions (Huang et al., 2021). Finally, machine learning enables computers to process large amounts of data, understand patterns, and develop new knowledge (Huang et al., 2021; Raspopov & Belousov, 2020). This is like developing human cognitive abilities inside computers.

Combining these technologies results in a complex system that can learn, reason, and perform tasks like humans. Figure 4 illustrates the constructs of AI and how they work together to simulate human intelligence.

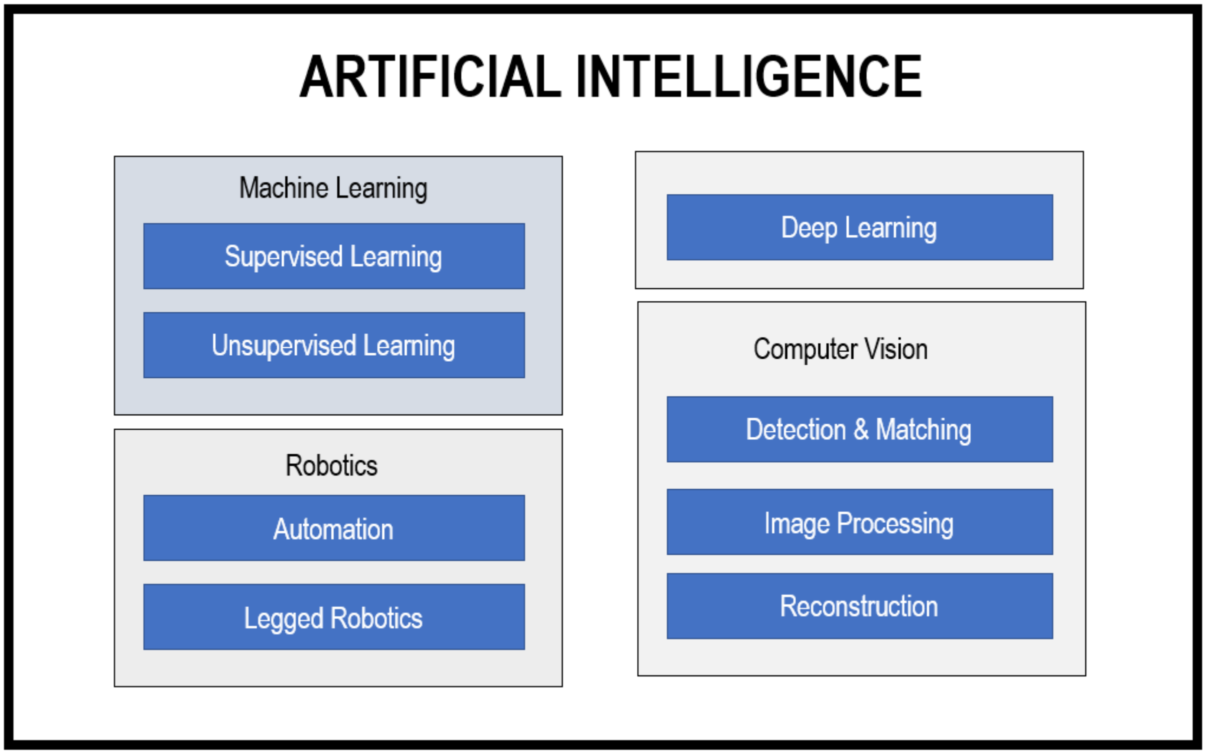

Figure 4: Categories of AI

The application of AI in various products and services has been a significant trend among organizations like Microsoft, Google, and Amazon, which have invested heavily to maximize their capabilities (Ghandour & Woodford, 2019). For instance, Microsoft introduced an AI-based chatbot called 'Tay' that could interact with Twitter users in a human-like manner (Du & Xie, 2021). Other AI experiments, such as IBM Deep Blue and Google AlphaGo, have demonstrated their ability to surpass human cognitive abilities by defeating human champions in games, including Jeopardy (Raspopov & Belousov, 2020) and Go (Szu et al., 2018). These examples demonstrate that AI capabilities are either on par or superior to human cognitive abilities (Lake et al., 2016; Martínez-Plumed et al., 2021).

As a result, AI capabilities are being applied in various industries, like healthcare, education, and retail, among others. The drivers that influence the application of AI in various sectors include the need to improve efficiency, increase productivity, reduce costs, and enhance customer experiences (Du & Xie, 2021), and some of these drivers in different sectors are exhibited in Table 1.

Driver	Outcome expected	Business function	Business stream	Reference
Economic	Innovation	Academic	Driving innovation in research	Khan et al., 2018
	Productivity	Business management	Efficiency in business processes	Fantinato, 2015a
		Manufacturing	Production planning	Guo et al., 2011
	Cost	Healthcare	Efficiency in business process	Khan et al.,2018
			Reducing equipment cost	Patrico D.I, et al., 2018
			Reducing human interaction	Patrico et al., 2018
Social	Customer Experience	Business management	Multiparty resource integration	Kaartemo & Helkkula, 2018
Productivity	Accuracy	Healthcare	Reducing human errors in disease assessments	Patrico et al., 2018
	Efficiency	Transportation	Reducing traffic congestion	Namazi & Lu, 2019
	Decision making	Healthcare	Assisting clinicians during patient assessments	Larnajo et al., 2018
Social	Sustainability	Agriculture	Sustainable agriculture processes with consumer demands	Patrico D.I, et al, 2018

	Wellbeing	Healthcare	Decreasing the workload of health care workers	Kachouie et al., 2014

Table 1: AI application drivers in different businesses

Similarly, strategic leaders in HRM have demonstrated interest in the integration of AI into HRM practices, particularly in relation to RS (Marler & Parry, 2016; Shen & Zhao, 2021), as the use of AI in RS has the potential to increase the efficiency, accuracy, and objectivity of recruitment processes, leading to improved organizational performance (Cappelli et al., 2021). The key performance indicators (KPIs) that HRM strategic leaders aim to achieve by incorporating AI into RS include reduced time-to-hire, improved candidate quality, increased retention rates, and decreased recruitment costs (Dhar, 2021; Gupta et al., 2022; Yadav et al., 2021). These outcomes are explained in the following subsection in detail.

2.5 HR Key performance indicators (Outcomes)

The effectiveness of RS is often measured using various key performance indicators (KPIs) related to RS (Hmoud & Laszlo, 2019). The literature suggests several KPIs or metrics, including time to hire (TTH), cost of hire (COH), quality of hire (QOH), retention rates (RR), and diversity targets (Colovic & Williams, 2020; Howard, 2020; Montoya & Rivas, 2019; Y. S. Lee et al., 2019). These KPIs are discussed in detail in the next sub-section.

2.5.1 Time to hire (TTH)

The TTH is defined as the ratio between the time taken for every hire made for a specific period and the total number of hires made for the same period (In & State, 2020). TTH can vary depending on the type of job, but on average, it can range from a few days to a few months (Li et al., 2021). According to a recent study, US agencies report an average TTH of 25 working days to fill a vacancy (Li et al., 2021). However, in some cases, it can take several quarters, as in the case of a government agency that took 310 days to fill a specific vacancy (In & State, 2020).

Several factors can contribute to increasing TTH, such as skills shortages, reduced talent pool, (poor) organizational branding and reputation, competition from other companies, candidates' workplace preferences, and workforce shortages in the HR department (Howard, 2020; In & State, 2020; Laurim et al., 2021). Increasing TTH can have significant adverse organizational consequences, such as higher recruitment costs, reduced productivity, and negatively impacting the employer's reputation (Zhang et al., 2021). Therefore, reducing TTH has become a crucial goal for many organizations, and HR departments are implementing various strategies such as automation, streamlining processes, and utilizing recruitment technology, including AI, to improve their recruitment efficiency (Laurim et al., 2021; Li et al., 2021).

2.5.2 Cost of hire (COH)

In organizational settings, the cost of hiring new employees is crucial as it can significantly impact the organization's performance and growth (Faisal & Naushad, 2021). These costs include expenses such as sourcing and advertising costs, referral bonuses, agency fees, employee relocation or visa fees, and onboarding and training costs which are considered direct costs (Milkovich & Newman, 2017). The cost of hiring may vary depending on the organization, the type of job being hired, location, or country - for instance, the cost of hiring is generally lower in countries like the Philippines or India compared to countries like the UK or USA (DILI et al., 2022).

In addition to the direct costs associated with hiring, the cost of hiring also includes indirect costs, such as the time spent by HR personnel and hiring managers on hiring, which can be a significant cost (Breaugh, 1992). It also includes time for reviewing resumes, conducting interviews, and making hiring decisions. Moreover, it also includes lost productivity during the hiring process, including the time the position was vacant and the time it takes for the new hire to become fully productive (Rynes et al., 1991). Thus, organizations must consider the direct and indirect costs of hiring new employees.

Given that hiring can be expensive, with some organizations spending thousands of dollars per each hire (Griffin, 2018), organizations are constantly focusing on reducing the cost of hiring (Black & van Esch, 2021). For example, Google was estimated to spend around \$2,000 to \$4,000 on each employee it hires (Griffin, 2018), which has increased to 29,000 in 2019 (CNBC,2019), while IBM was estimated to spend approximately \$4,000 to \$6,000 on each employee it hired in 2012, and Microsoft was estimated to spend around \$12,000 per hire in 2011 (Stice et al., 2012; Haycock,2022). When organizations are required to hire several thousand employees in a year, the cost of hiring can quickly add up to millions, making it crucial for organizations to focus on reducing COH (Black & van Esch, 2021).

2.5.3 Quality of hire (QOH)

The concept of quality of hire is an essential metric that determines the value and effectiveness of newly hired employees and their ability to meet the expectations and needs of an organization (Collings et al., 2020). Collings et al. (2020) demonstrated that quality of hire is positively related to job performance, employee engagement, and retention rates; organizations with a higher quality of hire also have a more positive impact on the overall enterprise performance. Also, Sartain and Schumann (2016) emphasized the significance of aligning the definition of quality of hire with an organization's strategic objectives. The authors suggested that the quality of hire should be defined based on job-specific competencies, skills, and cultural fit.

Moreover, (Hmoud & Laszlo, 2019)revealed that hiring quality is a significant predictor of job performance, and the quality of the selection process is positively related to the quality of hires; thus, poor practices lead to poor quality of hires. For example, Wilk & Cappelli (2006) investigated the impact of unconscious bias on the quality of hire and found that unconscious bias can lead to poor hiring decisions, resulting in a lower quality of hire. The authors suggested that organizations should implement strategies to reduce unconscious bias in RS, such as blind resume screening and structured interviews. Thus, the quality of hire is a critical metric that impacts the success of an enterprise.

To improve the quality of hire, organizations should focus on developing effective recruitment, selection, and placement processes, minimizing human errors, and reducing unconscious bias (Collings et al., 2020). Moreover, organizations can design and implement training and development programs that provide new hires with the required skills and knowledge to do their job effectively (Cox & Blake, 1991). Finally, organizations can define hiring quality based on their specific strategic objectives and cultural fit (Breaugh, 1992; Shet & Nair, 2022).

2.5.4 Retention Rates (RR)

Retention rates are a critical performance indicator for organizations as they can significantly impact organizational and financial performance (Jiang et al., 2012). According to Boxall and Purcell (2011), higher retention rates can lead to higher employee commitment and engagement, resulting in improved organizational performance. In contrast, lower retention rates can increase hiring demands, increase recruitment and training costs, and decrease productivity (Tanwar & Prasad, 2016).

Organizations have implemented various strategies to increase retention rates, including providing competitive compensation and benefits packages, professional development opportunities, and opportunities for career growth (Boxall & Purcell, 2011; Wright & McMahan, 1992; Schuler & Jackson, 1987). These strategies help employees feel valued and invested in their careers, leading to higher levels of job satisfaction. In addition, hiring the right candidates for the right job can also contribute to higher retention rates, as employees are more likely to stay in a job that aligns with their skills and interests (Boxall & Purcell, 2011).

Research has also shown that a positive organizational culture can increase retention rates. According to a study by Hartog and Verburg (2019), a positive corporate culture characterized by high levels of trust, support, and employee involvement can increase employee retention by creating a sense of belonging and loyalty (Hartog & Verburg, 2019). Similarly, a study by Aleem et al, (2020) found that employees who perceived their organization as having a strong culture were more likely to stay with the organization long-term (Aleem & Bowra, 2020). Thus, retention rates are a critical measure of organizational success. Organizations should also implement various strategies to improve retention rates, including providing competitive compensation and benefits packages, professional development opportunities, opportunities for career growth, and creating a positive organizational culture.

Although HR outcomes such as reducing time to hire, reducing the cost of hire, and increasing retention rates are often prioritized in organizational HR strategic goals (Barua, Mukherjee, & Gupta, (2019), the adoption of AI is becoming a strategic means of achieving these objectives, as elucidated in the subsequent sub-section.

2.6 AI and HR outcomes

The utilization of AI has become increasingly prevalent within the field of HR and RS (Holford, 2020). Wang and Chen (2018) conducted a study on the application of AI in RS and reported that AI has the ability to aid HR professionals in identifying suitable candidates, reduce recruitment time and expenses, and enhance the quality of hire. Additionally, using AI in RS can decrease human bias and increase diversity in the hiring process.

Furthermore, Riggio & Tan (2017) examined the use of AI in predicting job performance and found that AI can accurately forecast job performance based on data in resumes, job applications, and social media profiles and similar. This can lead to improved hiring decisions and an overall increase in the quality of hire. Prentice et al., (2020, investigated the use of AI in employee retention and concluded that AI could help to identify at-risk employees and develop strategies to retain them(Prentice & Nguyen, 2020). Also, the authors found that AI can also analyze employee feedback and sentiment to enhance employee engagement and job satisfaction, which ultimately can predict retention rates. Thus, the incorporation of AI in HR can potentially elevate the quality of hire and increase retention rates while simultaneously reducing recruitment expenses and increasing efficiency in the RS. For example, Kupfer et al., (2023) argue that AI-powered recruitment systems can accurately analyze resumes and social media profiles to identify the most qualified candidates for a job, reducing the time and effort spent reviewing resumes and screening applicants(Woods et al., 2020). Similarly, Koh et al., (2020)suggest that AI algorithms can process large volumes of data from various sources, such as job postings and candidate profiles, to match candidates with the right job requirements, thus improving the quality of hire.

Moreover, AI can enhance the candidate experience and reduce recruitment costs by automating routine tasks, such as scheduling interviews and sending reminders, freeing up recruiters' time to focus on higher-value activities, such as conducting interviews and building relationships with candidates (Robertson & Thangaratinam, 2020). According to PwC (2018), AI-powered recruitment systems can also analyze data on recruitment sources, job postings, and applicant tracking to optimize recruitment strategies and reduce recruitment costs.

Therefore, it can be expected that RS professionals will be more inclined to adopt AI to achieve these HR outcomes. The following sub-section examines how RS professionals have used AI in the RS function.

2.7 AI use in RS

The implementation of AI in RS is expected to reduce the manual workload of HR professionals, as AI is being applied in various stages and functions of the RS process. Table 2 provides examples of companies using AI technologies in their RS process.

AI product name	URL	Application of AI	Companies using the specific technology
Fetcher	www.fetcher.ai	By incorporating AI technology alongside human expertise, organizations can establish an internal team to monitor their candidate database and quickly source diverse, highly qualified candidates. Automated email centers, robust analytical dashboards, team tracking, and individual performance metrics can enhance recruitment processes and improve overall outcomes.	Sony Music, Velcro, Maersk, Getty images, Drone deploy, Lyft

XOR	www.xor.ai	Chabot as a modern communication tool, XOR connect, XOR apply, XOR video, and live chats in career fairs	McDonald's, Exxon, Manpower, MolGroup, MARS
Hiretual	www.hiretual.com	AI-powered talented data system, AI sourcing, real-time data to match the workflow, powerful diversity hiring.	Nike, Intel, continental, Ceridian, Novo Nordisk, Wayfair
Eightfold	www.eightfold.ai	AI-powered talent management, acquisition, development, and diversity platform. Automatically update the information from organization ATS, HRIS, and CRM. Deep Learning technologies to evaluate internal and external candidates	Tata Communications, Nutanix, Dolby, Booking.com, Dexcom, Micron, Netapp, Bayer
Pymetrics	www.pymetrics.ai	Uses behavioral science and assessment to erase all human bias effects and audited AI technology with talent algorithms in the Pymetrics environment.	Colgate Palmolive, Kraft Heinz, Boston Consulting Group, McDonald's, PWC
Textio	www.textio.com	AI-integrated writing platform free from gender, age, and ability biases, expanded language performance data insights.	McDonald's, Atos, Zillow Group, nestle, Atlas Sian, Micron.
My interview	www.myinterview.com	Could be integrated into HR System or used as a standalone product.	Salesforce, greenhouse, zappier, pinpoint, formstack, Hubspot
Humanly	www.humanly.io	AI-powered chatbot designed for midmarket companies, candidate screening, scanning, reference checks, and follow-up.	Swiss monkey, Inyore, Brady, Armoire, NexGent, Guide, The Klienbatch group

Paradox	www.paradox.ai	Make job applications easier, fast, and mobile. Schedule interviews along with reminders in different languages. Reduce administrative tasks.	Wendy's, go wireless, Disney, McDonald, Unilever
Talkpush	www.talkpush.com	Uses CRM-supported communication tool (Chatbot) for both voice and chat, a customized pipeline for different roles	Amazon, Walmart, McDonald's, [24]7. AI, iCollege, VXI, Adecco
AllyO	www.allyo.com	Integrate with an organization's HR system, Scheduling interviews, robust security system, and analytical intelligence for talent acquisition.	G4S, The Andersons, Staples, Dave & Buster's, Fried Man Real estate
Loxo	www.loxo.co	AI recruitment automation software on a CRM Platform using ATS with a database of 530 million people with their personal information reduces time and cost.	Bank of America, Trinity Health, Lockheed Martin, Amazon, Randstad
Seekout	www.seekout.io	More searching capabilities than LinkedIn, act as a talent market intelligent solution, and Can integrate into the Firm's ATS system.	Rover, VMware, Salesforce, X23, and me
Kaya	Stanford university	AI-based virtual chatbot that conducts interviews through a human language processing	(Zhou et al., 2019).
HireVue		AI virtual interviewer	(Langer et al., 2020; Suen et al., 2019).
Amelia		AI virtual interviewer	

Table 2: AI platforms/ products for RS (Aljanabi et al., 2023)

Research reveals that while there is a wide range of AI platforms available for organizations to utilize (Table 2), some companies have begun developing their own AI products for use within their HR departments and in RS in particular (Mishra et al., 2021; Shen & Zhao, 2021). This trend toward developing in-house AI products reflects a growing need for organizations to tailor their HR practices to their specific needs and context (Mishra et al., 2021). For instance, IBM has started developing AI technologies for use in its HR department to recruit its workforce (Guenole & Feinzig, 2018a). Similarly, other companies are utilizing AI in various stages of the RS, as elaborated on in the following sub-section.

2.7.1 AI in Sourcing

AI is being utilized in various process stages, including sourcing and job description creation (Zhou, 2021). Kupfer et al., (2023) have pointed out the use of AI in targeted candidate searches, personalized candidate recommendations, and similar functions during the sourcing stage. Moreover, AI is being employed in automated resume generation via social media feeds and other AI technologies (Li et al., 2020).

Traditionally, job descriptions were created manually by recruiters. However, with the help of AI technologies, job descriptions can now be generated within seconds. For example, natural language processing (NLP) can automatically generate job descriptions from existing job postings (Awan et al., 2019). Their results showed that the NLP system could generate accurate and comprehensive job descriptions, saving time and effort for recruiters.

In sourcing, AI tools have been utilized to target suitable candidates from diverse communities, both active (individuals who are actively seeking employment opportunities) and passive (employed individuals not actively seeking job opportunities but may be open to considering new options if presented to them), to increase the candidate pools and chances of finding the right candidate for the job (Feloni, 2017). Using language that is more natural and relevant to the candidates in job descriptions has been identified as one of the easier ways to attract the right candidates (Feloni, 2017). For example, US-based company Nvidia uses an AI-integrated chip on mobile phones to detect and extract the local language using natural language processing and then uses it in job descriptions. Similarly, Johnson & Johnson uses AI technology to add more personalized words in job advertisements or campaigns to remove gender bias and increase the diversity of the candidate pool (Dodson, 2018).

One of the critical aspects of contemporary candidate sourcing is using social media as a recruitment channel. The trend is emerging as the younger generations, particularly millennials, use social media as one of the primary social engagement places (Wachyuni & Priyambodo, 2020). Empirical research suggests millennials are more integrated with social media and use it even for professional work, making it an effective platform for advertising jobs or job campaigns (Becton et al., 2019)). As a result, AI technologies have sometimes been used to personalize job posts based on potential candidates' social media profiles (Armstrong & Taylor, 2014).

Other applications include scraping social media profiles to generate resumes and assess the applicability of such candidates to jobs (Van Esch & Black, 2019). Such proactive methods identify potential candidates for job vacancies amongst passive job seekers. Empirical studies also suggest that companies increase the candidate pool considerably at a lower cost by using Facebook, WayUp, Muse, and similar social media platforms following the trend (Van Esch & Black, 2019). Thus, it can be said that sourcing is one of the recruitment phases where many AI technologies are being used, especially via social media platform interactions with AI technologies (Feloni, 2017; Oblinger & Oblinger, 2005).

2.7.2 AI in Pre-screening

The use of AI in the pre-screening phase of recruitment has become increasingly popular due to the labor-intensive work involved in selecting candidates from the larger pool of applicants. Hilton, for instance, has implemented AI technology to scan resumes and shortlist top candidates, leading to a 70-90% faster turnaround time than manual screening (Yin et al., 2017). AI algorithms have also proven effective in reducing both conscious and unconscious bias in manual screening processes. In a study conducted at the University of Minnesota, AI-based algorithms outperformed humans in eliminating such biases (Greenfield, 2015). Wang and Siau (2019) similarly assert that AI programs can efficiently sift through thousands of applications and eliminate unconscious bias, outperforming humans in this task.

As a result, larger organizations with high-volume recruitment needs, such as IBM, Amazon, Johnson & Johnson, PepsiCo, McKinsey, Unilever, Credit Karma, Hallmark, SONY, and SpotX, are increasingly using AI in the pre-screening phase of recruitment (McKinsey & Company, 2018; Cam., 2019; van Esch & Black, 2019). Therefore, it can be expected that the use of AI in this phase is more prevalent in larger organizations.

2.7.3 AI in interviews

The use of AI in the interview process has gained traction, with numerous AI technologies, including computer vision, deep learning, neural networks, and natural language processing, being utilized in this process (Yang et al., 2021; Zhang et al., 2021).

Facial recognition technology, which employs computer vision and deep learning algorithms, is particularly noteworthy, as it enables AI to detect candidates' emotions and confidence levels during interviews (Kumar & Sharma, 2021; Zhang et al., 2021). By leveraging facial recognition technology, AI can reduce the reliance on human recruiters, hiring managers, or interviewers during the interview stage and presumably their associated bias (Kumar & Sharma, 2021).

Research has shown that AI-powered facial recognition technology has demonstrated a high level of accuracy in identifying candidates' emotional states and overall confidence levels, with accuracy rates ranging from 75% to 96% (Chen et al., 2020; Yang et al., 2021). This expedites the recruitment process, reducing hiring time and the ability to conduct multiple interviews simultaneously, which may not be feasible with human interviewers (Guchait & Ruetzler, 2014).

Numerous companies have implemented AI-based video interviews as a part of their recruitment process, including Accenture, Dunkin Donuts, Starbucks, Disney, Hilton Worldwide, and others (van Esch & Black, 2019). Starbucks, for instance, has reported reduced costs and increased diversity as AI-based video interviews enable candidates to take interviews from rural areas without traveling to the city (Frost, 2006, Stone et al., 2012).

Apart from video interviews, AI technologies are also used to conduct various tests and assessments. These assessments provide hiring managers with objective data points that enable them to make informed decisions. This technology helps reduce subjective biases in the selection process, as it is based on standardized assessments (Suen et al., 2019; Wanner et al., 2021). For example, Stanford University has developed an AI-based conversation tool called Kaya, which can converse with candidates and assess their personality traits for job suitability (Zhou et al., 2019). However, scant empirical evidence fully supports the use of AI throughout the interview process. Instead, AI tools appear to be implemented at the initial stage of the recruitment process, followed by human involvement at a later stage.

2.7.4 AI in Candidate engagement and communication

The integration of AI in candidate engagement is becoming more prevalent in organizations seeking to enhance their recruitment processes (Sahay, 2014; Allal-Chérif & Yela Aránega, 2019). AI tools such as chatbots are integrated into companies' career pages to provide potential candidates with the information they need by chatting with the AI chatbot, reducing waiting times and giving recruiters more time to focus on other activities (Sahay, 2014). Some companies, such as Coca-Cola, L'Oréal, Ernst & Young, The Home Depot, BNP Paribas, Walmart, and GE, have adopted conversational AI-based chatbots to reduce their dependency on human recruiters in HR functions (Allal-Chérif & Yela Aránega, 2019). These uses of AI in RS are summarized in Table 3 below.

Recruitment phase	AI technology	AI function	Reference
Workforce planning (pre-planning)	AI-based workforce predictions and forecasting tools	Predicting retention rates, turnover rates Predicting resource requirements based on the organization's strategic forecasts	(Guenole & Feinzig, 2018)
	AI-based financial forecasts	Cost-benefit prediction of the RS function	Guenole & Feinzig, 2018a)
Sourcing	Natural language processing	Job description generation and job campaigns	Dodson, 2018

Sourcing	Natural language processing	Personalized job description generation	(Feloni, 2017).
Prescreening	AI algorithmic prescreening	Prescreening candidates from resumes	(Yin, Camacho, Novais, & Tallon, 2018).
Selection /Interviews	AI-based automated tests, assessments	Conducting tests, exams, preliminary assessments, simulated tests, case study-based tests	(Coombs et al., 2021).
	AI-based interviews	Conducting face-to-face interviews using AI technologies like HireVue, Amelia	(Langer et al., 2020; Suen et al., 2019).
Candidate engages and communication.	Automated candidate engagement tools such as automated emails, status updates, chatbots	Increase candidate experience. Updating the status of the candidature, Communicating the feedback of the interview	Guenole & Feinzig, 2018a), (Allal-Chérif et al., 2021; Katta, 2020). (Leong, 2018; Savola & Troqe, 2019; Vivek & Yawalkar, 2019)
	AI-based virtual assistants	-Scheduling interviews between candidates and interviewers	(Allal-Chérif et al., 2021; Katta, 2020); (Zhou et al., 2019).
		Generating assessment reports after interviews	(Langer et al., 2020; Suen et al., 2019).
		Background and reference checks	(Allal-Chérif et al., 2021; Katta, 2020).

Table 3: AI applications in RS

However, implementing AI in RS presents several challenges, including ethical concerns, legal issues, and data privacy, which may hinder the adoption of fully automated

AI-based interview systems (Savola & Troqe, 2019). This may suggest that AI applications in RS are applicable in certain circumstances. In the next sub-section, the contextual factors that impact (I.e., accelerate or weaken) AI adoption in RS are discussed.

2.8 AI use in RS – influence of contextual factors

AI has been utilized in RS in specific circumstances. The contextual factors influencing the use of AI in RS include the hiring volume, the specific job types being recruited for, the industry sector, and the professional characteristics of the RS practitioners, such as their level of experience.

2.8.1 Effect of hiring volume.

Research indicates that the use of AI in RS is influenced by hiring volumes; however, there is a lack of consensus on its effects, with some studies suggesting that higher hiring volumes drive AI adoption in recruitment, while other research suggests that low hiring volumes drive AI adoption.

For example, Aggarwal and Singh (2019), suggest that AI is particularly effective in high-volume recruitment situations. This is because AI can screen and filter candidates much faster than traditional recruitment methods, reducing the time and cost involved in the recruitment process. Thus, recruiters prefer using AI in high-volume hiring situations because it can increase efficiency and reduce their hiring workload, including administrative work (Robertson, Bondarouk, & Looise, 2019).

According to Bock, Krcmar, and Vom Brocke (2018), Peck and Levashina (2019), and Matzler, Bidmon, and Grabner-Kräuter (2018), AI can be beneficial in low-volume hiring situations (Bock et al., 2018; Matzler et al., 2018). The use of chatbots and AI can automate the initial stages of recruitment, screening, and filtering candidates and reduce the administrative and repetitive workloads of recruiters (Peck & Levashina, 2019). However, risks associated with automation, such as bias, job loss, and negative candidate experience, prevent recruiters from adopting AI in high-volume recruitment. Thus, this research suggests that recruiters are more likely to accept the use of AI in recruitment when it is used in low-volume hiring situations, as they perceive it to be fairer and more objective than traditional recruitment methods (Bock et al., 2018).

Based on the arguments provided above, it seems more likely that AI is more applicable in high-volume recruitment situations due to its ability to increase efficiency, reduce workload, and reduce the time and cost involved in the recruitment process. However, AI can also be useful in low-volume hiring situations by automating the initial stages of the recruitment process and reducing the workload of recruiters. Thus, it can suggest that the adoption of AI in the recruitment process depends on the specific needs and context of the organization and also the individual needs of the RS professionals.

2.8.2 Effect of Job Type

A growing body of literature suggests that the use of AI in recruitment does not apply to all job types, and recruiters tend to use these tools primarily for recruitment for certain types of jobs. According to research studies, using artificial intelligence (AI) in recruitment is most effective in hiring certain job groups with clear and repetitive selection criteria. These job groups include positions such as customer service or retail sales workers, where AI can automate the process of filtering or shortlisting candidates (Kumar et al., 2021; Robertson et al., 2019). In fact, a study conducted by Capterra (2019) found that 94% of recruiters believe that AI can aid in identifying the most suitable candidates for such roles (Capterra (2019). This highlights the potential benefits of using AI in recruitment processes for specific job groups (Kumar et al, 2021).

Studies found AI is more commonly used to hire non-blue-collar workers. According to Callanan et al. (2006) and Form and Putnam (1985), blue-collar workers can be classified into five categories based on their skill level and industry. These categories are self-employed, skilled or craft employees, semi-skilled or unskilled employees in core sectors, semi-skilled or unskilled employees in peripheral sectors, and marginally employed individuals working less than 27 weeks per year. Thus, non-blue-collar workers are workers who do not belong to those categories.

For example, Dickey et al. (2020) found that AI tools were most frequently used in recruiting tech-related jobs, such as software developers and data scientists, which are considered white-collar jobs. Cappelli et al. (2019) report that AI tools were less commonly used in recruiting blue-collar jobs, such as manufacturing and construction jobs. This was because these jobs tend to have more specific skill requirements that are difficult to assess using AI tools. Hence, it is expected that recruitment professionals tend to use AI tools primarily for white-collar jobs that require a good level of education, training, experience, and similar.

However, AI may not be as effective for white-collar jobs that require more nuanced skills or interpersonal abilities, such as leadership, creativity, or problem-solving, requiring workers to use critical thinking and decision-making skills to solve complex problems. In a study by LinkedIn, 82% of recruiters stated that AI is less effective in hiring candidates for these types of jobs (LinkedIn, 2019).

Thus, it can be expected that the use of AI tools in recruiting blue-collar jobs is less common, as these jobs tend to have more specific skill requirements that are difficult to assess using AI. Therefore, recruiters are likely to use AI to hire candidates for certain types of jobs, including white-collar roles.

2.8.3 Effect of RS professionals' experience

The relationship between recruiter experience and the adoption of AI in RS is not clear-cut, with some research suggesting that less experienced or less senior recruiters may be more likely to adopt AI in their selection processes (Karaboga & Vardarlier, 2020), whereas other research reveals that more experienced and more senior recruiters are more likely to adopt AI (Liu et al.,2021).

Liu et al. found that recruiter experience played a role in adopting AI in recruitment, suggesting that experienced recruiters may be better equipped to integrate AI into their RSP. Furthermore, Kim and Kim (2020) found that both experience and seniority were positively related to AI adoption in recruitment, suggesting that more experienced and senior recruiters may be more likely to adopt AI in their selection processes. Similarly, Valdivia et al. (2021) report that experience and seniority were positively related to using both AI and human judgment in hiring processes. Finally, Kim and Yoo (2020) revealed that experience and seniority were positively related to adopting AI in recruitment and selection processes.

However, Khalid et al. (2021) suggest that the adoption of AI in RS is greater among less experienced recruiters and that recruiter experience moderates the relationship between AI adoption and recruitment outcomes. Specifically, the findings indicate that less experienced recruiters were more likely to adopt AI in RS, and the reasons are associated with increased efficiency and effectiveness of recruitment processes. Findings also reveal that the relationship between AI adoption and recruitment outcomes was stronger for less experienced recruiters than for more experienced recruiters. Overall, the findings of the study suggest that recruiter experience plays a moderating role in the adoption of AI in RS and that less experienced recruiters may be more likely to adopt AI and experience greater benefits from its adoption.

Similarly, Lotti et al. (2020) investigated the use of AI in the recruitment process by early adopters and observed that less experienced recruiters were more likely to adopt AI (Lotti et al., 2020). The study also found that the use of AI in recruitment and selection processes was driven by the need to reduce the time and costs associated with recruitment and improve the hiring process's quality. Furthermore, the study suggested that less experienced recruiters may perceive AI to improve the recruitment process' accuracy and objectivity and overcome their lack of experience and expertise. Fasbender et al., (2021) also report that less experienced HR professionals, hiring managers, and recruiters are more receptive to use of AI in the RS. In addition, this effect was mediated by perceived usefulness, ease of use, and subjective norms. In other words, less experienced HR professionals were more likely to adopt AI when they perceived it as useful and easy to use and when they perceived a social norm or pressure to do so. The study also highlighted the importance of considering the behavioral and psychological factors that can influence the adoption and use of AI in recruitment and selection processes.

2.9 Challenges of using AI in RS

Integrating artificial intelligence (AI) in RS has had positive and negative impacts. AI can potentially increase efficiency, reduce bias, and improve overall decision-making (Dery, Grant, & Wiblen, 2020). However, the use of AI in RS also presents challenges such as ethical concerns, technology resistance, and affordability of AI technologies (Kapoor, Kapoor, & Grover, 2021). Some studies even show that decisions made by algorithms are perceived as less fair (Newman et al., 2020).

Data privacy and governance are major ethical considerations in using AI for recruitment. The General Data Protection Regulation (GDPR), introduced in many European countries and equivalent to the Privacy Act 1988 in Australia, aims to protect candidate data privacy. According to GDPR, candidate data must be collected and secured with their consent and can only be used for specified purposes, such as consideration for job opportunities (GDPR.Eu, 2023). However, AI applications in recruitment collect a wide range of data, including information on facial expressions, gender, racial backgrounds, personality, age, health conditions, level of confidence, and linguistic abilities (van Esch, Black, & Ferolie, 2019). In some cases, candidates are not asked for their consent before collecting such data, leading to potential privacy breaches.

The lack of transparency in how data is collected and used in AI technologies presents a significant challenge in complying with regulations that demand transparency in data use (Avocats, 2017). Furthermore, research suggests that using AI in RS may negatively impact an organization's brand reputation, reducing talent pool (Vanderstukken et al., 2016). Additionally, empirical research indicates that AI algorithms may not always produce accurate results and have the potential to discriminate against certain candidates or end-users (Kodiyan, 2019; Dastin, 2018).

The potential ethical implications of using AI in business processes are demonstrated by incidents such as Microsoft's Twitter experiment and Google's photo recognition AI application (Wolf et al., 2017; Dougherty,2015). As a result, some organizations and business users may be reluctant to use AI in RS processes due to accuracy issues and concerns about the company's image and culture. Candidates have indicated that they do not like to engage with companies that use AI in the recruitment process as they perceive it as organizations trying to automate everything and not providing enough human connection and importance to the candidate experience (Li et al., 2021).

AI has the potential to automate many of the manual tasks human recruiters perform in RS, leading to concerns about job displacement among RS professionals (Kaplan & Haenlein, 2019; Su & View, 2018). The displacement of jobs by AI could lead to increased resistance to adopting and harnessing the potential of AI, with industries such as retail and hospitality already using AI-based technologies to replace human labor (Ives et al., 2019; Grundner & Neuhofer, 2021; S. Kim et al., 2021; Koo et al., 2020). This could result in socio-economic impacts such as increased unemployment (Vrontis et al., 2022). Figure 5 summarizes these risks.

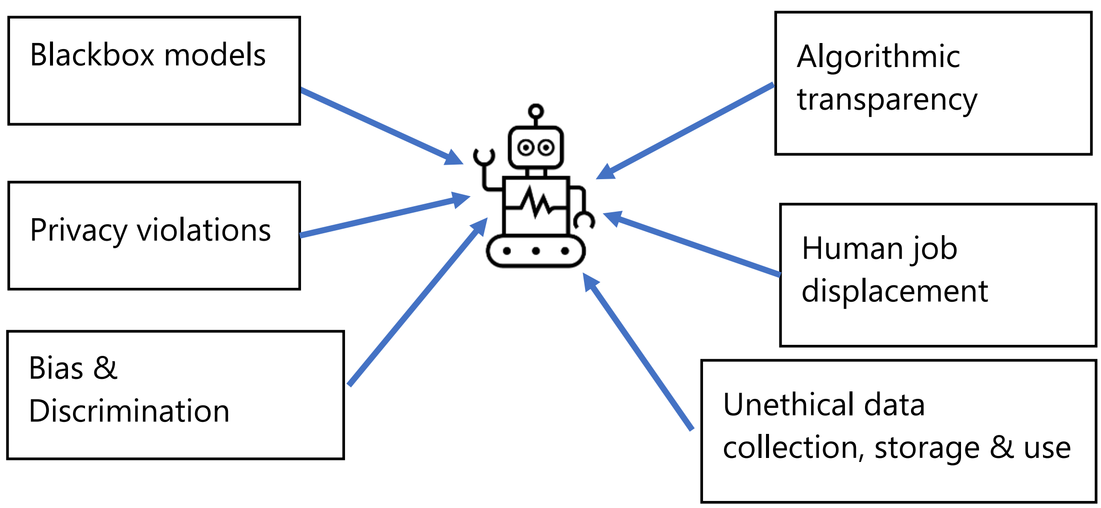

Figure 5: AI in RS Risks, Issues, and Concerns

Thus, implementing ethical frameworks and governance around data privacy when using AI in RS is essential to address concerns about accuracy, ethical implications, and job displacement. Thus, in the next sub-section, these research gaps are explained.

2.10 Research gaps

AI in RS is an emerging research area leading to many literature gaps. Firstly, a considerable gap in the extant literature pertains to comprehensive coverage of all the phases involved in recruitment and the role of AI in those phases. Alam et al.'s (2020) systematic literature review identified that the research in AI-based recruitment and selection had been predominantly focused on certain phases, namely sourcing, pre-screening, and candidate engagement. The existing literature highlights a partial adoption of AI within organizations, indicating that while certain phases of the recruitment process, such as initial screening, commonly utilize AI technology, other critical phases like demand planning or interviews have yet to integrate AI solutions. For instance, a recent study conducted by Aysha Khatun, K. et al. (2021) examining companies such as CGI, KPMG, Ericsson, and others in Sweden revealed that AI is predominantly employed in resume screening and selection stages, with limited or no usage in other recruitment phases. This underscores the need for further investigation into the applicability of AI across all stages of the recruitment cycle, as well as an exploration into the reasons behind the underutilization of AI in these areas. By delving into AI's potential in these neglected domains, researchers can gain valuable insights into its effectiveness and unearth opportunities for improvement.

For example, recruitment planning, or pre-planning, is widely regarded as a complex and critical phase in the RSP. However, due to its complexity, some organizations opt not to perform this function (Kaplan & Haenlein, 2019). Existing research on AI in RSP is fragmented. AI applications in each phase of the recruitment process and their implications have not been subject to research. Consequently, this research gap represents an opportunity for future studies to explore the potential benefits and limitations of AI in these neglected phases of RS.

Conversely, AI can outperform humans in certain processes, especially in data processing for informed decision-making (Brynjolfsson & Mitchell, 2017). Thus, AI can be leveraged in complex areas such as recruitment planning and interviews. Consequently, further research is necessary to understand the impact of AI in these RSP phases to gain an understanding of the overall impact of AI in RSP (Alam et al., 2020; Kaplan & Haenlein, 2019).

Secondly, the extant literature exhibits a dearth of attention to the contingencies or contexts conducive to implementing Artificial Intelligence (AI) within the realm of Recruitment and Selection Practices (RSPs). To illustrate, the potential applicability of AI in the recruitment of blue-collar or vocational workers, or its suitability for all industrial sectors, remains an underexplored area, as per the observations of the researcher.

Thirdly, the existing literature has a limited focus on how AI usage contributes to overall HR outcomes. Extant research has primarily focused on time-to-hire, with minimal attention given to other crucial outcomes, such as cost-of-hire, retention rates, and quality-of-hire (Wu et al., 2020). Thus, there is a need for further research on HR outcomes beyond Time to hire to include cost-of-hire and retention rates.

Relatedly, the specific conditions or circumstances under which these outcomes can be achieved are poorly understood. Therefore, there is a need for research to comprehend the specific conditions or circumstances under which these outcomes can be achieved and how AI can be utilized to accomplish them effectively. Understanding the conditions and mechanisms underlying AI's benefits in RSP will enable HR practitioners to make informed decisions and develop appropriate strategies to facilitate beneficial HR outcomes.

The utilization of Artificial Intelligence (AI) within Recruitment and Selection Practices (RSPs) has garnered significant attention in extant literature. While prior studies have extensively explored the role of AI in the recruitment process, there remain research gaps concerning the implications of human resource (HR) and AI collaboration within RSPs. Empirical investigations have highlighted the pervasive use of AI in various stages of the recruitment process, where AI is regarded as another worker in the recruitment process. However, this usage of AI raises concerns regarding job displacement (Savola &

Troqe, 2019). Despite such concerns, the implications of AI on the HR workforce remain largely unexplored and warrant further research to comprehend its potential impact on the HR profession fully.

The introduction of AI in the RSP has the potential to automate certain job functions and displace human HR workers, particularly if the primary goal is to reduce time-to-hire. This could lead to anxiety among HR employees and raise socio-economic implications that organizations and policymakers need to address, potentially introducing societal issues (Frey & Osborne, 2017). Therefore, future research should focus on exploring the potential impact of AI adoption in the RSP, including the socio-economic implications and how organizations can mitigate any potential negative consequences that may arise for the HR workforce.

Fourthly, the literature lacks research on human collaboration with AI in the RSP, although such co-existence is likely to be a feature of future RSP. Savola et al., (2019) contend that the introduction of AI will elevate the job of HR recruitment professionals from administrative to strategic. Other studies propose that HR professionals can be AI advisors to develop machine learning algorithms and train data models to support recruitment (Black & van Esch, 2020a; Jatobá et al., 2019). These studies suggest two important points. Firstly, the RSP process will include both AI and humans. Secondly, the job of RSP professionals will transform due to the integration of AI. However, there is a gap in the literature regarding the perceptions of RSP professionals, who are the primary stakeholders affected by this transformation. Further research is necessary to understand the potential impact on their roles, responsibilities, and job satisfaction.

Finally, it is worth noting that the research community's attention to the complexities brought forth by AI in the RSP extends to AI governance frameworks. In particular, transparency and accountability of AI technologies in the RSP process require investigation, as there is a potential for inaccurate algorithms leading to bias and unreliable decision-making (Samek et al., 2017). Therefore, understanding how AI produces what results is crucial to increase the reliability and confidence of recruitment professionals and encouraging candidates to engage in the recruitment process. This highlights the need for a robust AI governance framework that ensures the ethical use of AI in the RSP process and mitigates potential risks associated with its application.

The research gaps indicate that AI in RSP requires more empirical research to understand its implications which is the focus of this research.

2.11 Chapter summary

This chapter discusses the existing literature on RS processes in HRM, the use of AI in RS, the factors driving AI adoption in RS, and gaps in the literature. The literature suggests that the RS process has transitioned from traditional to e-recruitment and is now moving towards smarter recruitment with the integration of AI. The limitations of traditional and e-recruitment have led to the emergence of smart recruitment. Empirical research on AI adoption in RS has shown various benefits, such as reducing the time and cost of hiring. However, the research also identifies impediments to AI adoption in RS, such as concerns about job losses, algorithmic bias, and privacy issues. Nonetheless, research gaps indicate that there is still much to learn about the relationship between HR outcomes and the adoption of AI in RS.

CHAPTER 3

TECHNOLOGY ADOPTION

3.1 Introduction

This chapter discusses the theoretical background for the proposed study. In addressing the gaps identified in Chapter 2 (section 10) on using AI in RS, this chapter reviews the technology adoption literature. It examines various technology adoption frameworks and justifies the selection of the Unified Theory of Acceptance and Use of Technology as the theoretical foundation for this research, which is built upon and extended through the development of a new AI-RS model in this research.

3.2 Technology adoption

Technology adoption frameworks can be used to facilitate the investigation of the key enablers and barriers to adopting new technologies. This research aims to investigate the effect of AI on HR outcomes in the RS. A review of various technology adoption theories was conducted to achieve this objective. The Technology Acceptance Model (TAM) proposed by Davis (1989), the Technology-Organization-Environment (TOE) framework developed by Tornatzky & Fleischer (1990), and the Unified Theory of Acceptance and Use of Technology (UTAUT) put forward by Venkatesh et al. (2003) were considered as the most relevant theoretical frameworks for this research.

Theoretical frameworks offer distinct perspectives. TAM and UTAUT emphasize the end-user or consumer viewpoint, while TOE provides an organizational perspective on technology adoption. The Researcher looked at the three theoretical models to understand these different perspectives, as explained next.

3.2 TAM

In the field of technology adoption, the Technology Acceptance Model (TAM) has been extensively utilized to comprehend the viewpoints of individuals and is influenced by the theory of reasoned actions (Davis, 1989; Ajzen & Fishbein, 1980). TAM proposes that technology acceptance is influenced by perceived usefulness (PU) and perceived ease of use (PEOU), as depicted in Figure 6. TAM has been applied to investigate technology adoptions across various disciplines, such as general-purpose systems, communication systems, office systems, and specialized business systems (Lee et al., 2003). TAM has evolved as additional constructs, such as behavioral intentions (BI) and actual system usage, was introduced. In terms of the constructs of perceived usefulness and perceived ease of use, system quality, self-efficacy, enjoyment, support, and experience have been added as the contents of these constructs in that evolvement process (Chau, 1996a).

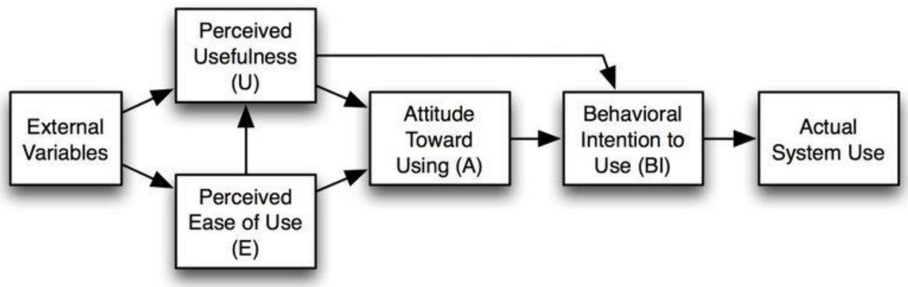

Figure 6: Technology Acceptance Model (TAM) main constructs (Davis, 1989)

Although TAM has the end-user's perspective, which is partially the intention of the current study, the researcher considers the model insufficient to understand complex systems like AI due to the simplicity of TAM. The limited ability of the TAM model to comprehensively capture the complexities of AI-based technologies has been acknowledged by Venkatesh et al., (2003) and Drennan et al., (2005). These scholars suggest that the model needs to be expanded to account for the unique features of AI, such as the need for continuous learning and adaptation.

Furthermore, Kowatsch et al., (2010) emphasize the importance of understanding user perceptions and acceptance of AI-based assistants in e-commerce (Kowatsch et al., (2010). The complex nature of AI systems necessitates the development of theoretical models that can adequately capture the intricate interplay between human users and technology. Therefore, this research argues that further investigation and development of theoretical models are needed to enhance our understanding of AI systems.

In light of the aforementioned arguments, it is evident that the Technology Acceptance Model (TAM) is inadequate for comprehensively capturing the complexities of AI-based technologies. Hence, there is a need for more advanced and sophisticated theoretical models that can effectively account for the unique features and intricacies of AI systems (Venkatesh et al., 2003; Drennan et al., 2005; Kowatsch & Maass, 2010).

3.3. TOE

The Technology-Organization-Environment (TOE) framework is a widely recognized theoretical model that facilitates analyzing and comprehending technology adoption and diffusion in organizations and their broader social and economic contexts (Rogers, 2003). The framework posits that technology adoption is influenced by three primary factors: technology, organization, and environment (Chen et al., 2010). The technology factor relates to the features of the technology, such as its usability and reliability. The organization factor encompasses internal factors such as leadership, culture, and resources, whereas the environment factor involves external factors such as market forces, government regulations, and technological trends (Al-Kharusi & Al-Zadjali, 2015).

The TOE framework offers a comprehensive and effective approach to understanding technology adoption and identifying opportunities and obstacles for technology diffusion. It has been widely applied in information technology and used in various domains, such as healthcare, education, financial services, and HRM (Yaghoubi et al., 2019; Rahman and Aydin, 2019). However, the TOE framework's organizational perspective may not completely understand technology adoption from the end-user's viewpoint (Moghavvemi et al., 2014). While organizational and environmental factors are important, the user perspective is also critical in determining technology effectiveness in achieving desired outcomes. User acceptance and personal innovativeness significantly affect technology adoption, and motivation theory is also essential. User perceptions shape the diffusion of innovation, and thus, the user-centered perspective must supplement the TOE framework to achieve a comprehensive understanding of technology adoption and effectiveness in organizations (Davis et al., 1989; Venkatesh et al., 2003; Agarwal & Prasad, 1998; Lin & Lu, 2011; Rogers, 1983).

Despite its usefulness in comprehending technology adoption in organizations, the TOE framework's organizational perspective may not completely understand technology adoption, especially from the end user's viewpoint (Moghavvemi et al., 2014). As a key gap that this study focuses on is the RS professional perspective, which is under-researched in the literature, this study will investigate an individual-level perspective, this is justified as the user perspective plays a crucial role in determining the technology's effectiveness in achieving desired outcomes (Davis et al., 1989; Venkatesh et al., 2003), as personal innovativeness also affects adoption (Agarwal & Prasad, 1998). The integration of HR outcomes in this study will be from the perspective of RS professionals in terms of their key job outcomes associated with their individual roles.

3.4. UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh (2000, 2003, 2012, 2021), is a comprehensive framework that draws from eight different technology acceptance models, including the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), a combination of TA and TPB, the Motivational Model, the Personal Communication Utilization model, the Diffusion of Innovation, and the Social Cognitive Theory. The UTAUT is designed to explain the drivers behind technology adoption from the end-user's perspective, to use technology, and the actual use of the technology identified as key concepts (Venkatesh et al., 2003).

UTAUT is the most effective framework for explaining up to 70% of the variance in technology adoption usage (Venkatesh et al., 2003). It considers various factors influencing behavioral intentions and actual use, including performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to the perceived usefulness of technology, while effort expectancy refers to the perceived ease of use. Social influence relates to the influence of others in the organization, such as peers or superiors, while facilitating conditions refer to the availability of resources and support to use technology effectively (Venkatesh et al., 2003).

As suggested in this framework, separating the two factors, behavioral intention and use behavior is crucial as the intention to adopt or use technology may not necessarily result in actual use (Sheppard et al., 1998). These constructs are depicted in Figure 7.

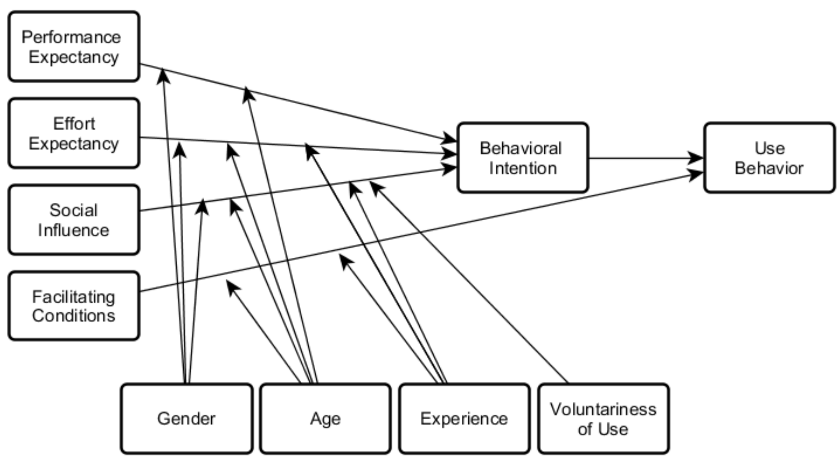

Figure 7: UTAUT framework (Venkatesh ,2000)

Organizations can improve their adoption rate by identifying the factors that drive end-users to use technology and maximize its benefits. The model's constructs are discussed in detail in the next sub-sections.

3.4.1. Behavioral intentions (BI)

Behavioral intentions (BI) have been defined as "the subjective probability that a person will perform a given behavior" (Sheppard et al., 1998, pp. 198). In the context of the Unified Theory of Acceptance and Use of Technology (UTAUT), BI has been identified as the strongest predictor of use behavior (Venkatesh et al., 2003a).

However, intentions do not always translate into actual user behavior, and other factors can influence the relationship between intentions and behavior (Sheppard et al., 1998). For example, performance expectancy, the perceived usefulness of technology, and social influence can impact actual use behavior (Venkatesh et al., 2003a; Venkatesh et al., 2003b). Therefore, while BI is an important predictor of technology use, it is crucial to consider other factors affecting actual behavior to gain a more comprehensive understanding of technology adoption and use.

3.4.2. Performance Expectancy (PE)

According to Venkatesh et al. (2003a), performance expectancy refers to an individual's belief about how much using a system will enhance job performance. This construct is considered the most robust predictor of behavioral intentions and has been operationalized through various measures, including task completion speed, productivity improvement, and ease of use. Nevertheless, some argue that performance expectancy alone may not adequately capture all of the expectations that individuals have regarding technology.

In certain industries, such as healthcare, regulatory compliance may be a critical consideration, irrespective of productivity or efficiency gains (AlQudah et al., 2021).

Therefore, the notion of perceived usefulness, which encompasses expectations of usefulness, applicability, and performance, may be more suitable in such situations.

To overcome the limitations of the performance expectancy (PE) construct in technology adoption research, AlQudah et al. (2021) proposed the use of benefit expectations (BE) as an alternative construct. BE is a more comprehensive construct encompassing various factors such as performance, usefulness, and applicability. According to AlQudah et al. (2021), BE better captures individuals' expectations of technology, and hence it may be more appropriate to use BE instead of PE in business functions such as RS. Thus, this research will utilize the BE construct instead of PE to better understand individuals' expectations and perceptions of technology.

3.4.3. Social influence (SI)

According to Venkatesh et al. (2003a), social influence is the degree to which an individual perceives the beliefs of others they consider important and should use the new system. This construct considers the influence of multiple sources in the organization, including managers, supervisors, and colleagues. Studies have shown that social influence is a significant predictor of behavioral intention, and its impact arises from different sources, including compliance and internalization (Venkatesh & Davis, 2000). Therefore, the UTAUT model recognizes the importance of social influence in technology adoption and highlights the need to consider the influence of various actors.

3.4.4. Facilitating Conditions (FC)

Facilitating conditions, as defined in the UTAUT model, refer to the degree to which an individual perceives that the organizational and technical infrastructure is in place to support the use of the system (Venkatesh & Davis, 2000). This construct is determined by considering the influence of perceived behavioral control on the system, compatibility, and facilitating conditions. In addition to predicting behavioral intentions, it has also been identified as a predictor of technology use behavior within the context of the current study (Ouirdi, 2016). The measurement of this construct is based on several factors, including the availability of resources to generate knowledge about the system, the compatibility of the system with other systems, and the availability of help or support, among others (Taylor & Todd, 1995; Venkatesh & Davis, 2000).

However, it has been suggested that when both performance expectancy and facilitating conditions are present, the impact of facilitating conditions on behavioral intentions is non-significant. Venkatesh et al. (2003) suggest that facilitating conditions only significantly impact behavior when performance expectancy is low. Venkatesh and Bala (2008) further suggest that facilitating conditions may directly impact behavior, but only when performance expectancy is not a significant factor. For example, Wu and Wang (2005) provide empirical evidence that facilitating conditions only significantly impact mobile commerce usage when performance expectancy is low. This observation implies that facilitating conditions do not significantly impact behavioral intentions when performance expectancy is high. Therefore, it can be concluded that facilitating conditions play a more significant role in influencing behavioral intentions when performance expectancy is low (Venkatesh et al., 2003a).

3.4.5. Effort expectancy (EE)

Effort expectancy is defined as the degree of ease associated with using the system (Venkatesh, 2000). This construct is based on the concepts of perceived ease of use, complexity, and ease of use. Effort expectancy is measured through metrics such as the clarity and understandability of system interaction, the ease of acquiring proficiency in using the system, the ease of using the system, and the ease of learning to use the system. The effort expectancy is expected to have a positive impact on behavioral intentions. However, it has been suggested that this factor is significant only in the early stages of technology adoption and becomes less significant over time (Venkatesh, 2000). Thus, it can be suggested that EE is not applicable in all phases of the life cycle of the technology, instead, it is applicable only during the early stages of the technology adoption.

3.2.1 Use behavior (Actual use)

The UTAUT model defines use behavior as the actual extent to which a technology or system is employed. Venkatesh et al. (2000) have identified that behavioral intention is the strongest predictor of user behavior, and this intention is influenced by facilitating conditions. The UTAUT model acknowledges that these influences are moderated by various contextual factors such as gender, age, experience, and voluntariness of use, which are specific user attributes (Venkatesh et al.,2000). This framework integrates organizational and job-related aspects with individual human behavioral attributes, creating a practical and unique theoretical framework. Additionally, the UTAUT model has evolved over time by integrating new constructs based on empirical research and emerging technology needs, as explained in the next sub-section.

3.5. Evolution of UTAUT

The UTAUT 2 model, updated by Venkatesh (2009), introduces new constructs such as hedonic motivation, price value, and habits to enhance the understanding of technology adoption (Venkatesh, Thong, & Xu, 2012). However, the relevance of these constructs may be context-dependent, as they may only be relevant in certain situations (Chen et al,2012). For instance, the relevance of cost may vary depending on the user's perspective, as end-users may not consider the cost when technology is imposed on them, while the cost could be significant for strategic leaders making financial investments (Chen et al., 2012). Additionally, hedonic motivations may only apply to personal technology use rather than organizational purposes (Chen et al., 2012).

The more recent UTAUT model, the UTAUT Operation Management (OM) framework, seeks to predict the effectiveness of artificial intelligence technology adoption by considering both individual and operational perspectives (Yeh, Hsieh, & Tsai, 2020).

This framework retains the core constructs of perceived performance expectations, effort expectations, facilitating conditions, social influence, and behavioral and usage intentions, as illustrated in Figure 8 and explained in the section 3.4. Furthermore, it includes new constructs such as individual characteristics, environmental characteristics, technology characteristics, and interventions influencing main constructs.

The new constructs introduced in the UTAUT Operation Management (OM) framework—individual characteristics, environmental characteristics, and technology characteristics—expand the scope of factors considered in predicting the effectiveness of artificial intelligence technology adoption.

Individual Characteristics:

This refers to the personal attributes and traits of individuals involved in the adoption of AI technology. It may encompass factors such as prior experience with technology, cognitive abilities, attitudes, and skills. Understanding how these individual characteristics influence the adoption process helps in tailoring strategies to address specific needs and concerns, ensuring a smoother integration of AI technology into individual workflows.

Environmental Characteristics:

This category involves aspects related to the external environment within which AI technology is implemented. Factors like organizational culture, external policies, and industry trends can significantly impact the adoption and success of AI initiatives. Analyzing and considering these environmental characteristics provide a more comprehensive understanding of the contextual factors influencing the integration of AI into operational processes.

Technology Characteristics:

Technology characteristics pertain to the specific attributes and features of the AI technology itself. This could include aspects such as usability, compatibility with existing systems, reliability, and scalability. Evaluating these characteristics helps in identifying the strengths and limitations of the technology, allowing organizations to make informed decisions about its adoption and potential impact on operational efficiency.

By incorporating these new constructs into the UTAUT OM framework, the model recognizes the importance of individual attributes, environmental context, and technology-specific features in determining the success of artificial intelligence adoption. This more holistic approach facilitates a nuanced analysis of the diverse factors influencing the adoption process, offering a valuable framework for organizations aiming to leverage AI in their operational management.

Nevertheless, the model is still experimental and has yet to guide on measuring these new characteristics.

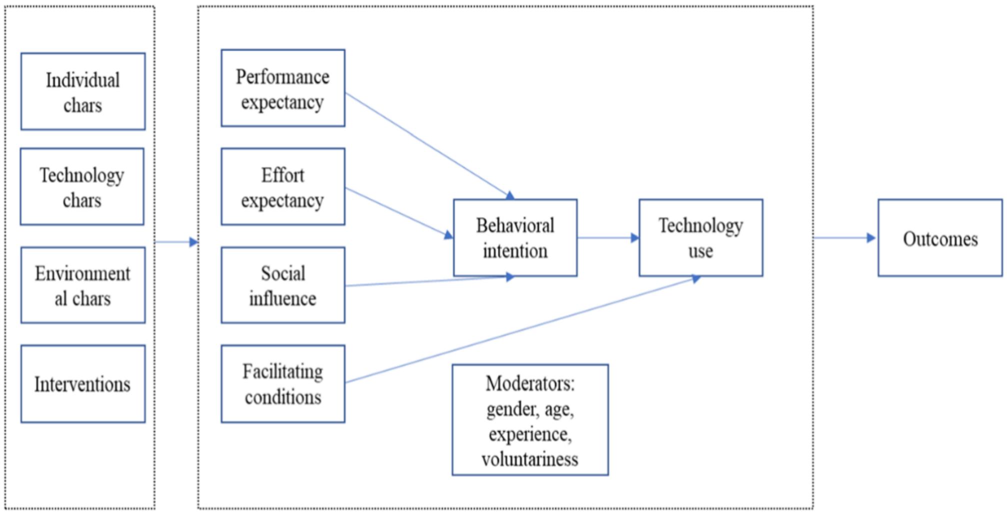

Figure 8: UTAUT-OM model for AI adoption (Venkatesh, 2021).

Other advancements of the UTAUT model include specific models developed to understand AI adoption, such as in the study of AI adoption in HR systems by scholars Moud & Arallyai (2020). The study developed a conceptual framework by incorporating Trust into the UTAUT model and revealed that trust has a significant impact on the behavioral intentions of adopting AI for HR information systems (Moud & Arallyai, 2020).

Trust in AI

In recent years, there has been a growing recognition of the critical role of trust in shaping the adoption of innovative technologies, particularly Artificial Intelligence (AI). Building upon the foundation laid by the Unified Theory of Acceptance and Use of Technology (UTAUT), researchers have sought to integrate trust as a fundamental construct within the model to enhance its explanatory power in understanding AI adoption behaviors.

One notable development in this regard is the study conducted by Moud & Arallyai (2020), which focused on AI adoption in HR systems. By incorporating trust into the UTAUT model, the researchers aimed to provide a more comprehensive understanding of the factors influencing the adoption of AI for HR information systems. Their study revealed that trust exerts a significant impact on the behavioral intentions of AI adoption, highlighting the importance of considering trust as a key determinant in technology acceptance models.

This integration of trust into the UTAUT model represents a significant evolution, as it acknowledges the crucial role that trust plays in shaping individuals' attitudes and intentions towards adopting AI technologies. By intruding trust into the UTAUT framework, researchers can better capture the complex interplay between trust, perceived usefulness, perceived ease of use, and other factors influencing technology adoption.

Overall, the incorporation of trust into the UTAUT model represents a promising avenue for enhancing our understanding of AI adoption behaviors. By recognizing trust as a central determinant, researchers and practitioners can develop more effective strategies for promoting the acceptance and utilization of AI technologies in various domains, including HR systems.

3.6. Gaps in UTAUT to study AI in RS

To achieve the research objectives of understanding AI in RS from the perspective of RS professionals in HRM, the details from various theoretical models exhibited above were analyzed. As a result, it was found that the UTUAT framework is the most suitable for this study's objectives. However, given the complex nature of AI adoption as an emerging technology and the challenges still emerging, a framework that goes beyond the basic UTAUT framework is necessary (Liu et al., 2021). The UTAUT OM provides a foundation for this research to consider multiple factors, including individual perspectives, job function characteristics, and organizational perspectives.

Characteristics related to job functions play an important role in driving AI adoption in RSP from the perspectives of RSP professionals. For example, Abdullah et al., (2021) identified expected benefits, facilitating conditions, and social influences that influence the adoption of AI technology in RSP. Additionally, characteristics related to the organization have also been identified as playing a critical role in the AI adoption in RSP. For example, the type of the organization (corporate or agency recruitment), culture of the organization (innovative versus traditional), size of the organization (small versus large, the facilitated technology platforms and interventions from regulatory bodies or institutions were identified as influencing the AI adoption amongst RSPs (Liu, Chen, Zhang, & Chen, 2020).

Individual characteristics, such as the job function performed by RSP professionals (recruiter, hiring manager, or HR executive) and experience, are also important factors that influence technology adoption (Abdullah et al., 2021). Empirical studies suggest that individual characteristics, including personality, can significantly impact attitudes towards emerging technologies, with some personalities viewing them as opportunities while others perceive them as threats and thus reject or have passive reactions towards such technologies (Vishwanath, 2005; Ryan et al., 2015).

Therefore, this thesis proposes a new conceptual model influenced by UTAUT and UTAUT OM and insights from wider empirical research on RS-related characteristics. In proposing this new conceptual model, the researcher argues that some of the moderation factors suggested in the original UTAUT model, such as age, gender, and voluntariness, are not applicable in the context of AI use in RS. Instead, the researcher suggests that other moderating factors, such as recruitment phase and hiring volume, apply more to AI adoption, as identified in other interdisciplinary studies (Nguyen & Malik, 2022).

For example, Oyibo (2020) proposes a new conceptual model for AI adoption in the context of recruitment service providers that consider the industry, the type of job being hired, the recruitment phase, and hiring volume as moderating factors rather than age, gender, and voluntariness. This suggests that the original UTAUT model's moderating variables may not apply to all settings and that context-specific factors must be considered.

Similarly, Kwon (2019) and Ali et al., (2020) suggest that the original UTAUT model may not be universally applicable and propose modifications to the model based on the specific context of their studies in the recruitment process. This highlights the importance of understanding the unique characteristics of the context in which technology is being adopted and the need to tailor adoption models accordingly.

Thus, the proposed conceptual model includes the factors that apply to AI adoption in HR for RS. The proposed conceptual model includes the core constructs of UTAUT, such as performance expectancy (benefit expectations), effort expectancy, social influence, and facilitating conditions. It also incorporates the individual, technological characteristics, and interventions, as suggested in UTAUT OM. Furthermore, the model includes the moderating factors of a professional’s experience and hiring volume, which are considered relevant in AI adoption in RSP. These moderating factors affect the relationships between the core constructs and the intention to use AI in RSP for HR outcomes, as well as the actual use of AI in RSP for HR outcomes which, together with the model, is explained in detail in Chapter 4.

3.3 Chapter Summary

This chapter aimed to identify the most suitable theoretical framework to investigate the phenomenon of AI-RS in HRM, which is the main objective of this research. To achieve this goal, the chapter explored several technology adoption frameworks, including TAM, TOE, UTAUT, and UTATU-OM, a conceptual framework extension of UTAUT. It was observed that these frameworks are generic and lack the conceptual RS components crucial to comprehend RS professionals' perspective on the present research phenomenon. As a result, the current research will develop a conceptual framework that builds upon UTUAT and UTAUT-OM, which have been identified as the most appropriate frameworks for studying AI-RS.

CHAPTER 4

PROPOSED AI-RS CONCEPTUAL MODEL

4.1 Introduction

The chapter commences with a description of the Artificial Intelligence in Recruitment and Section (AI-RS) conceptual model proposed by this study. This model builds upon the UTAUT and UTAUT OM models extending it by integrating key RS constructs. This chapter explains the hypotheses stemming from this model, which will be validated and tested in subsequent chapters.

4.2 Conceptual model- AI-RS and hypothesis development

This study intends to make a theoretical contribution of a new AI-RS model which explains the effective adoption of AI in RS by integrating the technology adoption and RS literature.

First, the proposed model incorporates relevant UTAUT constructs such as benefit expectations, facilitating conditions, social influence, behavioral intentions, and user behavior (see Chapter 3, section 4). The construct of performance benefits has been redefined as "benefit expectations," which encompasses a wider range of benefits beyond performance-related expectations. While the effort expectancy construct has been proposed to be removed, further research is necessary to validate this decision. Additionally, the conceptual model introduces two new constructs specific to AI adoption in RS: the recruitment phase and trust in AI, which are specific to the focus of the present research subject.

In contrast to the original UTAUT model's moderation of gender, age, and voluntariness, the conceptual framework incorporates RSP experience and hiring volume as the new moderating variables. This proposed conceptual model is illustrated in Figure 9.

The reasoning behind these new constructs and moderations will be elucidated in the subsequent section and the subsequent hypothesis development.

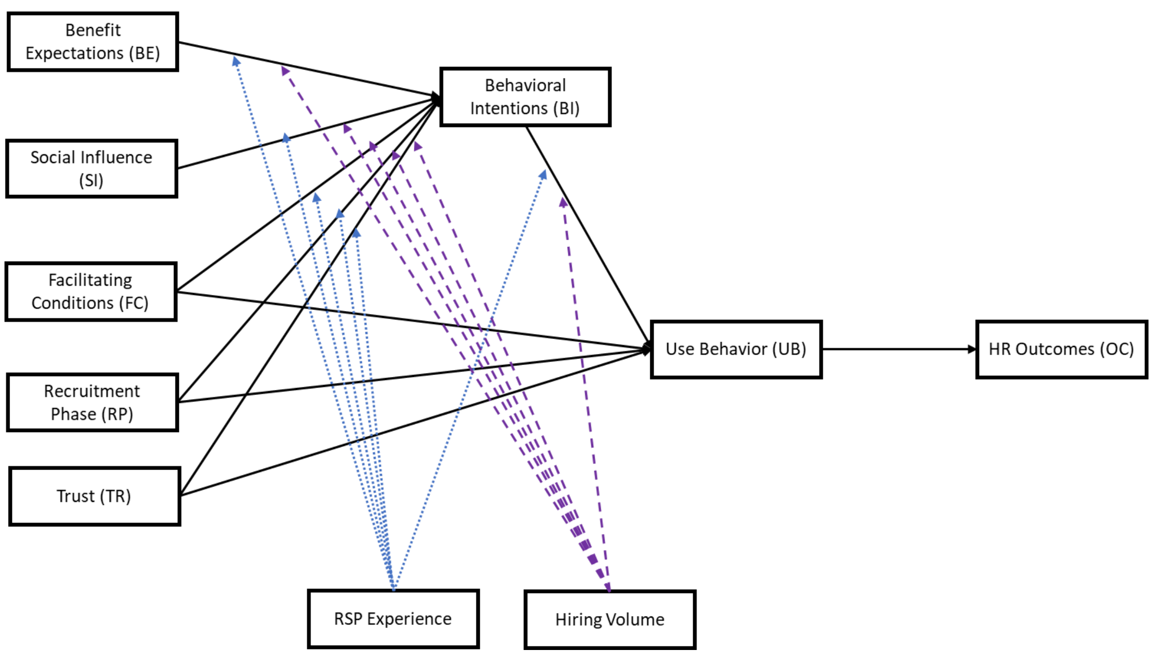

Figure 9: Proposed conceptual model: AI-RS

4.2.1 Benefit Expectations

The Unified Theory of Acceptance and Use of Technology (UTAUT) model elucidates performance expectations as the extent to which an individual perceives that the utilization of a system will augment their job performance, and it is measured through answers to the following questions (Morris et al.,2003):

- "I would find the system useful in my job."
- "Using the system enables me to accomplish tasks more quickly."
- "Using the system increases my productivity."
- "If I use the system, I will increase my chances of getting a raise."

Despite its prevalence in the UTAUT model, the definition and measurement criteria of performance expectations (PE) have been subject to criticism from scholars (Legris, Ingham, & Collerette, 2003). They argue that the concept of performance expectations in the model does not align with the general understanding of performance.

The notion of performance is a multifaceted, intricate concept that has been conceptualized and examined by various academic disciplines such as sociology, psychology, and management (Bagozzi & Yi, 2012). Performance generally refers to effectiveness. Evaluating performance is often based on a set of criteria such as quality, speed, efficiency, and effectiveness, as noted by Robbins, Judge, & Sanghi (2017).

Furthermore, the measurement criteria of PE are too broad in general and do not necessarily reflect efficiency or speed. For instance, the item "getting a salary raise" is not directly linked to efficiency, and there are many other factors that can contribute to a salary increase, such as skills and competencies, market trends, length of service, and company performance (Armstrong, 2015; Milkovich & Boudreau, 2015; Rynes & Gerhart, 2018). Thus, usefulness and salary increases are more broadly classified as "benefits." In the context of recruitment, recruiters may also expect to provide a better candidate experience, which is not directly related to task completion or performance increase (Heveron Jr, 2007).

Thus, the current study incorporates the concept of "benefit expectations," which refers to the extent to which end-users anticipate gaining benefits from the utilization of artificial intelligence (AI) in RSP (Hong et al., 2019). Empirical findings presented in section 2.6.1 indicate that adopting AI in RS yields diverse benefits, such as minimizing repetitive work, streamlining manual efforts in interviews, enhancing work-life balance, and mitigating unconscious human bias. These results have been supported by previous research studies, including (Becton et al., 2019; Black & van Esch, 2020a; Chassagnon et al., 2020; Feijóo et al., 2020; H. Suen et al., 2019; Hemalatha et al., 2021; Melão & Reis, 2020; Nawaz, 2019, 2019; Torres & Mejia, 2017).

Based on these empirical findings, it can be expected that professionals involved in RS anticipate the benefits of implementing AI in RS. Consequently, the following hypothesis is posited:

H1: The behavioral intentions (BI) of AI in RS are positively influenced by the benefits expectations (BE -> BI).

4.2.2 Effort Expectations

Effort Expectancy (EE) is a construct used to measure the ease associated with using technologies or systems (Venkatesh et al., 2003). This construct is gauged based on factors such as perceived ease of use, complexity, and ease of use.

Despite its utility, previous empirical research has demonstrated that the significance of EE tends to diminish over time (section 3.1.3.5). Additionally, in the context of AI as a technology (not as a product such as Video interview product which AI is being used), the perceived ease of use, complexity are deemed irrelevant from the end-user's perspective. This is because AI algorithms like machine learning, natural language processing, and computer vision are backend technologies rather than frontend technologies (Duthie, 2021). Hence the integration with the AI is via another system, such as LinkedIn or chatbots, as AI technologies are integrated with those systems (Choudhary, 2017). Consequently, it can be argued that the ease of use of AI from the recruiter's perspective is relevant to LinkedIn or chatbots (for example) and not to AI itself.

For instance, Nguyen and Rose-Anderssen (2020) examined the use of AI as a technology in recruitment and selection and found that AI adoption was influenced by factors such as data availability, the degree of automation, and the level of transparency and not by the ease of use. Similarly, a study by Dwyer and Hogan (2019) explored the factors that influence the adoption of AI in HRM, including recruitment and selection. They found that the perceived usefulness of AI, its compatibility with existing HR systems, and its complexity were significant factors that influenced its adoption, and ease of use was not identified as significant.

Thus, in this research, the ease of use of AI is not suggested to be significant, thus, the concept of effort expectancy is deemed irrelevant as the focus is on the perspective of AI from recruitment professionals. Consequently, no hypothesis is developed for this construct in this study.

4.2.3 Social influence

In the Unified Theory of Acceptance and Use of Technology (UTAUT), social influence emerges as a fundamental construct, delineating the sway of external factors on individuals' behaviors, attitudes, and intentions toward technology adoption (Venkatesh et al., 2003). Despite its acknowledged significance, the UTAUT model primarily gauges social influence through two queries, neglecting the nuanced contextual perspectives pertinent to recruitment specialists.

In the realm of recruitment, social influence manifests as the sway exerted by recruiters throughout the hiring process, shaping candidates' perceptions, attitudes, and behaviors (Akhtar, 2021). As pivotal gatekeepers, recruiters wield considerable power in molding candidates' perceptions of organizational culture, job roles, and likelihood of selection (Rynes & Barber, 1990). Leveraging this influence, recruiters deploy various strategies, ranging from personal reputation to organizational branding, to sway candidates' decisions. Additionally, external influencers such as peers, senior managers, and other departments like IT and Finance play crucial roles (Eckhardt et al., 2009).

Moreover, empirical evidence underscores the substantial impact of external influencers on the adoption of emerging technologies in human resource management (Becton et al., 2019; van Esch & Black, 2019). Particularly, social media emerges as a potent force driving technology adoption, indicating the need to incorporate these novel influences into the study of adoption dynamics, especially concerning AI.

However, within the recruitment sector, candidates remain pivotal influencers whose preferences and reactions significantly shape the adoption of AI-driven processes. While some candidates perceive AI adoption as indicative of organizational innovation, others express reservations, perceiving it as a deviation from human-centric engagement (van Esch et al., 2021; Albert, 2019; Min et al., 2018; van Esch & Black, 2019). These insights underscore the necessity for recruitment specialists to consider and accommodate candidates' perspectives in integrating AI into the recruitment process.

In light of these considerations, this study seeks to explore the multifaceted social influences on AI adoption within recruitment settings, encompassing influences from candidates, clients, peers, senior management, and technology entrepreneurs. Consequently, we propose the following hypothesis:

H2: Social Influence positively influences the behavioral intentions of AI adoption in recruitment settings (SI → BI).

By empirically examining the interplay between social influence and AI adoption intentions, this study aims to offer nuanced insights into the dynamics shaping technological adoption within recruitment contexts.

4.2.4 Facilitating conditions

In accordance with UTAUT, facilitating conditions entail contextual factors that may either enable or impede the adoption and utilization of technology. Examples of such conditions comprise external factors, such as organizational backing, accessibility to resources, compatibility with current systems, and the perceived value of the technology (Venkatesh, Morris, Davis, & Davis, 2003). According to Venkatesh et al., (2003)and Huanget et al., (2018) facilitating conditions can be elaborated as follows:

- Organizational support: Does the organizational structure provide adequate resources and support for using the technology?
- Availability of resources: Are the necessary resources (e.g., hardware, software, training) readily available to use the technology?
- Compatibility with existing systems: Does the technology fit well with the existing systems and processes in the organization?
- Perceived usefulness: To what extent do users believe the technology will enhance their job performance or make their work easier?

Based on the literature review (Venkatesh, Morris, Davis, & Davis, 2003), it has been established that facilitating conditions are crucial in the context of technology adoption, such as AI. These conditions primarily entail the availability of AI tools, regulatory measures, training opportunities, and organizational support (Zhang, Huo, & Tian, 2021). Therefore, it is logical to consider that these facilitating conditions determine the adoption of AI in RSP, and their influence on HR outcomes warrants further analysis. As such, this research aims to test the hypothesis that the adoption of AI in RSP is significantly influenced by facilitating conditions, thereby contributing to the overall understanding of the factors that drive AI adoption in RS. accordingly, the following hypothesis is proposed:

H3: The behavioral intentions of AI in RS are positively influenced by facilitating conditions available to RS professionals.

4.2.5 Recruitment phase

Empirical evidence, as cited by Bhatt (2023), suggests a notable influence of specific recruitment phases on the adoption of Artificial Intelligence (AI) within Recruitment phrases (RP). Analysis reveals that adoption rates tend to fluctuate across different phases of the recruitment process. Specifically, lower rates are observed during the pre-planning phase, while higher rates are noted during phases such as sourcing, pre-screening, interviews, and candidate engagement.

Moreover, a cursory examination of AI tools through a basic Google search for the text "*AI tools for recruitment phases*" supports these findings. The search yields a plethora of AI tools tailored for sourcing, pre-screening, and interviews, indicating a robust presence of AI technology in these phases. In contrast, tools designed for the pre-planning phase are relatively scarce.

Similarly, a Google Scholar search conducted in March 2024 for the search criteria " AI tools for recruitment phases " reveals a substantial body of scholarly literature on AI adoption within phases such as resume screening, candidate sourcing, and interviews. Conversely, research on AI adoption in pre-planning stages appears to be comparatively limited.

This evidence underscores the notion that recruiters' intentions to use, or actual utilization of AI technologies are contingent upon the specific phase of the recruitment process they are involved in. Consequently, the recruitment phase emerges as a pivotal determinant influencing behavioral intentions towards AI adoption within RS.

By recognizing the differential impact of various recruitment phases on AI adoption, it becomes apparent that the recruitment phase plays a crucial role in shaping technological integration within RS. Therefore, it is pertinent to introduce the recruitment phase as a new construct within the conceptual model. Thus, the research aims to validate the influence of recruitment phases on AI adoption in RS, and the following hypothesis is proposed:

H4: The behavioral intentions of AI in RS are positively influenced by certain recruitment phases.

4.2.6 Trust

The proposed conceptual framework augments the established UTAUT model through the introduction of a novel construct: Trust in AI. This extension is underpinned by a theoretical rationale derived from the UTAUT-OM framework, which acknowledges the imperative of incorporating Trust as a central determinant (Venkatesh, 2021), particularly in the examination of the nuanced dynamics associated with Artificial Intelligence (AI) (refer to Section 3.5 for a detailed discussion). As per Venkatesh,"*often, the underlying model itself is blackboxed and the user has little or no visibility into the underlying algorithm or process that renders the decision. Users are unlikely to always embrace this, especially if there is account- ability on the part of the user for the consequences" (Venkatesh, 2021,p.3). This lack of trust leads to skepticism towards algorithm-based decision-making, which is often employed in AI.*

In alignment with the UTAUT-OM model, the conceptual model for AI in Recruitment Systems (RS) strategically integrates 'Trust' as a principal construct. This inclusion is substantiated by existing literature on AI adoption, where Trust has emerged as a pivotal factor influencing users' decisions to adopt or abstain from AI technologies (Allal-Chérif et al., 2021). As underscored in prior research (Allal-Chérif et al., 2021), the significance of Trust as a principal driver underscores its substantial impact on users' willingness to embrace AI applications. However, what encapsulates trust is a broader research question, as it is complex and a standardized definition does not exist (Jacovi, A,2021).

The incorporation of Trust in the AI in RS conceptual model is motivated by its recognized role in shaping users' perceptions and acceptance of AI technologies. Trust, in this context, encapsulates users' confidence in the reliability, security, and ethical considerations associated with AI systems. By acknowledging Trust as a main construct within the conceptual model, the framework acknowledges the multidimensional nature of AI adoption, affording a comprehensive lens through which to examine the intricate interplay of factors that contribute to users' decisions regarding AI integration. This deliberate integration of Trust aligns with contemporary perspectives in AI adoption research, which increasingly highlight the centrality of Trust as a pivotal determinant in shaping users' attitudes and behaviors in the context of AI utilization.

Trust serves as a pivotal factor influencing the adoption of Artificial Intelligence (AI) by recruiters, acting as a major integrator for various factors driving AI integration. The lack of trust in AI represents a significant barrier to the widespread adoption of AI-based technologies among end-users. This sentiment is underscored by the Australian Government, which prioritizes the establishment of trust in AI as a cornerstone action outlined in their AI Action Plan (Australian Government, 2021). This recognition reflects the government's acknowledgment of the necessity to manifest trust in AI, especially for its utilization across diverse consumer levels (Australian Government, 2021).

Furthermore, trust in AI is recognized as a critical determinant across multiple interdisciplinary domains such as finance, technology, energy, healthcare, retail, and hospitality (Toufaily et al., 2021; Catania, 2021; Du & Xie, 2021; Meszaros & Ho, 2021). Within the context of the Recruitment and Selection Process (RS), previous studies have identified trust in AI as a significant barrier to its adoption (Allal-Chérif et al., 2021; Braganza et al., 2020; Shin, 2021).

For instance, the lack of transparency regarding how AI makes decisions contributes to resistance in adopting AI for decision-making processes within the RS (Laurim et al., 2021). Similarly, the opacity surrounding how AI reduces algorithmic bias leads candidates involved in the RS process to resist engaging with AI-driven processes (Lacroux & Martin-Lacroux, 2022).

Based on these observations, it is plausible to hypothesize a negative relationship between trust in AI and the behavioral intentions of AI adoption within RS. Hence, the following hypothesis is proposed:

H5: Trust in AI is negatively influencing the behavioral intentions of AI adoption in RS (TR → BI).

4.2.7 Behavioral intentions (BI)

The conceptual model proposes that behavioral intentions are composed of benefit expectations (BE), facilitating conditions (FC), social influence (SI), and the new constructs of the recruitment phase (RP) and trust in AI. According to Venkatesh et al. (2003), empirical evidence suggests that BI can be predicted based on its constituent predictors, BE, FC, SI, RP, and trust, with a positive prediction suggested from BE, FC, SI, RP, and a negative influence expected from RP and trust.

Collectively, the researcher assumes that these constructs will inform the driving factors or barriers to using AI in the RS.

4.2.8 Use behavior.

The literature highlights the difference between behavioral intentions and the actual use of technology (Davis,1989). The utilization of technology may not align with the intended purpose due to a myriad of factors, including the influence of colleagues or superiors. Conversely, individuals with no prior intentions of using technology may do so under certain circumstances (Agarwal & Prasad,1999). Thus, predicting or quantifying the actual usage of technology is a complex task that draws upon various constructs, such as behavioral intentions and facilitating conditions (Fishbein & Ajzen, 1975; Taylor & Todd, 1995).

Venkatesh (2003) suggests that behavioral intention plays a significant role in determining usage behavior and is regarded as the most robust predictor. Consequently, the researcher proposes the following hypothesis:

H6: The used behavior is positively influenced by behavioral intentions (BI→UB).

However, it can be argued that to realize intentions, facilitating conditions, such as the availability of AI technologies and access to training or support, are also needed (Ajzen,1991). Use behavior (UB) is influenced by these facilitating conditions (FC), thus the following hypothesis is posited:

H7: The used behavior of AI is positively influenced by facilitating conditions (FC→UB).

Additionally, recruitment phases, such as pre-selection, sourcing, and interviewing, have higher suitability to utilize AI leading to the expectation that there is a higher use of AI in some of the recruitment phases than others (Li, Liang, & Huang, 2020). Thus, the recruitment phases are a consideration factor for user behavior. Thus, the following hypothesis is posited:

H8: The used behavior of AI is positively influenced by the recruitment phase (RP→UB).

Trust plays a major role when predicting the actual use of AI (Cho & Lee (2019). Unless users trust AI technology, they may not use it. The literature (Li & Liang,2020) supports this assumption and suggests that trust in AI is one of the biggest influencers of the active use of AI. Thus, the following hypothesis is developed:

H9: Trust in AI negatively influences the user behavior in RS (Trust → UB).

Collectively, these hypotheses, once validated, will contribute to answering research question 1 of the factors driving AI adoption in RS.

4.2.9 HR Outcomes

HR outcomes can be defined as the extent of accomplishment of recruitment and selection process goals. As explained in the literature review (see Chapter 2, section 5), time-to-hire, cost of hire, quality of hire, and retention rates are metrics that assess HR outcomes associated with the RS process. As detailed in section 2.5.5, Rs professionals' use of AI can aid in achieving these outcomes. Thus, by using AI, HR outcomes can be achieved, leading to the hypothesis below:

H10: Use behavior positively influences HR outcomes (UB→OC).

Upon validation through the research, these hypotheses will contribute to answering research question 2 of this research.

4.3 Moderating factors

The review of the literature (see Chapter 2, section 9) indicates that intention to use AI, actual use of AI, and HR outcomes depend on contextual factors. For instance, the industry in which AI technologies are utilized, volume of hiring, and the experience of recruitment professionals have been identified as warranting investigation, as they indicate the circumstances under which these factors are effective and ineffective.

4.3.1 Experience of recruitment professionals

4.3.1.1 Exp x BE->BI

According to Collard and Pauw (2019), a potential relationship exists between recruiters' benefit expectations from using AI in recruitment and their technology experience. If recruiters have high expectations for the benefits of using AI, such as increased efficiency, better candidate matching, and reduced workload, they may perceive AI as beneficial. However, if the technology fails to meet these expectations or causes unintended consequences such as errors or biased results, recruiters may view AI as a hindrance.

Additionally, more experienced professionals may hold higher positions and have greater responsibilities, leading to higher expectations for AI which will lead to a weaker relationship between BI and BE. On the contrary, less experienced professionals may have lower expectations, which could potentially strengthen the relationship. Therefore, RS professional's experience may moderate the relationship between behavioral intentions and benefit expectations. Based on this understanding, the following hypothesis is developed:

H1.1: The strength of the relationship between benefit expectations and behavioral intentions (BI) is stronger for RS professionals with less experience.

4.3.1.2 Exp x SI->BI

As explained in section 3, behavioral intention is influenced by external factors like other managers, entrepreneurs, social media, or media influencers. Thus, SI and BI are correlated. In consumer behavioral studies, it is suggested that the relationship between social influence and BI is moderated by end users' experience (Li & Zhang, 2015). Li & Zhang found that consumers with less experience are more likely to be influenced by online reviews, while consumers with more experience are less likely to be influenced (Al-Gahtani, 2011). Additionally, research has shown that younger and older adults may have different levels of susceptibility to social influence and different benefit expectations, influencing behavioral intentions (Hess, Osowski, & Leclerc, 2005). For example, younger adults may be more susceptible to social influence from peers and be more influenced by social norms, while experts' opinions may influence older adults and have more stable benefit expectations based on their prior experiences.

Thus, in the context of RS professionals, it can be assumed that less experienced RS professionals are more susceptible to adopting AI and are influenced by external factors compared to their more experienced counterparts, leading them to expect greater benefits than experienced professionals. Thus, the hypothesis below is applicable.

H2.1: The strength of the relationship between social influence and behavioral intentions (BI) is greater for RS professionals with less experience.

4.3.1.3 Exp x FC->BI

Empirical evidence suggests that the experience of RS professionals may play a crucial role in the association between facilitating conditions and BI towards the use of AI in recruitment (Hossain, Hasan & Rahman, 2021). The research indicates that experienced RS professionals may better understand the specific facilitating conditions necessary to effectively implement and use AI in recruitment processes. As a result, they may be more likely to perceive AI as a useful tool in their work and be more likely to engage with it (Klaas et al., 2020). On the other hand, less experienced RS professionals may struggle to identify the necessary facilitating conditions. Therefore, it is likely that the experience of RS professionals moderates the relationship between facilitating conditions and BI towards AI use in recruitment in such a way that the relationship between BI and FC is stronger for more experienced professionals. Thus, the following hypothesis is posited:

H3.1 The strength of the relationship between facilitating conditions and behavioral intentions (BI) is stronger for RS professionals with more experience.

4.3.1.4 Exp x RP->BI

Based on the literature, a potential relationship may exist between the recruitment phase and behavioral intentions (BI) toward using AI in recruitment (Datta & Mukherjee, 2021). In the early recruitment phases, such as candidate sourcing and screening, RS professionals may perceive AI as more useful and necessary (Farooqet al., 2021). This is because these phases often involve a high volume of applicants, which can be time-consuming and labor-intensive to manage without the assistance of AI (Bock et al, 2012). However, in the later recruitment phases, such as candidate selection and offer negotiation, RS professionals may have more reservations about using AI due to the importance of human judgment and personal interaction in these stages.

Furthermore, the experience of RS professionals may play a moderating role in this relationship. Experienced RS professionals may have a better understanding of the strengths and limitations of AI in different recruitment phases and may be better equipped to make informed decisions about its use. Thus, their usage of AI in RS may be limited compared to less experienced professionals. Therefore, the relationship between all recruitment phases and BI will be weaker for experienced professionals. Accordingly, the following hypothesis is proposed:

H4.1: The strength of the relationship between recruitment phases and behavioral intentions (BI) is greater for RS professionals with less experience.

4.3.1.5 Exp x Trust->BI

Previous research has suggested that trust in AI can significantly shape behavioral intentions toward its use in recruitment (Benoit et al., 2019). Cheng and Skrypnyk, (2021) suggest that experienced recruiters who have had positive experiences with AI in the past may have higher levels of trust and favorable behavioral intentions towards its use. On the other hand, recruiters who have had negative experiences with AI or lack experience with AI use may have lower levels of trust and negative behavioral intentions towards its use.

It is possible that more experienced RS professionals may have a greater understanding of the limitations and potential risks associated with using AI in recruitment, which may lead them to be more cautious and less trusting of AI use. Alternatively, more experienced RS professionals may have developed a greater sense of trust in AI through their exposure to its use and may therefore be more likely to endorse its use in recruitment. This suggestion is made based on the assumption that longevity in a job is associated with more experience.

This can suggest that more experienced (in years) professionals would better understand AI capabilities and thus apply the technology selectively rather than using it across RS (Kim & Lee, 2021). In contrast, professionals with less experience may trust AI more and, as a result, intend to use AI throughout all stages of the recruitment process. Thus, the following hypothesis is developed:

H5.1 The strength of the relationship between trust in AI and behavioral intentions (BI) is greater for RS professionals with less experience.

4.3.1.6 Exp x BI->UB

Adopting new technologies, such as AI, often requires changes in user behavior (Suseno et al., 2022). The literature suggests that the experience of recruitment professionals may influence the association between BI and UB. Therefore, behavioral intentions may not necessarily translate into the actual use of AI. More experienced RSs may have developed difficult habits and routines to change (Maclachlan & Doherty, 2019). This may lead to not adopting certain technologies even though intentions to use the specific technology (AI in this case) is high.

In contrast, less experienced professionals or users are adopting new technologies faster, thus increasing user behavior, which ultimately may contribute to value realization (Davis, 1989). They may be more open to change and more likely to modify their behavior to realize professional benefits such as achieving work-life balance or career progression, particularly as they are juniors compared to seniors and to succeed on the career ladder.

Thus, RS professionals with less experience may use AI-based technologies more than their more experienced peers. Thus:

H6.1 The strength of the relationship between user behavior and behavioral intentions is greater for RS professionals with less experience.

4.3.2 Hiring volume

4.3.2.1 Vol x BE->BI

A theme in the literature is that most AI applications in RS are concentrated in large organizations, such as Amazon, Hilton, Disney, Walmart, and others(van Esch & Black, 2019). These global organizations have workforces numbering in the hundreds of thousands of employees. For instance, Walmart, as of 2021, employed approximately 2.2 million people worldwide (Walmart, 2021). According to Amazon's 2021 annual report, the company had approximately 800,000 employees globally as of December 31st, 2021 (Amazon.com, 2021). In an example reported by the media channel CNBC, Walmart hired 20,000 employees in 2021 due to the expansion of grocery deliveries (CNBC, 2021). Additionally, the same year, Business Insider reported that Walmart was hiring another 10,000 employees (Business Insider, 2021).

Given that these large organizations have a high volume of hiring demands, high hiring demands may influence the adoption and utilization of AI in RSs. This may suggest that the decision to use AI in RS is driven by the need to overcome the challenges posed by high hiring demands and limited HR personnel. However, when considering trust in AI, it may suggest that AI will be intended for use in low hiring volumes initially until RS professionals build trust in it. The literature supports that suggestion.

According to Bock et al., (2018), chatbots (although not AI) is a valuable tool for low-volume hiring by automating initial recruitment stages and assisting with candidate screening and filtering. Matzler et al., (2018) found that individuals are more receptive to AI in recruitment for low-volume hiring as it is considered more objective and fairer than traditional recruitment methods. The use of AI in low hiring volume situations is preferred for various reasons, including managing uncertainties and complexities, mitigating negative effects on candidate experience, and reducing potential adverse implications.

For example, in high volume hiring situations, where many candidates are being considered, AI can potentially lead to a perception of unfairness(Guo et al., 2021). Candidates may feel they are being reduced to mere data points and not evaluated as individuals. This can result in a negative perception of using AI in recruitment. But in low-volume hiring situations, where fewer candidates are being considered, AI can be perceived as a fair and objective tool for evaluating candidates (Lepak et al., 2020). It may also be perceived as experiments and innovation to improve processes and help eliminate potential human biases that may exist in the traditional recruitment process. This can lead to increased acceptance of AI in recruitment among individuals.

Thus, the literature presents divergent views regarding the relationship between hiring volume and AI adoption. While some studies suggest that higher hiring volumes may drive AI adoption (Davenport & Kirby, 2015; Guo et al., 2021), others propose the opposite (Lepak et al., 2020; Shao & Lyu, 2021). However, this study proposes an alternative perspective by examining the influence of AI adoption on organizational and individual perceptions.

From an organizational perspective, high hiring volumes may encourage the adoption of AI in recruitment and selection processes (RS) (Chen et al., 2021; Lepak et al., 2020). However, from the perspective of individual RS professionals, which is the aim of this study, AI adoption in low hiring volumes may be preferred to balance candidate perceptions and the job security of the professionals.

Thus, the following hypothesis is proposed:

H1.2: The relationship between behavioral intentions (BI) and benefit expectations (BE) is stronger for low hiring volume.

4.3.2.2 Vol x SI→BI

Organizations with high volumes of hiring often face resource constraints and require effective means of managing their recruitment and selection process (RS), leading senior management to consider AI use in RS (Nguyen et al., 2020). This trend may be driven by RS professionals who seek guidance from others who have successfully managed similar hiring volumes using AI. Thus, the prevalence of AI adoption in the RS may increase as hiring volumes rise, indicating a positive correlation between the behavioral intentions of AI and social influence. Thus, the following hypothesis has been formulated:

H2.2: The relationship between behavioral intentions (BI) and social influence (SI) is stronger by high hiring volume.

4.3.2.3 Vol x FC->BI

In instances with high hiring volumes, it may be reasonable to assume that there are corresponding expectations for the presence of many facilitative conditions. For example, facilitating conditions like more technology tools are expected when hiring is high (Armstrong-Stassen et al.,2009; Zhang et al., 2020).

In contrast, RS professionals may not anticipate many facilitating conditions when managing low volumes of hiring, especially if they are experimenting with or considering the use of AI technologies. This suggests that the relationship between facilitating conditions (FC) and behavioral intention (BI) may be stronger when hiring volumes are low. This leads to the following hypothesis:

H3.2: The association between behavioral intentions (BI) and facilitating conditions (FC) is stronger for low hiring volumes.

4.3.2.4 Vol x RP→BI

Given the importance of hiring volume in the organizational context, it is conceivable that it could moderate the relationship between behavioral intention (BI) and the different recruitment phases. While organizations may be inclined to use AI across multiple recruitment phases to manage high hiring volumes (Armstrong-Stassen & Cameron, 2016), RS professionals may selectively choose to implement AI in specific phases to avoid the risks. Their decisions may reflect considerations such as preserving the candidate's experience, safeguarding organizational reputation (avoiding the perception of cost-saving at the expense of the candidate experience), and maintaining job security. Therefore, from the perspective of RS professionals, it can be inferred that low hiring volumes will strengthen the relationship between recruitment phases and BI. Thus, the below hypothesis is developed:

H4.2: The relationship between behavioral intentions (BI) and the recruitment phase is stronger for low hiring volumes.

4.3.2.5 Vol x TR→BI

Prior research has established that trust is a critical factor influencing users' adoption and use of technology (Venkatesh et al., 2003; Mayer et al., 1995). This is especially pertinent in the context of AI, where users' trust in the technology is pivotal for its successful adoption and use (Liao et al., 2019). Studies have consistently demonstrated that users who trust AI are more likely to use it and hold more favorable attitudes toward it (Bhattacherjee et al., 2018; Gefen et al., 2003). Thus, the literature suggests a strong relationship between trust in AI and behavioral intention (BI), wherein users who trust AI are more likely to intend to use it. Conversely, users who lack trust in AI are less likely to intend to use it.

However, the literature also suggests that the relationship between trust in technology and BI can be influenced by various factors, such as the criticality of the function and associated risks, to name a few (Venkatesh et al., 2003). In the context of hiring, the perceived importance or risk associated with the task may vary depending on hiring volume. That means for large hiring volumes, the risks are higher, thus, RS professionals may be less likely to trust AI in cases of large hiring volumes unless it is proven accurate in all the cases.

Thus, the following hypothesis is proposed:

H5.2: The relationship between behavioral intentions (BI) and Trust in AI is stronger for low hiring volumes.

4.3.2.6 Vol x BI->UB

The adoption of artificial intelligence (AI) in recruitment processes is increasing as organizations aim to improve Human Resource (HR) outcomes through enhanced efficiency, reduced costs, and increased accuracy in selecting suitable candidates. UTAUT suggests that behavioral intentions (BI) strongly predict individuals' engagement in a specific behavior. Additionally, external factors such as social influence (SI) and facilitating conditions (FC) also impact actual use behavior (Venkatesh, 2003)

However, research indicates that RS professionals exhibit varying levels of actual use of AI, which may be influenced by external factors such as hiring volume (Kumar & Shukla, 2021). It is suggested that RS professionals may be more cautious about AI use in high hiring volume situations where the risks associated with selecting the wrong candidate are greater unless it is properly tested to be accurate. Thus, they may be more willing to use AI in low hiring volume situations where there is less pressure to fill vacancies quickly, which also may allow them to validate the accuracy of AI.

Thus, the following hypothesis is developed:

H6.2: The relationship between behavioral intentions (BI) and user behavior is stronger for low hiring volumes.

To test the above hypothesis and answer the research questions, the researcher employed a mixed-method approach, as explained in the next sub-section.

4.4 Research approach

The present study follows a mixed-method research approach which consists of qualitative and quantitative, as depicted in Figure 10.

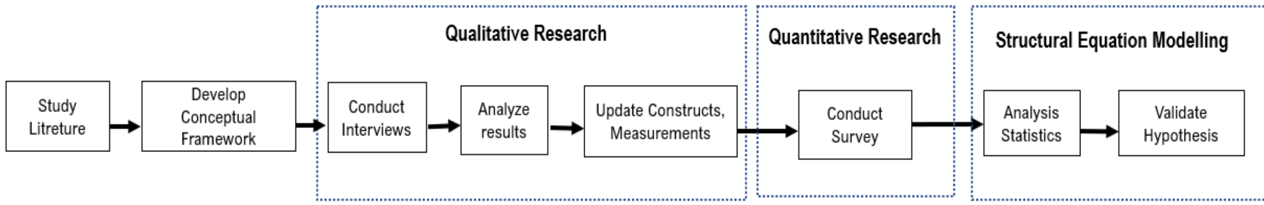

Figure 10: The research approach

The rationale for choosing a mixed methods approach is multifaceted and has been influenced by literature. For example, Ivankova et al., (2009) posit that the increasing complexity of the modern world necessitates more sophisticated approaches to comprehending it. Many scholars (Bulsara, 2015; Leech et al., 2010; Maxwell & Loomis, 2003; Schensul & LeCompte, 2012) support this notion.

The mixed-method approach involves combining qualitative and quantitative methods to examine a phenomenon, which allows for a more comprehensive understanding by leveraging the advantages of both approaches (Creswell & Plano Clark, 2011; Johnson & Onwuegbuzie, 2004). These advantages include:

- Triangulation of data: the findings from qualitative and quantitative methods can be combined to provide a more comprehensive understanding of the phenomenon being studied.
- Complementary strengths: Both qualitative and quantitative methods have complementary strengths, and mixed methods approaches exploit these

strengths. For example, quantitative methods allow for examining patterns and relationships in the data, whereas qualitative methods provide rich and in-depth data on exploration.

- Increased validity and reliability: By using multiple methods to collect and analyze data, mixed methods research approaches increase the validity and reliability of the findings. And reduces the weaknesses of each method.
- Better representation of complexity: Mixed methods approaches are suitable for studying complex phenomena (such as AI), as they allow for examining the phenomenon from multiple angles and provide a more nuanced understanding of the issue.
- Addresses limitations of single-method approaches: Mixed-methods research approaches can address the limitations of single-method approaches, such as the limitations of qualitative methods in generalizing findings to a larger population and the limits of quantitative methods in capturing the richness and depth of experiences.

Therefore, using a mixed method approach in this study is expected to help understand the challenges of adopting AI in the complex function of recruitment and selection in human resource management. Human resource management is a multifaceted field that encompasses various strategies, processes, and technologies to manage the workforce in an ever-changing organizational environment (Boxall & Purcell, 2000; Vardarlier, 2019). These complexities involve several factors, including labor market fluctuations, governance policies, workforce arrangements, organizational strategies, skills demand, and shortages, economic aspects like the impact of gig economies, trade unions, stakeholder expectations, and regulatory issues such as data privacy policies (Kuhn et al., 2021; Kaplan et al., 2019; GDPR.Eu, n.d.). Therefore, as Boxall & Purcell (2000) noted, building theory in strategic HRM is challenging (pp. 186).

The following chapters will discuss the details of each research method and its results.

4.5 Chapter summary

This chapter presents the rationale behind the proposed conceptual, theoretical framework, AI-RS, its underlying hypothesis development, and the chosen mixed method approach to testing the hypothesis.

The proposed AI-RS model extends UTAUT constructs, and the Trust construct from UTAUT-OM. By extending these theoretical models, the AI-RS intends to adopt a more contextual framework to address RS professionals' viewpoints on AI adoption in RS. Through this approach, the theoretical framework is expected to generate a closer look at the AI adoption phenomena in RS, providing a unique perspective compared to existing theoretical frameworks.

Additionally, it is expected to generate insights more relevant to RS professionals, which can drive managerial interventions required in the RS regarding AI adoption.

Furthermore, the theoretical framework is expected to be more contextualized to study the adoption of other emerging technologies, such as Robotic Process Automation (RPA) and Metaverse, and similar technologies in the RS.

CHAPTER 5

QUALITATIVE RESEARCH OVERVIEW

5.1 Introduction

This chapter introduces the qualitative research design and explains the reasoning behind choosing the method of interviews. It also discusses the important considerations when selecting suitable interviewees and determining the optimal sample size for data collection. Furthermore, the chapter outlines the data collection approach, including the interview process, formulating questions, and a summary of the data analysis techniques. The results of the qualitative research will be presented in Chapter 6.

The approach used in this qualitative research is marked in the frame in Figure 11.

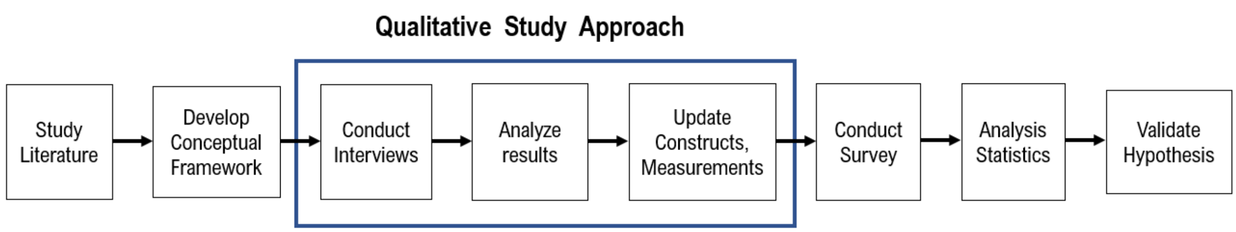

Figure 11: The qualitative study approach

5.2 Qualitative research overview

When developing a new conceptual model (such as the AI-RS) model, validation of new constructs is crucial, and the measurement model of these constructs requires definition. To achieve this, qualitative research methods are deemed appropriate due to their advantages in validating new constructs or identifying measurement criteria for such constructs (Creswell, 2014). An inductive approach is often used to develop concepts and insights from patterns in the data, which then help to develop theories, as explained by

Glaser and Strauss (Glaser & Strauss, 1967). Such an approach helps to gain a holistic understanding of a problem, exploring its complex and interconnected aspects that may not have been initially anticipated or expected.

Qualitative research also offers other advantages, such as providing an in-depth understanding and perspectives from end users, allowing for a more nuanced understanding of the issue (Creswell, 2014; Maxwell, 2013). Qualitative research also offers flexibility to allow for adjustments as research progresses (Denzin & Lincoln, 2011) and can be used to generate theory and advance an understanding of a phenomenon (Creswell, 2014).

To collect data from the perspectives of RS professionals, interviews were employed as the primary qualitative data collection method due to its ability to allow for a deeper exploration of participants' experiences and perspectives on the research topic and the opportunity to ask follow-up questions (Kvale, 1996; Spradley, 1979; Denzin & Lincoln, 2011). The reason for conducting interviews was to gather information that could help improve how certain concepts are defined and measured (Creswell, 2014). These concepts have an impact on the quantitative research conducted in Chapter 7, as well as the overall AI-RS conceptual model. The refined model is then tested in the quantitative phase of the study using statistical analysis to answer the research questions.

5.3 Designing interviews

This study employed semi-structured interviews, which offer the benefits of both structured and unstructured interviews (Fylan, 2005). Structured interviews provide a framework for navigating and focusing on the area of information required to answer the research question (McGraw & Harbison-Briggs, 1989). On the other hand, unstructured interviews allow for flexibility and exploration of data beyond the framework, potentially revealing information not initially considered in the research design (Carruthers, 1990; Dearnley, 2005).

The exploratory nature of the interviews is particularly pertinent in this research as this study is intended to extract the subject matter expertise from the RS professionals. The interview was designed to provide a basic framework of questions aimed at gathering information necessary to answer the research questions while also being open to exploring areas that may offer useful insights into broader perspectives from these experienced professionals.

5.4 Sampling process

The researcher used purposive sampling to select participants. Purposive sampling is ‘used to select respondents most likely to yield appropriate and useful information’ (Kelly, 2010, pp. 317). The sampling criteria were threefold: 1) RS professionals actively participate in the RS as recruiters, hiring managers, or HR executives; 2) RS professionals who have some knowledge of AI; and 3) RS professionals who have at least one year of experience in the RS.

Thus, the RS professionals holding official titles, as delineated in Table 4 with knowledge of AI, comprised the sample. Industrial occupation lists from the United States (Rounds et al., 1999) and the occupation list published in Australia (Authority et al., 2018) were consulted to construct this taxonomy of job titles.

<table>
<tr><th>Role</th><th>Official Title</th><th>O*NET title</th><th>Australian occupation list title</th></tr>
<tr><td>Recruiter</td><td>Recruiter
Recruitment consultant
Executive recruiter
Talent acquisition manger
Talent acquisition consultant/partner</td><td rowspan="2">Human resource managers
Labor relations managers
Employee assistance specialists
Employment interviewers
Job and occupational analysts
Employer relations and job development specialists
Employee relations specialists
Employee training specialist
Personal recruiters
Labor relations specialists
Talent directors
Technical directors /managers
First-line supervisors/managers - executive workers</td><td rowspan="2">Human resource manager
Human resource advisers
Recruitment consultant</td></tr>
<tr><td>HR Executive</td><td>HR Manager
HR business partner
HR Director
Vice President – Human Resource Development</td></tr>
<tr><td>Hiring Manager</td><td>Project manager
Program manager
Managing Director</td><td></td><td>Chief executive/managing director.</td></tr>
</table>

	Director Business Development Manager Sales Manager Country Manager Partner Chief Executive Officer Chief Operating Officer Founder		Corporate general manager Project manager IT manager Sales Manager Business development manager Operations manager/supervisor

Table 4: AI applications in RS

The current study employed two distinct approaches to recruiting suitable interviewees: leveraging professional networking sites such as LinkedIn and offline professional networking groups and communities, including university alumni associations. By utilizing both strategies, the research aimed to assemble a diverse group of individuals with varying backgrounds and experiences.

Using online professional networking sites, like LinkedIn, offers access to a larger pool of potential participants who may possess the requisite knowledge of recruitment and selection processes (Crawford et al., 2020). This approach facilitated the researcher's ability to engage a wider audience and increase the likelihood of securing suitable interviewees who fulfill the study's eligibility criteria of being a RS professional with some knowledge of AI.

The offline professional networking communities, such as university alumni, were beneficial in obtaining access to working professionals who may not be as active on online networking sites (Hagenauer, Glückler, & Delmestri, 2016). The use of alumni groups from universities such as Oxford also ensured that the participants had a certain level of experience and expertise in their field, especially those who studied HRM and MBAs and executive MBA programs, as these courses are attended by working professionals (Joshi, 2019).

By employing both approaches, the researcher aimed to recruit a wider representation of participants rather than a saturated group of people who are only active in either online or offline groups. The use of diverse recruitment methods may increase the specifics related to the research subject of RS. The process followed for both sources is explained in the next sub-section.

5.4.1 Recruitment through LinkedIn

Recruiting research participants from LinkedIn has gained widespread popularity due to its numerous advantages (Griffiths et al., 2017; Rutsatz et al., 2017). Firstly, LinkedIn's user base of over 700 million professionals from diverse industries offers a larger pool of potential participants. Secondly, LinkedIn provides a platform for researchers to engage with prospective participants, build relationships, establish trust, and increase the likelihood of their participation. Finally, LinkedIn's Posts feature allows researchers to request referrals from their network, which is more effective than traditional advertising methods (Topolovec-Vranic et al., 2016). Therefore, recruiting research participants from LinkedIn offers distinct advantages in finding relevant recruitment professionals for research.

The researcher utilizes a few methods to recruit participants from LinkedIn. One such method is to use the 'LinkedIn post' feature, which allows the researcher to introduce the researcher's project and invite potential participants to contact them (Topolovec-Vranic et al., 2016). Additionally, the researcher used LinkedIn's network group function, allowing members to create or join groups focused on specific topics, interests, or industries (LManca & Ranieri, 2016). The researcher selected groups such as 'The recruitment network' group, which has over 664,095 registered professionals as of 01/06/2022 and effectively reached recruiters, hiring managers, and HR executives. Finally, the researcher searched for professionals with specific job titles and sent them a LinkedIn connection request and an invitation to participate in the research.

5.4.2 Recruitment through offline professional networking groups

The current study employed the Oxford aluminum network as an offline professional network. The university's alumni community comprises distinguished professionals from diverse disciplines, including politics, science, literature, and the arts, thereby rendering it a valuable resource for networking and professional opportunities

(Litan & Mitchell, 2013). To solicit participants, the researcher contacted several chapters of the network, including the Asia Pacific Oxford aluminum chapter, and provided a succinct overview of the study's objectives, inviting recruiters, hiring managers, and HR professionals to express their interest in participating in the research. The combination of techniques resulted in 17 interviews with recruitment professionals.

5.4.3 Sample size

Determining sample size for qualitative research interviews is debated among scholars. Nevertheless, scholars such as Patton propose that saturation be achieved as the point when sufficient data is obtained to address the research question and no further variations in responses are observed (Patton, 2002). According to Patton, the sample size for qualitative research is influenced by various factors, including the research purpose, the significance of the inquiry, the credibility and usefulness of the findings, and the availability of resources and time.

On the other hand, Saunders et al., (2016) propose that the norm for the number of participants in qualitative research should fall within the range of 15 to 60 individuals. Therefore, the researcher aimed to surpass the minimum threshold recommended by Saunders and Townsend while simultaneously ending the data collection process at the saturation point, in accordance with Patton (2002)'s recommendation.

5.5 Interview process and structure

Given the geographic dispersion of participants, remote interviews were intended to be conducted using online meeting tools such as Zoom and Microsoft Teams. The interviews were designed to last for a period of 60 minutes and followed a general structure as outlined in Table 5 and discussed further below. Additionally, the interviews provided an opportunity to explore participants' areas of expertise and gain further insights to enrich the research data, thus allowing for flexibility within the framework.

Duration	Goal	Steps
5 minutes	Receiving Consent	To begin the interview process, participants were greeted and provided with a brief introduction to the research study and its objectives. The data collection, recording, archiving process, and policies were also explained, along with instructions on how to exit the interview and contact the ethics committee if necessary. Finally, the researcher checked with each participant to ensure they wished to proceed with the interview process.
5 minutes	Scoping the interview	Before commencing the data collection process, participants were provided with detailed explanations of the various recruitment phases and the AI tools being utilized in the study. Any questions or clarifications were also addressed at this stage to ensure that participants clearly understood the research process before proceeding with data collection.
45 minutes	Detailed interview and data collection	The researcher asked the pre-designed interview questions outlined in the table during the interview process. Additionally, follow-up

		questions were asked based on the participant's responses, allowing for a deeper understanding of the topic at hand.
5 minutes	Closure	Upon conclusion of the interview, the researcher provided participants with information regarding the follow-up process. This included details on how to contact the researcher or the ethics committee should the participant decide that they do not wish to have their data used in the research after the interview has taken place.

Table 5: The Structure of the Interview

To preserve the anonymity of the participants, data collection was limited to voice recordings. Additionally, using audio recordings was intended to optimize time management for both the interviewer and the interviewee by eliminating the need for written notetaking. The recorded interviews were advantageous for the researcher, enabling post hoc analysis through transcription and subsequent data analysis.

5.5.1 Interview questions

The interview questions were designed to collect essential information, including consent and data relevant to the research questions. Firstly, the researcher prioritized obtaining consent and ensuring adherence to data collection protocols. Secondly, participants were introduced to AI terminologies used in the research to align their understanding. The interview process then proceeded with demographic information, participants' roles, recruitment phases, types of AI technologies used, benefit expectations, efforts, facilitating conditions, level of trust in AI, and insights from their experiences. The specific questions are outlined in Table 6.

Question focus	Interview question
Demographic	▪ Can you explain your role in the recruitment process, the industry you work in, the number of years of experience you have, and the country you are in?
Job-related conditions	▪ On average, how many candidates do you typically recruit in a month?
	▪ Are you part of a recruitment agency, HR department, or business unit?
Current AI use	▪ What kind of knowledge do you have about AI and its use in recruitment?
	▪ Are you currently using any AI technologies, and if so, what are they?
Social Influence	▪ How did you first become involved in using AI in the recruitment process? Who introduced you to the use of AI?
	▪ Who influenced you to use AI in the recruitment process? How did you learn about AI, and how did you educate yourself on the topic?
Benefit expectations	▪ What benefits do you expect from using AI in recruitment, and why?
Recruitment phase	▪ In which recruitment phases would you use AI, and why would you choose to use or not use it in those phases?
Effort expectations	▪ What is your understanding of the level of effort required to implement or use AI in the recruitment process? ▪ What efforts are you willing to spend to adopt AI? ▪ What do you expect from AI technologies to start using it?
Facilitating conditions Facilitating conditions	▪ What kind of support and facilities do you expect, and from whom, to use AI in the recruitment process?
Trust in AI	▪ How much do you trust AI in the recruitment phases you mentioned, and why would you trust or not trust it in those phases?"
HR outcomes	▪ What HR outcomes can you achieve by using AI in the recruitment process? ▪ Why do you think you can achieve those HR outcomes from AI? ▪ What HR outcomes cannot be achieved by using AI in the recruitment and selection process?

Table 6: List of questions asked during the interviews.

Before issuing the survey to the research participants, the interview questions underwent a thorough review process. Two academics with expertise in HR and technology adoption, particularly in the context of AI, along with a few HR professionals, carefully assessed the questions for clarity, relevance, and readability. This review ensured that the interview questions were well-designed and suitable for capturing the necessary data from the participants.

5.6 Data analysis approach

A thematic content analysis (TCA) will be utilized to comprehend the data gathered from the interviews. Due to the diverse range of industries, demographics, and experiences represented by the three participant groups in this study, a data comprehension mechanism like TCA was deemed necessary (Holton, 1975; Jørgensen, 2001; Vaismoradi et al., 2013). TCA can interpret qualitative and descriptive data, such as verbal conversations or expressions, and extract concepts to explain the data more deeply (Braun & Clarke, 2006). TCA identifies word patterns, encodes them, groups them into themes, and verifies existing or new themes according to the research questions and conceptual model based on insights derived from the interview data (Anderson, 2007).

The purpose of qualitative data analysis is to uncover patterns, themes, and relationships in the data and obtain measurements required for the conceptual model

(Strauss & Corbin, 2017). The iterative and flexible process of qualitative analysis involves several stages, including data preparation through transcriptions to gain an initial understanding of the data, followed by coding the data, which entails breaking it down into smaller segments and assigning codes or labels to each segment. These codes are developed based on research questions and conceptual model constructs and help to identify patterns and relationships in the data, thus enabling its organization and categorization for further analysis (Lincoln & Guba, 1985). Coded data is then categorized and organized, with similar codes or data segments grouped into categories or themes, providing a deeper understanding of the research question. For example, if an interviewee expresses, "*I expect AI to reduce my time involved in sourcing candidates*" this response would be coded and classified under "*time reduction*". Furthermore, it would be grouped under the broader theme of "benefit expectations".

Thus, in the process of analyzing the interview data in the first step, the researcher intends to engage in multiple listens of the audio recordings and utilize online software to generate transcripts. The transcripts were then cross-checked with the recordings to ensure accuracy. According to research ethics guidelines, personal information was intended to be encoded (see Chapter 5, section 7). This included participant and company names, which were pseudo-coded to maintain confidentiality. The researcher's name will be replaced with 'Researcher.' The company names will be replaced with ‘ABC.’ The interviewees will be assigned a classification code (R for recruiter, HM for hiring manager, HRE for HR executive) codes and a sequential number. For example, candidate one, a recruiter, was coded as R1, and candidate two, a hiring manager, was coded as HRM1. HR Executives were coded as HRE1 etc. (Table 7).

Candidate category	Category Code	Example of the codes
Recruiters	R	R1
Hiring Manager	HRM	HRM1
Human Resource executives	HRE	HRE1

Table 7: Interviewee classification.

To develop these codes and themes, the researcher used the NVIVO software to develop a set of themes from the transcript (Clarke & Braun, 2017). The themes focused on the research questions and constructs of the conceptual model. New themes were identified and added to extend the model. The identified codes and themes were used to analyze and derive meaningful information answering the research questions, with the results presented in Chapter 6.

5.7 Ethical framework

The study was conducted per the ethical standards set forth by the Flinders University Ethics Approval Committee, and informed consent was obtained from all participants before participating in the interviews. To protect the participant's privacy and confidentiality, confidentiality and anonymity were maintained throughout the study.

5.8 Chapter summary

This chapter first provided an overview of the mixed-method research design used in this study. It then focuses on the qualitative research approaches employed in this study, including the selected method of data collection through semi-structured interviews, the approach to data collection, and the data processing methodology. The study gathered data from 17 participants comprising hiring managers, recruiters, and HR executives with more than a year of experience using online tools such as Zoom. The research utilized a deductive approach from thematic content analysis (TCA) to extract meaningful data and information for subsequent analysis. The findings of this analysis will be utilized to design the next phase of the research, which will involve a quantitative analysis to statistically validate the conceptual model and hypotheses and provide answers to the research questions.

CHAPTER 6

QUALITATIVE RESEARCH RESULTS

6.1 Introduction

The main objective of this chapter is to provide a comprehensive and detailed analysis of the qualitative data collected, as explained in Chapter 5. The chapter is organized into three sections. The first section provides demographic data of the participants. The second section focuses on the current usage of AI amongst the research participants. The third section focuses on AI technologies RS professionals use, including application areas and specific technologies.

6.2 Data collection: results

Personalized messages sent to selected LinkedIn contacts proved successful, with 30 individuals expressing interest in participating in the research. Additionally, offline networking groups, specifically Oxford Alumni WhatsApp groups, generated interest from 20 individuals. After applying the selection criteria, 17 individuals were ultimately chosen to participate in the interview process.

6.3 Research participant profile

The criteria ensured consistency in participant selection and aimed to avoid bias by including individuals from a diverse range of countries, as summarized in Table 8.

Number	Reference	Country	Experience	Industry	Role	Official Title
1	R1	Saudi Arabia	13	Manufacturing Retail	Recruiter	National Talent acquisition manager
2	R2	Australia	10	IT and Telecom	Recruiter	Talent acquisition partner
3	R3	Pakistan	5	HR & Admin services	Recruiter	Human Resource Manager and operations manager
4	R4	India	14	IT and Telecom	Recruiter	HR Business partner
5	R5	Philippines	10	HR and Admin Services	Recruiter	Human Resource Specialist
6	R6	Philippines	4	Business process outsourcing (BPO)	Recruiter	Recruitment specialist
7	R7	India	4	Transportation and logistics	Recruiter	Recruitment and payroll manager
8	R8	Pakistan	12	IT and Telecom	Recruiter	Talent Acquisition Manager
9	R9	Nigeria	9	Aviation	Recruiter	Talent Acquisition Manager
10	R10	United Kingdom	16	IT and Telecom	Recruiter	Global Talent Acquisition offering lead
11	HRE1	India	8	Banking & Financial	HR Executive	Human Resources Manager
12	HRE2	India	13	IT and Telecom	HR Executive	Vice President-Human

						Resources Management
13	R11	Australia	13	Professional Services	Recruiter	Talent Acquisition business partner
14	HM1	Australia	15	Natural resources	Hiring Manager	Business Development Manager
15	R12	Australia	3	HR and Admin services	Recruiter	Recruitment consultant
16	R13	Netherlands	2	Legal	Recruiter	Recruitment consultant
17	R14	Netherlands	15	IT and Telecom	Recruiter	Partner and recruitment consultant

Table 8: Demographic data of the interviewees

In terms of the job groups, 14 participants out of 17 represented recruiters, two represented HR executives, and one represented a hiring manager. Those recruiters were hiring different job groups, as summarized in Table 9 below.

6.4 Research participants experience in the RS.

The research participants showcased a diverse range of RS experiences, with some participants responsible for hiring C-level executives while others were focused on recruiting for junior positions. Table 9 below provides a comprehensive summary of the participants' experiences.

Reference	Candidate details	Types of roles hired
R1	• Responsible for the entire recruitment process and candidate engagement • Did not use external recruitment firms for sourcing	• Middle to senior-level positions, • manufacturing workers, • retail workers
R2	• Responsible for managing HRM activities, including recruitment and strategic planning. • Specialized in recruiting for IT companies. • Involved in all phases of the recruitment process. • Did not use external recruitment firms for candidate sourcing. • Did international recruitment.	• Middle to senior positions, • Retail workers
R3	• Dual roles as HR Manager and Operations Manager, including recruitment responsibilities. • Also managed own recruitment agency for few companies. • Involved in all aspects of the recruitment processes. • Not responsible for final hiring decisions • Worked in IT, hospitality, and facilities management industries.	• Blue collar workers • Junior level
R4	• Internal recruiter and HR business partner • Associated with a global IT consulting company with a large workforce. • Involved in all phases of the recruitment phases. • Recruited junior to mid-level experienced candidates. • Managed a high recruitment workload of 250 candidates per month. • Competed with other IT consulting companies. • Led hiring of MBA graduates from prestigious Indian universities	• IT professionals • Junior to senior-level engineers
R5	• Dual role as HR specialist and a recruiter	• Junior to middle-level roles

	• Helped US companies by managing Philippine-based recruitment.	
R6	• Primarily focused on business process outsourcing (BPO) positions • Clients are mainly based in the USA with call centers or administrative services in the Philippines. • Average monthly fulfillment target of 65 positions.	• Junior to middle-level roles
R7	• Multiple roles as an Internal recruiter and Payroll Manager in India • Main experience in the transportation and logistics industry • Specialized in recruiting blue-collar workers, particularly drivers. • Responsible for end-to-end recruitment process, including sourcing, screening, interviewing, and onboarding. • Average monthly fulfillment target of 28 positions.	• Blue collar workers, • Drivers • Transportation business partners • Truck drivers (rural)
R8	• Technical Recruitment Specialist • Internal recruiter • Hired an average of 20 candidates per month. • Also worked as an external recruiter for IT and startup firms • Established own recruitment agency.	• Middle to senior levels • IT professionals (CTOs, Software engineers, director level IT executives)
R9	• Specialized in recruiting skilled and senior positions. • Responsible for overseeing the entire recruitment process, from sourcing to hiring decisions. • Working in a country where traditional recruitment methods are dominating	• Middle to senior level • Cabin crew • Pilots • Airport security specialist, Airport ground handling staff
R10	• Talent Acquisition and Offering Lead • Clients are fortune 100 companies in US and Europe. • Responsible for designing and implementing talent acquisition strategies for global corporations. • The company he works for has more than 1500 AI patents and AI products specialized in HR	• Middle to senior-level roles • Tech professionals such as software engineers

HRE1	• HR Executive and Human Resource Manager for financial institutes • Acted as an internal recruiter. • Responsible for hiring approximately 150 candidates monthly. • Resulted in 1800 candidates hired annually.	• credit analysts • risk analysts • credit monitoring professionals • sales, and marketing managers
HRE2	• Dual role as HR Manager and Recruitment Specialist • Owns a recruitment agency and has worked with various companies in India. • Utilizes LinkedIn as the primary sourcing platform. • Has experience with AI technologies requested by client companies	• Middle to Senior level professionals • Director level executives • Tech professionals including Chief Technology Officers • Mechanics (in her previous role), showroom officers in auto dealerships
R11	• Internal recruiter in an Australian professional services company • Dual role as Talent Acquisition and HR Business Partner • Involved in all phases of the recruitment process. • Collaborated with external recruitment agencies for candidate sourcing	• middle to senior positions, • director-level positions, • accounting and auditing profession
HM1	• Dual role as Business Development Manager and hiring manager. • Average hiring volume of 2-4 hires per year • Relied on HR department. • Preferred internal recruitment team over external agencies due to low hiring volume. • Previous experience in retail companies in Russia before moving to Australia	• Sales and marketing professionals, • Retail workers
R12	• Experience in recruitment agency • Specialized in serving accounting clients and recruiting CPA-certified professionals. • The average monthly hiring rate of 15 candidates or 180 candidates per year.	• Accounting professionals • Junior to senior professionals
R13	• Internal recruiter at a legal firm in the Netherlands	• legal professionals such as lawyers and partners

R14	• Internal recruiter • Provided recruitment services to client companies, • focusing on executive-level hires • Average monthly recruitment of 3 individuals or 36 annually, including C-level executives.	• C-level executives

Table 9: Interviewee profile

Analyses of the interviews revealed significant trends highlighting the current use of AI in RS and AI tools and technologies explained in the next sub-sections.

6.5 Current usage of AI

11 out of 17 participants (R2, R3, R4, R5, R6, R8, R10, R11, R12, R14, and HRE2) reported using AI in their RS. However, AI usage was mostly confined to professional networking platforms like LinkedIn.

LinkedIn was the primary platform used by most participants, who understood that it leverages AI algorithms to recommend candidates and target job advertisements. This is supported by the product architecture of LinkedIn's recruiter tool, which uses machine learning (ML)-based training models to train algorithms using a recruiter and candidate search patterns (Geyik et al., 2018). Additionally, some participants (R6 and R8) utilized social media platforms such as Facebook and WeChat to advertise job posts and were also aware of the use of AI in these platforms.

Social media companies such as Facebook, TikTok, and WeChat employ ML to identify member data to identity patterns and curate personalized content based on member and close contact search, likes, views, and click histories (Grandinetti, 2021; Meng et al., 2020). Thus, even participants (R1, R7, HM1, and HRE1) who claimed not to be using AI were, in fact, utilizing AI through LinkedIn and other social media platforms in their daily work in RS. Based on these findings, it can be concluded that almost all interviewees used AI in some form. Based on these findings, it can suggest that almost all interviewees were using AI in some form although predominantly via LinkedIn or Social media platforms.

Four interviewees (R2, R4, R10, and HRE2) however, used AI beyond LinkedIn or other social media platforms in the form of customized AI products in RS. For instance, R4 utilized several in-house developed AI tools, such as candidate recommendation and preselection tools, which had been developed by the IT consulting company she worked for. According to R4, her company invested heavily in these AI technologies to gain a competitive advantage in the market, recognizing that the competition for IT talent in India is high (Fortune India: Business News, Strategy, Finance and Corporate Insight, 2021):

> *"In India, the competition for IT talent is extremely high, and we need to be smart in identifying and recruiting candidates better and quicker than the others in the market"*.

Thus, the findings suggest that AI is currently being used in RS processes, mostly in the form of professional networking and career development platforms like LinkedIn, but there were also some instances where custom-built AI applications were in place.

6.5.1 AI Tools used by interviewees in the RS process.

This section presents the findings regarding the AI tools or technologies used in the RS processes.

6.5.1.1 Targeted job advertisement tools

Most participants (except R7 and R14) expressed interest in using AI-based targeted job advertisement tools to improve productivity and promote diversity. These tools were primarily associated with professional networking platforms like LinkedIn, Facebook, or WeChat. Some participants had already implemented these technologies and highlighted their effectiveness in reaching targeted candidates. For instance, R5 in the hospitality industry found success with Facebook and WeChat job advertisement tools stating that "*most of the targeted candidates in the hospitality industry are already using social media; hence, it is effective for us*", while R3 used an AI tool on top of LinkedIn's native campaign tool which she found more powerful. These findings indicate that AI-based targeted job advertisement technologies are planned for adoption by many interviewees and are currently in use.

6.5.1.2 Candidate recommendations tools

The study found that interviewees tended to adopt AI-based candidate recommendation tools, citing potential advantages such as reduced workload for recruiters and increased productivity. However, R9 shared a negative experience using an AI-based recommendation tool to identify a suitable candidate.

R9 had employed a customized AI candidate recommendation product from LinkedIn, costing AUD$30,000, to find a suitable candidate for a critical position. However, none of the profiles recommended by the product met her expectations, and the role was ultimately filled manually using other sourcing methods. R9 stated:

"*We spent AUD$30,000 to tailor the product for recruiting one person as the role was critical. Nevertheless, it did not prove to be effective at all. None of the recommended profiles by AI met our requirements. We had to resort to manually contacting candidates to fill the position. Our efforts, time, and money spent on developing the technology were futile*."

However, she stressed that it was just one example and emphasized that she would continue to use AI technologies, highlighting that building accuracy is an ongoing process. This indicates that even when results were unfavorable, some RS professionals remained open to AI candidate recommendation tools.

6.5.1.3 Job description generators

The findings revealed that only a small fraction of the RS interviewees intended to use AI-based job description generators. Only R3 is currently utilizing this technology. The perceived benefits of this tool centered around automating tedious and time-consuming tasks, while R3 believed it would particularly assist recruiters with limited skills or experience in crafting diverse job descriptions. However, most interviewees (R2, R4, R5, R6, R14, and HM1) expressed no interest in using AI-based job description generators.

6.5.1.4 Resume scarpers.

Most recruiters (R10, R12, R2, R3, R5, R9), hiring manager (HM1), and HR executive (HRE2) expressed their intention to utilize AI-based resume scrapers. HRE2 justified using this technology, stating, "*We get irrelevant resumes all the time. If AI can help get the right resumes with the right information, that will benefit us in many ways*." The adoption of AI-based resume screening tools was perceived to bring benefits such as increased productivity, reduced workload for recruiters, and improved quality of hire through easier identification of suitable resumes.

However, R7 noted that not all candidates in industries, including in transportation for positions like drivers, would have accessible data for scraping. This highlights the influence of industry and job type on the effectiveness of AI-based resume screening tools. Thus, the findings suggest that while AI-based resume screening tools are generally considered advantageous, their effectiveness may depend on the industry and job type.

6.5.1.5 AI chatbots

According to the findings, most interviewees acknowledged the value of AI chatbots in the recruitment process. Notably, most of the interviewed recruiters represented large corporations with high recruitment volumes, indicating that the recruitment volume may influence the effectiveness of AI chatbots. Interviewees highlighted the role of AI chatbots as an extension of human resources, enabling recruitment services to be available to candidates beyond regular working hours. For example, R13 emphasized that "*AI chatbots provide 24/7 service and ensure availability of recruitment services to candidates even when the recruitment staff is not available to provide round-the-clock service*".

The use of AI chatbots is regarded as an effective method to enhance the recruitment process, especially in terms of candidate engagement (Smith & Jones, 2020). AI chatbots alleviate the workload of recruiters and provide an efficient means of addressing candidate inquiries. This preference for AI chatbots aligns with the increasing adoption of conversational AI across diverse industries (Bughin et al., 2018). Integrating AI chatbots in recruitment services is particularly prominent in candidate engagement and recruitment marketing (Bughin et al., 2018). Consequently, the popularity of utilizing AI chatbots in the recruitment process is expected to continue growing, with many RS owners already planning to implement this technology (Huang & Handy, 2021)

6.5.1.6 Candidate screening tools

Most interviewees, including several recruiters (R2, R3, R4, R9, R10, R12, R13) and a hiring manager (HM1), expressed an intention to use AI-based candidate screening tools. However, interviewees such as R1, R7, and HR managers HRE2 did not intend to use this tool, indicating a possible moderating effect from the RS professional’s role.

Furthermore, the analysis of R1 and R7 reveals that the industry and the type of hiring role moderate the intention to use AI tools in candidate screening. Specifically, R1 operates in the manufacturing industry, where candidates are primarily blue-collar workers who may not have resumes that AI can be screened. Similarly, R7 operates in the transportation industry, where data limitations may affect the integration of AI-based candidate screening tools. These findings highlight the importance of considering the industry and hiring role when evaluating AI tools' potential benefits and limitations in candidate screening.

6.5.1.7 Interview tools

Findings revealed that most interviewees had a negative perception of AI-based interview tools, with only R2 and R3 expressing interest in using such tools. The reasons for this negative sentiment varied, indicating potential influences on the intention to use these tools. HM1 highlighted the inability of AI technology to fully evaluate complex skills assessments required for their hiring process, while R13 expressed concerns about losing good candidates in a skills shortage scenario and preferred human-moderated interviews. These rationales suggest that industry and the type of hiring job may play a moderating role in the intention to use AI-based interview tools.

Additionally, R12 pointed out that small companies rely heavily on referrals for candidate sourcing, which limits the candidate pool and therefore reduces the intention to use AI tools for crucial referrals. This underscores the moderating effect of recruitment volume on the intention to use the tool. Although the rationales of HR managers were not explicitly stated, the contrasting views among interviewees indicate that the use of AI-based interview tools is influenced by industry and the type of role. While R2 and R3 expressed intentions to use AI-based interview tools, with R3 specifically highlighting the utilization of AI capabilities like facial recognition for analyzing facial expressions in the hospitality industry, a negative association was observed between the use of AI interview tools and behavioral intentions. Consequently, various moderating factors may constrain the potential benefits of AI-based interview tools.

6.6 Findings relevant to Main constructs

This section discusses the findings related to the main constructs of the conceptual model (AI-RS).

6.6.1 Recruitment phases (RP)

The research findings reveal that interviewees strongly favor incorporating AI in recruitment. However, the reasons behind this preference varied among the participants, and these divergent rationales are further explained in the subsequent sub-sections.

6.6.1.1 Recruitment pre-planning

The study found that most interviewees (R1, R2, R3, R4, R5, R6, R7) intended to use AI for pre-planning recruitment. HR managers indicated a stronger intention to use AI in pre-planning compared to recruiters and may suggest a link between professionals' roles in the recruitment system and their inclination towards AI in pre-planning. According to Melchor (2013), recruitment planning is more of a function of HR executives, thus, HR managers may find AI more beneficial in this phase than recruiters. Therefore, the study suggests that HR executives may adopt AI in pre-planning more than recruiters or hiring managers.

Additionally, findings shed light on factors influencing the decision not to use AI in recruitment planning, such as hiring volume, job category, industry, and interpretations of AI capabilities. For instance, HM1, which hires only four individuals annually, stated that "*companies with a larger hiring volume may derive benefits from AI in recruitment planning*." R13 shared a similar view, suggesting that some professionals in the recruitment system believe that AI may not be necessary for low-volume hiring. However, it is important to note that this perspective was expressed by only two individuals, indicating that others may still be utilizing AI even in situations involving low hiring volumes.

Furthermore, some participants, including R2, R3, R5, R6, and R11, cited limitations in AI capabilities as the main reason for their decision not to use AI in recruitment pre-planning. R2 explicitly stated concerns about the effectiveness or suitability of AI technologies for their specific recruitment needs, emphasizing that "*recruitment planning requires a huge volume of business data to plan the future workforce with the market conditions changing which needs to reflect in the business, such data will not be available. That is why AI cannot be used to do any recruitment planning*". This indicates that the current use of AI in recruitment pre-planning may be limited due to the lack of technology provisioning. Moreover, the study suggests that the intention to use AI is moderated by factors such as hiring job group and volume, as highlighted in the findings from HM1 and HRE1.

6.6.1.2 Sourcing

15 out of 17 interviewees expressed their intention to use AI as a sourcing tool, with LinkedIn being the primary platform. The recruiter, R7, who was in the transportation industry, did not intend to use AI in the sourcing phase, suggesting a connection to the industry and role type.

According to R7, in the transportation industry, the recruitment of roles such as "vendor developers" "marketing and sales managers" differs from those in other industries like Finance or IT. According to him, vendor developers, who are small rural businesses owning one or two trucks, play an essential role in the supply chain of larger transportation networks. These rural drivers deliver goods to rural areas in India as international transportation companies do not operate in rural villages. These drivers are recruited through word of mouth and referrals from rural areas. R7 highlighted that "*most of these people don't have resumes. And they are not on social media or LinkedIn. They must be sourced through local references*".

This indicates implications for integrating AI in specific industries such as transportation and agriculture. The nature of the associations with blue-collar or vocational work in these industries may impede the realization of the full benefits of AI (Beaudry & Pinsonneault, 2019). Moreover, infrastructure limitations in related sectors, such as public health services, education, and agribusiness, particularly in rural areas, have resulted in a need for policymaking at the national and international levels (Dhanabalan & Sathish, 2018). Thus, it may suggest that AI use in the souring stage may be limited to some industries and job categories.

6.6.1.3 Pre-Selection

Most recruiters are willing to use AI technology in pre-selection, except for recruiters R5, R7, and HRE2. Recruiter R4 reported a higher success rate from utilizing AI technology in pre-selection, where technology assesses candidates against predetermined criteria and recommends which candidates should proceed to interviews.

The accuracy rate is 70-80 %, indicating that out of every 10 pre-selected candidates by AI technology, 8-9 people were hired. R4 attributes the use of AI to the large volume of hiring that she manages and claims it would be impossible to handle without AI assistance. There, R4 stated,

> "*The accuracy of this AI technology is 70-80% and we ended up hiring 8-9 people from every 10 people pre-selected by the AI technology. Based on the volume we managed it is impossible to achieve such good targets without AI being in place*".

In contrast, R5, who works in the hospitality industry, did not intend to use AI in the pre-selection phase. Instead, through direct interaction, R5 preferred to evaluate candidates' behavioral traits, including politeness, communication skills, and empathy. R5 stated, "*I prefer to talk to the candidates to get a feeling about them*". Although some AI technologies can process communication styles, existing literature does not provide insights related to empathy or mannerism, highlighting potential limitations of AI (Choudhury & Kiciman,2017). Similarly, R7 cited the unavailability of data for certain job groups, such as truck or lorry drivers, as a rationale for not using AI.

Hence, some HR professionals prefer not to use AI in pre-selection, assuming that AI cannot assess criteria such as empathy, mannerisms, or personal traits. This finding is also relevant to the assessment criteria for selecting candidates for blue-collar jobs, with HR professionals not planning to use AI to select blue-collar workers. It also indicates that some HR professionals intend to use AI only for high hiring volumes, while others will only use it in low-volume hiring to assess its suitability before applying it on a larger scale.

6.6.1.4 Selection (Interviews)

Except for HRE2, participants agreed that the selection or interview phase is the least amenable to AI, which is noteworthy since this stage is often the most time-consuming aspect of the hiring process, leading to increased hiring costs and a longer time-to-hire (Barron et al., 2009). HRE2, a vice president of a technology company in India, mentioned that HR departments face increasing pressure to reduce costs, often resulting in downsizing the workforce, and thus intend to use AI in the interviews. Thus, it can be inferred that HR executives such as HRE2 would adopt AI in the interviews as a cost-saving measure.

In contrast to the cost savings expected by HRE2, R1 expected that AI should be able to fill the skills gap hiring managers have, especially relevant to conducting interviews. R1 said, "*hiring managers might not have the necessary skills to conduct interviews*." The statement can be interpreted in two ways: either AI should replace untrained hiring/line managers with AI, or AI should be used to train the hiring managers to acquire interview conducting skills. Similar sentiments have been experimented with in other research where AI has been used to train those professionals who needed more training (Luo, 2021).

Recruiters expressed reservations about using AI in interviews based on their perception of AI capabilities. These concerns relate to their belief that AI may not accurately assess candidate skills, qualifications, and cultural fit. R2, for example, said that "*67% of the time, the candidates turned out to be completely different from the assessment provided by AI*." He formed his opinion based on his experience in a pilot program.

The rationale behind the decision of participants R10, R11, R5, R7, and R8 to not use AI in interviews was centered around their desire to provide a more personalized candidate experience by conducting interviews with human interaction instead of relying on AI. Participant R11 drew a parallel between hiring and dating and said, "*You would not marry a person whom you did date online. Would you? You want to meet and know the person better before selecting the person to get married to. Analogy is the same when it comes to hiring a person" and* emphasized the importance of meeting and getting to know the candidate before deciding. Participants R5, R6, and R8, who worked in the hospitality industry, shared this perspective and preferred the traditional interview approach. This concern is also reflected in research involving candidates (Keaney, 2021), highlighting candidates' common fear of being assessed solely by AI.

Participant R12 expressed her belief that AI is unable to capture essential human qualities and decided against utilizing AI in hiring for roles such as auditors and financial advisors said:

> "*We are hiring a person, and people have many attributes which are not comprehendible in data formats. It needs to be understood by human-based interactions, not through AI-based interactions. Furthermore, R12 added that "AI would not be able to do that," and this rationale is linked to the inherent limitations of AI.*

R4, who witnessed success rates ranging from 70% to 80% using AI technologies in pre-screening, also expressed reservations about using AI in the selection/interview phase. R4 argues that "*in the pre-selection phase, AI will provide insights on the positive and negative sides of the candidate. Those insights can be further probed during the interview phase by asking relevant questions*."

This approach involves a combination of AI and human evaluators to enhance the selection process. According to R4, AI is used initially to collect data on potential candidates. Human evaluators then verify these insights during interviews to identify the top candidates. This hybrid model aims to leverage the advantages of both AI and human expertise for an effective and reliable selection process.

The limitations of AI use in the interview process are also noted by R9, who recruits pilots: "*AI would not be able to assess complex behavioral-based criteria*" required by pilots. She emphasized that a pilot's personality is a crucial criterion, particularly the requisite cognitive and interpersonal skills underlying crew resource management which are assessed during interviews. Given the absence of AI technologies capable of assessing such traits, R9 mentioned that she has no intention of employing such technologies.

HM1, who is responsible for hiring sales and marketing professionals, explained the challenges associated with using AI in interviews. He further elaborated on these difficulties:

> "*a candidate may give the right answer by using many words and takes ten minutes to answer a question which should only take 2 minutes. The answer may be correct but if the communication skills are good, it should not take 10 minutes to answer. I don't assume AI is going to help with such situational-based complex assessments.*"

The diverse perspectives presented above provide insights into the complexities of the interview process, which aims to assess candidates based on various parameters such as skills, roles, personal characteristics, traits, and behaviors. The research participants indicated a lack of confidence in AI's ability to address all these complexities, resulting in a very low intention to use AI in the interview phase.

Hence, the decision of whether to utilize AI in interviews suggests not solely relying on the AI's capacity to process vast amounts of data and generate additional information, including assessment criteria and candidates' alignment with those criteria, as well as the AI's comparative accuracy to human evaluations. Other factors like providing a better candidate experience and establishing a human connection with the candidates are considered by HR professionals too.

6.6.1.5 Candidate engagement

Many enterprises consider candidate experience a critical aspect of the recruitment process (Keaney, 2021). However, it can be postulated that as the recruitment volume rises, more human resources may be necessary to maintain the same level of engagement based on human interaction. Thus, a noteworthy proportion of the interviewees (R2, R6, R8, R9, R10, HRE1, and HRE2) articulated their intention to employ AI in candidate engagement, citing expected benefits such as automation of certain recruitment activities. Specifically, they anticipated that AI could aid in answering candidates' questions, providing updates on recruitment progress, and scheduling interviews.

Nonetheless, R13's apprehensions regarding the utilization of AI in candidate engagement might signal a lack of commitment on the organization's part, ultimately resulting in a decline in the candidate experience. According to R13, "*Candidate engagement is the first interaction a candidate has with the company. So that first interaction should not be with a tool*."

Notably, R4 and R9, who had managed high recruitment volumes, did not express similar concerns as R13, indicating a possible mediating influence of recruitment volume.

A correlation with the type of positions being recruited for was identified in R14's opposition to employing AI in the candidate engagement phase. R14 was responsible for hiring candidates for executive-level positions and argued that candidate engagement at this level must be customized and involve human interactions. In R14's view, using AI in candidate engagement for executive-level positions might imply a lack of commitment on the organization's part and may not provide the desired level of engagement with the candidate. R14 stated,

> "*In executive-level recruitment, the majority of candidates are passive candidates. They are already employed in senior executive roles and require engagement through human connection rather than a mechanical approach using AI.*"

R14 elaborated by stating that connecting with candidates personally demonstrates the organization's appreciation for them, thereby justifying the investment of time and effort to establish a personal connection. He further explained, "*It is a way to show that the organization values the candidates hence worth investing time to connect with them personally*". Thus, it implies that the intention to use AI in candidate engagement is subject to multiple factors, including high-volume recruitment, non-executive hiring, industry type, and candidate experience expectations.

6.6.2 Interviewees Benefit Expectations from AI

This section presents the findings related to the inquiry of "*What benefits are anticipated by RS professionals that would motivate the intention to employ AI in the recruitment and selection process*?". From the interview results, common themes emerged, including extended availability of recruitment services, increased productivity, support for high-volume recruitment, reduced dependency on human involvement, decreased labor costs, improved work-life balance for RS professionals, enhanced career prospects, standardized recruitment processes, expanded candidate pool and diversity, facilitated decision-making, and assistance for inexperienced RS professionals.

6.6.2.1 Extending service availability

A novel theme that has emerged is the augmentation of recruitment services beyond the operational hours of human personnel, enabled by the non-restrictive nature of AI, allowing for uninterrupted HR services throughout the day, 24/7, 365 days.

For example, R13 highlighted that AI enables continuous accessibility to recruitment services for potential candidates beyond the limitations of human recruiters' working hours. This extended availability is facilitated by chatbots, which can be accessed by hiring managers or HR personnel at any time of the day. For example, chatbots facilitate candidate engagement and administrative tasks, like scheduling interviews, even in the absence of human recruiters, thereby enabling 24/7 service. This concept of employing chatbots to provide uninterrupted services is not new, as it has been successfully implemented in various industries, including education (Yang & Evans, 2020), the hospitality industry (Bisoi et al., 2020), and library services. Therefore, it can be argued that R13's expectations and views are already being met in other domains through the effective use of AI technology (Bisoi et al.,2020; Yang et al., 2020; Nawaz et al., 2020).

6.6.2.2 Increasing productivity

Findings indicate that AI-based technologies are a potential source of productivity gains in the recruitment process, including the reduction of manual effort and administration time and the ability to manage high-volume recruitment more efficiently (HRE1, HRE2, R2, R3, R4, R5, R6, and R8) (Kapoor et al., 2021; Palacios et al., 2020). AI-based tools alleviate the burden of labor-intensive and administrative tasks, freeing up the time and resources of recruitment staff, hiring managers, and human resource executives, in line with previous research highlighting the potential of AI technologies to automate repetitive tasks and enhance HR processes' efficiency (Kapoor et al., 2021; Palacios et al., 2020). In addition, a study by Anderson et al., (2018) found that using AI-based pre-screening tools could reduce the recruitment process's time-to-hire by up to 75%. Therefore, it can be suggested that the research participants' expectations that AI could increase productivity by automating repetitive work are aligned with previous studies.

6.6.2.3 Supporting high-volume recruitment

Many recruiters (R1, R4, R6, R9, R10, R12, and HRE1) are expected to manage high-volume recruitment using AI in the RSP. This sentiment aligns with the experiences of IT, business process outsourcing, and consulting industries in countries like India and the Philippines, where high-volume recruitment is commonplace (R6). R6 was responsible for hiring between 200 and 330 staff monthly for blue-chip companies in the USA, while R4 hired around 3000 people annually for a tech company; thus, they expected AI could help them to reduce the workload which involves high volume recruitment. According to R4, finding suitable candidates at that volume is an extremely challenging task, given the shortage of candidates in the market and the intense competition among companies. She said, "*It is an impossible task without the help of AI technologies*." R10 shared similar views, explaining that he had to process around 5000 resumes annually to fill 500 roles. They viewed AI as a solution to streamline the recruitment process and overcome the challenges of high-volume recruitment.

The expectation of benefits from AI in managing high-volume recruitment appears to be moderated by the volume and industry, as highlighted by the differing views of interviewees such as R14 and HM1, who manage only 4 to 6 hirings per year. Unlike other interviewees, these individuals did not express the same expectation of AI for managing high-volume recruitment. This suggests that the benefits of AI in this context may not be universal and are dependent on contextual factors such as the volume and nature of recruitment.

6.6.2.4 Reducing human dependency

Another emerging theme is the desire to minimize reliance on human labor and manual work by implementing artificial intelligence (AI) to automate repetitive and administrative tasks within the recruitment and selection (RS) process. For instance, R1, R13, and HRE1 proposed using AI-based chatbots to streamline candidate engagement and sourcing activities. HRE1 pointed out that pre-selection and interviews primarily depend on hiring managers, which can cause delays in the selection process when they are unavailable.

6.6.2.5 Reducing labor costs

The findings reveal contrasting opinions regarding the potential labor cost savings associated with using AI in RS (Robotic Surgery). For instance, R2 and HRE2 believe implementing AI in RS could save labor costs by replacing human resources. HRE2 expressed the perspective that "*cost savings are always a strategic goal of any organization, so if AI can perform the tasks of a few individuals, we are compelled to consider that option*." Moreover, R2 has witnessed firsthand the downsizing of human resources in their previous organization following the implementation of AI in RS. These accounts support the notion that AI will be perceived as a means to reduce labor costs in the context of RS.

Others, including R7, HRE1, R1, R3, and R10, expressed skepticism. They argued that labor cost savings were superficial, as the development, testing, and acquisition of AI technologies incurred additional expenses (R7; HRE1; R1; R3; R10). This aligns with existing literature, emphasizing that adopting AI may not yield cost savings due to the significant costs involved in procuring, managing, and continuously improving AI technologies

(Brynjolfsson & Mitchell, 2017). Furthermore, the displacement of jobs due to AI raises socio-economic concerns, as workers with outdated skills face limited employability, leading to unemployment and associated mental health issues (Arntz et al., 2016). Out of the 17 research participants, only two believed that AI implementation could result in cost savings, while the majority held the opposing viewpoint. Thus, it suggests that cost savings may not heavily influence the decision to adopt AI.

6.6.2.6 Increasing the work-life balance of RS staff

A new theme emerged regarding the use of AI to enhance work-life balance, as highlighted by participants R1, R2, and R13. These individuals expressed their belief in the potential of AI to contribute to achieving work-life balance. Specifically, R13 emphasized that AI could alleviate the workload of recruiters by automating their administrative tasks, stating that "AI can automate recruiters' administrative work, thereby reducing their workload." R2 supported this perspective, stating that "by increasing recruiters' productivity through AI, their work-life balance could be improved."

These insights highlight the potential benefits of integrating AI into recruitment processes, especially considering the typically high volume of work recruiters face. As the workload increases, the manual tasks involved in recruitment can impact recruiters' work-life balance. Therefore, the introduction of AI is seen to alleviate their workload and, consequently, enhance their work-life balance.

6.6.2.7 Increasing career progress

A new theme emerged, highlighting the utilization of AI as a catalyst for career progression. All recruiters expressed their belief that AI would generate new job opportunities and transform their roles, emphasizing the need to adapt and prepare accordingly. R7, for instance, remarked that "AI is the future" and shared her experience of being questioned about AI technologies in job interviews. Consequently, she eagerly sought to adopt AI and gain experience to maintain a competitive advantage.

Similarly, R8 echoed these sentiments, emphasizing the importance of organizational leaders prioritizing AI implementation in the RS. They believed that embracing AI would enable organizations to capitalize on its numerous benefits. Moreover, R10, with extensive experience in AI and RS, shared how many of his clients, prominent blue-chip companies, had integrated AI technologies and were demanding its usage. He recognized the trend and considered including AI in his product portfolio as a career breakthrough.

These insights collectively underscore the recognition among recruiters that AI is shaping the job market and presenting opportunities for professional growth. They acknowledge the need to embrace AI technologies to remain competitive and view its integration as a pivotal milestone in their careers.

6.6.2.8 Standardizing recruitment process

A theme emerged regarding the standardization of the RS process through AI implementation, with interviewees expressing the belief that AI can eliminate human bias, often leading to non-standardized outcomes. R1 and R4 specifically highlighted the potential of AI to neutralize human bias in recruitment. R4 stated, "AI can effectively neutralize human bias in the recruitment process."

Likewise, R5 shared similar expectations, noting that AI can provide recruiters with more information, enabling better decision-making and reducing human errors in the RS process. However, interviewees also acknowledged the possibility of biases in AI algorithms. Nonetheless, they anticipated that improvements would mitigate such biases. For instance, R4 mentioned that even human-managed systems exhibit bias, but AI could potentially reduce it through testing.

Overall, these observations suggest that many recruiters are optimistic about utilizing AI in the RS to standardize the process. They see AI as addressing human bias and equipping recruiters with enhanced information, aiming to achieve more consistent and objective outcomes.

6.6.2.9 Increasing candidate pool and diversity

Another theme that emerged was the potential of AI in the RS to increase diversity and expand the candidate pool. This is based on the belief that AI technologies, such as resume scrapers, can aid in achieving diversity targets, which are increasingly important for organizations, as highlighted by R5. He also mentioned that human recruiters might face limitations in reaching a diverse candidate population due to geographical barriers, whereas AI algorithms embedded in candidate recommendation tools could overcome such limitations. However, an opposing view was expressed by R1 and R10, who noted that AI may overlook certain candidates as they may not have resumes or be present on online professional networking platforms. R1 mentioned that "*some candidates like truck drivers may not have resumes or may not be present on online professional networking platforms*," thereby limiting the effectiveness of AI in accessing a diverse candidate pool.

6.6.2.10 Mediating decision making

A noteworthy theme emerged regarding the potential role of AI as a mediator between hiring managers and recruiters in the recruitment and selection process (RS). This perspective was articulated by R1, who suggested that AI could act as a neutral advisor in cases of disagreement between the two parties. R1 emphasized the challenges recruiters face in finding suitable candidates and how hiring managers may have different expectations and said,

> *"As recruiters, we know how difficult it is to find a good candidate, and hiring managers without understanding these difficulties expect the candidates to fit into each box. In our view, the candidate is a perfect match, but the hiring managers oppose and rejects the candidates. AI can be a neutral advisor in such cases where both the recruiter and the hiring manager can consider".*

According to R1, AI can provide a neutral assessment that both recruiters and hiring managers can consider, facilitating a resolution.

This theme highlights the common issue of different criteria for evaluating candidate suitability. R1 believes that AI's impartiality and unbiased assessments can help bridge the gap and facilitate decision-making. While no existing literature currently addresses AI's role as a mediator in the RS, R1's insights offer potential use cases and the possibility of leveraging AI in this capacity.

6.6.2.11 Helping inexperienced RSs

Another emerging theme revolves around using AI to support inexperienced recruiters or hiring managers in the recruitment and selection (RS) process. The envisioned support from AI includes writing effective job descriptions and providing training for individuals lacking the requisite skills to conduct interviews.

R8 highlighted the complexity of crafting job descriptions, requiring experience in branding the organization, specifying necessary skills, avoiding technical jargon, and promoting gender neutrality to attract a diverse candidate pool. R8 believes that AI can assist inexperienced recruiters in generating compelling job descriptions.

Additionally, R1 pointed out the challenges faced by some hiring managers lacking experience in conducting interviews. Effective communication skills, decision-making abilities, and subject matter expertise are among the crucial competencies required during interviews (Whetton & Cameron, 2002). In such cases, AI is seen as a potential tool to aid recruiters and hiring managers in making informed decisions.

6.6.2.12 Summary of benefit expectations

The findings of this study suggest that AI has the potential to offer numerous benefits in the recruitment process. These benefits include 24/7 recruitment service availability, increased productivity, support for high-volume recruitment, reduced human dependency, lower labor costs, improved work-life balance, enhanced career progression, standardized recruitment processes, increased candidate pool, mediated decision-making, and assistance for inexperienced staff.

6.6.3 Social Influence to use AI: Interviewees perceptions.

This section presents the findings related to the question: "*Who are the key influencers driving the use of AI in the recruitment process by RS professionals, and what motivates them and in what direction*?". The interview questions were based on the main influences of leadership/management, candidates, competitors, and colleagues per the UTAUT model. The following are the explanations of the findings.

6.6.3.1 Influence from candidates

According to participants, candidate preferences concerning AI use in RS significantly influence the adoption of AI in the recruitment process, with the extent of influence varying among RS professionals. While some recruiters are positively influenced, others are negatively influenced, while HR executives remain unaffected by candidate preferences.

For example, R11 expressed a positive inclination toward candidates' preference for AI in the recruitment process. R11 said, "*Some candidates tell us that they prefer AI to be used in the RS process*". This strong influence shapes R11's perspective on using AI in RS.

On the other hand, R10 held a negative view influenced by candidates who are reluctant to engage with AI-operated recruitment processes. R10 acknowledged that if candidates express a strong aversion to AI, they will refrain from using it in the RS. R10 said, "*If the candidates said they would not talk to companies that use AI in the process, then I will not use AI*".

While the remaining interviewees did not explicitly state their positive or negative influence from candidates, the perspectives of R10 and R11 highlight the significant role of candidates in influencing AI adoption in RS. Their views suggest that candidate preferences play a major role in shaping the decision to incorporate AI in the recruitment process.

6.6.3.2 Influence of colleagues

In the context of HR executives, recruiters, and hiring managers, peers refer to individuals who hold similar positions or job titles within an organization or industry.

These peers can be supportive, offer guidance, and help individuals learn, but they can also be competitors for career advancement (Sullivan, 2019).

Findings indicate that the influence of peers within their organization is somewhat neutral or negative. However, participants were positively influenced by external peer groups known as the "HR community", and R1, R2, R5, and HRE2 mentioned that the HR community was one of their biggest influences. RS professionals followed HR community groups on LinkedIn and other online platforms, where they received information about new trends like AI, policies, regulations, and technology insights, and R1 mentioned, "*I get more information from these communities, much more than what I get from my managers*". The rest of the interviewees followed a similar influence from HR communities.

However, R2 was negatively influenced by his colleagues, whom he referred to as "*administrative staff*," as they resisted the adoption of AI in the recruitment process due to job insecurity. Thus, can the data inform that HR communities are the biggest influences, whereas internal practitioners or peers are not positive influences?

6.6.3.3 Influence from leadership

Some participants provided diverse views on how important leadership support is in the process of AI adoption in RS.

For example, R2 emphasized the significance of leadership support in fostering an innovation-driven culture, which motivates him to introduce new technologies such as AI into the RS process. He stated, "*The leadership has provided me with the opportunity to explore and adopt cutting-edge technologies like AI. This encouragement serves as my greatest motivation to consider and introduce AI in the RS process actively*.".

R1, in contrast, perceived no support from the leadership team in his organization, which negatively influenced his decision-making. He sought inspiration and used cases from external sources, emphasizing that leaders must recognize the potential for the future. R13 and R14 indicated positive influences from their leaders in adopting the latest AI technologies in their respective areas, except for R14, who indicated that while leadership support is available, the applicability of AI may vary across different job groups being hired.

R12, as part of a global organization, highlighted the role of management in setting the direction for AI adoption and indicated she would be following their lead. However, he indicated that he needs the leaders to explain why AI should be adopted; without a strategy, HRE1 supported that notion and indicated that CEO-level leadership should take initiatives to include AI tools in the IT portfolio for HRE1 to consider using AI HR. This suggests that lead levels can impact the response of RS owners to new technologies such as AI, highlighting the crucial role of leadership in their introduction.

6.6.3.4 Influence from customers

Most interviewees (R7, R10, R13, R6, R11, R12, R14) worked for companies providing recruitment services, which meant they primarily served external customers. Consequently, they revealed that the impetus to adopt AI in the RS process often stemmed from these customers themselves.

R10, who provided recruitment services to enterprise-level customers, stated that their motivation to utilize AI in the Recruitment Service Provider (RSP) process was driven by their customers. They stated, "*At times, I don't have a choice. To secure business deals, I have to align with the systems they request us to use, and in this instance, those systems involve AI solutions*." He also felt that enterprise customers request the use of AI to manage high hiring volumes.

In contrast, participants R14 primarily focused on hiring executive-level roles, which typically involved low volumes, and were not keen on AI adoption in their context. As a result, the findings suggest that AI adoption for managing small hiring volumes is unlikely to be a significant driver.

The study found that customer influence is highly correlated with the adoption of AI in the RS industry. When customers insist on using AI in recruitment, RS professionals tend to follow that lead. However, when there is no high hiring volume or compelling reason to adopt AI, it is unlikely that RS professionals will be enthusiastic about its adoption. Therefore, it can be inferred that AI adoption may be negatively motivated for low volume hiring.

6.6.3.5 Influence from competitors

Participants were also driven to use AI in the RS process by competitors who were using it- the so-called bandwagon effect (Granovetter, 1978). R1 expressed this sentiment by saying, "*If it is working for them, it should work for us too*." Others including HRE1, HM1, R13, R2, R3, R4, R7, and R9, shared the same view. None of the participants reported negative motivation.

R4 shared that her motivation to incorporate AI in the Recruitment Service (RS) stemmed from hearing success stories of her competitors utilizing AI. On the other hand, R11 highlighted that her leadership team's motivation was driven by observing competitors' effective use of AI in achieving strategic HR outcomes. These instances suggest that higher-level leadership within recruitment agencies might be more influenced by competitive factors when considering AI adoption.

6.6.3.6 Other influences

Additionally, a few new themes of innovative AI advancements and the modern era also emerged, as explained next.

6.6.3.6.1 Innovative AI advancements

The findings reveal that marketing, educational, and community events are playing a crucial role in creating awareness among the public about AI which has an impact on the receptiveness of people towards it, as evidenced by R3 and R10. For example, R3 attended a conference in India where an AI-based robot guided him, and the experience influenced R3 to consider the use of AI in their area. R3 explained the experience as,

> "*That event used a walking AI robot to guide the visitors to the different exhibition booths. I could ask like where this event happens etc. and it provided me the walking direction to the booth pretty accurately, which blew my mind.*"

Similarly, R10, as part of his job, had to interact with AI entrepreneurs and was positively influenced by the potential AI has. R10 stated, "*Some technologies advertised by the AI innovators are really mind-blowing*."

Moreover, some interviewees, such as R2 and R4, were attracted to case studies and white papers explaining AI technologies and their applications beyond the RS or HR industries. Similarly, HRE2 was intrigued by stories published by AI entrepreneurs that explained AI capabilities like natural language processing and conversational AI.

This indicates that wider socio-technical events and media create AI awareness among professionals, positively influencing them to adopt AI in their respective areas.

6.6.3.6.2 Modern Era

Six of the research participants stated that they reside in an era that is undergoing a significant transformation driven by modern technologies like AI. Two participants, R6 and R9, explained that they gained this perception by watching science fiction movies and documentaries demonstrating AI capabilities. While acknowledging that movies may be fictional, they found them "*fascinating*" and “*intriguing potentials*”.

HRE1, on the other hand, worked in the financial sector and was influenced by the FinTech movement, where AI is a contributing technology (Qi & Xiao, 2018). He suggested that such movements also transfer to other sectors, thus intriguing his curiosity about AI in RS. Many participants noted that changing market conditions and the industrial revolution are altering the future direction, requiring them to consider and adapt to the modern era. R13 and R3 expressed similar views, while R9 stated that she already felt this way because every organization she applied to in the recruitment or HR field asked if she had experience using AI technologies.

6.6.4 Summary of social influence

The sections above reveal key influences on RS professionals' adoption of AI. Customers have a significant impact, as RS professionals are more likely to adopt AI if customers request it. Competitors also play a role, and leadership provides guidance. External factors such as media and science fiction spark interest, but AI entrepreneurs negatively influence those who already understand AI. However, these influences vary based on factors like job group and hiring volume. RS professionals may be more open to AI for low hiring volumes, but for enterprise-level customers, higher hiring volumes are considered.

6.6.5 Facilitating conditions expected

This section reveals the findings aligned with the question, "What facilitating conditions are influencing the behavioral intentions of AI in the RS?" It mainly focuses on providing training and development, technology availability, and support from leadership, as per the guidance of the UTAUT model.

However, new themes from the information shared by the hiring mangers, recruiters and HR executives also emerged during the interviews and are reported in the following subsections of 6.6.5.1 to 6.6.5.5.

6.6.5.1 Training & development

Most interviewees R1, HRE2, HM1, R11, R12, R13, R14, R3, R4, R6, R7, and R9, identified training and development as the primary facilitation condition for adopting AI in their organizations. They expressed their expectations of receiving training and development opportunities in various formats, such as classroom training, access to external events like conferences, curriculum development at the organizational level, and broader professional and executive education that would help their organizations adopt

AI. The hiring manager, HM1, and the recruiters, R4, R11, R13, and R14, expressed their willingness to leverage the knowledge of early adopters by learning from the lessons they had learned. They recognized the value of gaining insights and understanding from those who had already embarked on the adoption of AI.

The theme of "trying before using it" emerged from the interviews. Interviewee R6 expressed the expectation of AI capability demonstrations by AI developers and emphasized the importance of thorough testing before RS professionals adopt AI in the RS process.

Another theme that emerged is the question of who should provide the training. The interviews revealed that training should be provided to hiring managers, MBA graduates who will take roles in HR, and AI developers.

For instance, R1, a recruiter, emphasized the need to provide training to hiring managers. They pointed out that hiring managers sometimes oppose and discourage the use of AI, and offering AI training would help them understand how AI can benefit the RS process. This finding suggests that gathering further insight from hiring and line managers is necessary to confirm their views on AI adoption.

On the other hand, R3 suggested that education service providers should modify their curricula to include AI use cases, AI literacy, and AI technologies in MBA and HR higher education and said, "*HR training programs like MBAs should include AI technologies* *in the curriculum"*. By doing so, future leaders would be educated on AI technologies and their use cases in business. Supporting this view, the literature suggests gaps in the education policies in many countries regarding educating AI and its use cases (Schiff, 2022). These gaps may impact the ability of businesses to find qualified candidates with the necessary AI skills and knowledge to drive AI adoption and innovation in the RS.

6.6.5.2 Leadership support

The theme of leadership support as a facilitation condition emerged prominently during the interviews. This finding aligns with existing literature that highlights the significance of leadership support in successful AI adoption (Biemans et al., 2019; Ghobakhloo et al., 2011).

The interviews revealed that the lack of leadership support is recognized as a barrier to AI adoption in the RS process. For example, in R2's experience, the middle and operational levels may not be ready to adopt AI, which highlights the need for leadership to understand the concerns of these stakeholders and address them to drive adoption.

R4 suggested that these HR and other operational level leaders require reskilling so that they are equipped with the latest AI knowledge. This aligns with the literature, which emphasizes the need for reskilling and upskilling to support the adoption of AI in organizations (Brynjolfsson & Mitchell, 2017; World Economic Forum, 2018). R1 supported the same view, saying, "*HR leaders should not deny that AI can make a difference and* *should include AI in the roadmap"*. R5 also emphasized the need for managers to understand the benefits of AI and said, "*Managers should understand the benefits of AI. If they understand, then they will support"*, and R8 suggested that organizations should recognize the future of recruitment as being reliant on AI and should support the procurement and testing of AI tools and said, "*Organizations should understand that the future of recruitment is AI. Hence, they should support the procurement of tools and testing those tools, etc*.". R9 and HRE1 also shared the same views.

These findings strongly suggest that leadership support plays a crucial role as a major facilitation condition in adopting AI in the RS process. RS professionals expected strong leadership support throughout the AI adoption journey. Conversely, the lack of leadership support emerged as a significant impediment that hinders the successful adoption of AI in RS.

6.6.5.3 Funding and investments

During the interviews with R1, HRE2, R12, R4, and R6, a theme of facilitation through budgetary investments emerged. The participants highlighted the importance of allocating funds strategically to support AI applications in RS. They highlighted the cost of AI technologies as a significant barrier to adoption, and R1 mentioned, "*Leaders must allocate budget to procure new AI technologies, and the process of acquiring new tools should be easier*."

6.6.5.4 IT support and pilot programs

The theme of IT support and the provisioning of pilot programs also emerged (e.g., HRM1, HRM2, R12, R13, R4, R6, and R8). Interviewees expressed their reluctance to adopt AI without first trying it out in small projects. Additionally, they all expected the support of the leadership team in initiating such pilot programs and allocating budgets, as elaborated in the previous section.

Additionally, the support from the IT organization was also highlighted by HRE1 and R10. They emphasized the need for assistance from technology professionals, stating, "*We need support from technology people as HR staff may not possess the technical skills necessary to comprehend the intricacies of AI*." This expectation and suggestion align with existing literature, as demonstrated by studies such as Kavadias & Chao (2007) and Ross & Beath (2002), which support the notion that HR departments require technical support for successful AI implementations.

This suggests that a close collaboration between HR and IT is required to drive AI adoption, as highlighted by R10. The literature supports this idea, emphasizing that collaboration between HR and IT departments is vital for successful technology implementation in organizations (Kavadias & Chao, 2007; Ross & Beath, 2002). The nature of this close collaboration is primarily in three forms.

Firstly, the interviewees like R1, HRE1, R11, R12, R14, R3, and R6 expected that they would be involved in the testing of AI RS systems so that they could validate the AI solutions. This was stressed by hiring managers who expected the HR department to take the lead by working with IT to validate the AI systems and said "*I expect the HR to take the lead by testing these AI systems with IT before it is released to the business use*".

However, senior RS professionals such as R10 have expressed their expectation that AI developers and entrepreneurs take the lead in testing AI systems for algorithmic accuracy, particularly when it comes to addressing issues like removing human bias and integrating AI with other HR systems end-to-end. As a result, the findings underscore the importance of the IT department, along with AI developers and entrepreneurs, in facilitating RS professionals by ensuring that AI systems undergo thorough testing and validation before they are released for use by RS professionals.

6.6.5.5 Governance frameworks

The theme of provisioning of governance framework emerged from interviewees like R11 and R10, highlighting the importance of governance frameworks, particularly in the European Union, where governments enforce regulations like GDPR. R11 primarily focuses on candidate's privacy data and states, "*the AI technologies need to protect the candidate's data and ensure that they are not hackable*."

In contrast, R10 stressed the importance of traceability and accountability of AI technologies and stated, *"I would be very critical and need to know how AI has made the decisions it made, and the results should be traceable, auditable for me to use it"*. He further *explained:*

> *"AI innovators should make the process more traceable and auditable. Rather than developing isolated solutions, they should create an eco-system which integrates isolated solutions to support the end-to-end recruitment and selection proces*s".

It is noteworthy that R10's critical and demanding stance on governance frameworks, transparency of AI algorithms, and ecosystems between AI technologies may be correlated with his many years of experience in the role and expertise in AI. In contrast, R11 has only a few years of experience in her role, but her professional background working for a legal firm recruiting law enforcement professionals suggests she may inherently understand the legal implications or requirements of regulatory frameworks related to privacy and data protection. Thus, experience seems to play a crucial role in determining the level of understanding of professionals regarding the expected facilitating conditions for AI technologies.

6.6.5.6 Summary of expected facilitating conditions

The findings in these sections suggest that RS professionals expect training programs, pilot projects, leadership support, budgetary investments, IT support, and provisioning of governance frameworks for interviewees to adopt AI in the RS.

Furthermore, it also suggests that more experienced professionals have critical expectations and have more facility expectations, whereas less experienced professionals do not expect many facilitations conditions to be met.

6.6.6 Effort expectation (EE) to use AI.

During this interview section, the researcher explored the question, "What efforts are you expecting to spend to use AI in the RS (recruitment and selection) process?" The responses revolved around several themes related to the efforts required for utilizing AI in the RS process. These themes included efforts to learn about AI systems, establishing governance frameworks: Initiating pilot programs, and unwillingness to invest efforts in AI adoption, as explained next.

6.6.6.1 Efforts on learning to use AI technologies.

A theme of self-initiated training and development to become familiar with AI was discovered from R1, R4, R5, R8, R13, HRE1, and HRE2, as their endeavors largely lacked support or guidance from their managers or respective organizations. They resorted to publicly accessible sources of training, such as LinkedIn Learning, YouTube videos, webinars, and online magazines, and attended conferences and technical events as a means of acquiring relevant knowledge.

They mostly referred to “*use cases*" and "*white papers*" as these resources and indicated it provides more relevant information to AI applications in RS. Specifically, R4 expounded on how case studies of AI implementations in RS facilitated her comprehension of the applicability of AI in recruitment practices. These observations underscore the significance of contextually relevant educational resources in fostering effective AI integration in RS.

The voluntary actions undertaken by RS professionals highlight two crucial aspects. Firstly, in the absence of organizational provisions, RS professionals seek external resources to bridge the gaps in their AI-related knowledge. This observation implies that organizations implementing AI technologies in the RS may receive more significant support from those RS professionals who have already voluntarily acquired AI-related knowledge. Secondly, the training and development resources must explicitly address the specific concerns of how AI applications can be leveraged in the RS to be relevant to their respective work processes. Generic AI education may have a diminished impact on RS professionals. The self-directed learning efforts of RS professionals inform the requisite facilitation conditions necessary for the effective utilization or consideration of AI in the RS.

6.6.6.2 Starting pilot programs

The theme of starting pilot programs to ensure the accuracy of AI in RS emerged from R1, R4, R13, and HRE2. The key point to note is that they were willing to invest their time and efforts to initiate and execute these pilot programs without any initiative from the leadership teams. HRE2 explained, "I validated the AI tools by investigating how AI has deselected some candidates from the selection process. If it is the same candidates I would personally deselect, then I am happy about the results." Thus, it can be suggested that what matters to these RS professionals is the accuracy of AI rather than the ease of use or user-friendliness of AI, as explained in UTUAT (Venkatesh, 2003).

6.6.6.3 Developing governance and regulatory frameworks

Several interviewees, such as R10 and R12, expressed interest in and initiated initiatives to ensure the availability of governance frameworks. They were not willing to adopt AI without the appropriate level of governance frameworks in place. R10 and R12 actively educated AI vendors and entrepreneurs about the necessary frameworks for utilizing AI in the RS. R10 emphasized the importance of ensuring AI tools comply with regulatory requirements and highlighted the need for collaboration with AI developers and vendors. He was willing to invest his time in educating AI developers to establish the required frameworks.

Notably, both interviewees, R10 and R12, have extensive experience in the RS, with more than 10 years of professional experience. Furthermore, they hail from countries where regulations in the HR domain are strictly enforced. R11, who is from Australia, highlighted that fair-work commissions enforce regulations, while R10, from the UK, emphasized the importance of General Data Protection Regulation (GDPR) compliance in recruitment. This suggests that there may be a correlation between the experience, geographical location, and regulatory frameworks of RS professionals and the efforts they are willing to make in adopting AI in the RS.

6.6.6.4 Minimum or no efforts

Many interviewees were unwilling to invest time or effort in becoming familiar with or adopting AI technologies in the RS. Specifically, R12, R13, and R14 explicitly stated their reluctance to dedicate much time or effort to adopting AI. R12 expressed, "I don't want to spend my time or energy in understanding or testing AI". This suggests that these individuals prefer not to be involved in the testing or training process and instead rely on AI developers to handle such tasks. This lack of interest may stem from a perceived lack of relevance of AI to their work processes or a lack of confidence in their ability to learn and adapt to new technologies.

6.6.7 Trust in AI

The findings suggest that the level of trust in AI significantly influences the adoption of AI in RSs, with both positive and negative implications. Interviewees like R4 demonstrated high trust in AI, as she had been using AI in RS for some time and had positive experiences. Her trust in AI was so strong that she did not question or doubt the results provided by AI. She mentioned, "We never had a situation where we had to crosscheck the results given by AI". This indicates that R4 had confidence in the accuracy of AI and did not feel the need to verify its results through cross-checking.

However, it has also been found that negative experiences of RS professionals can impact their trust in AI, as indicated by R3, R11, R14, R7, and R10. They expressed their lack of trust in AI and insisted on the need for cross-checking and validating results before adopting AI. Furthermore, it was discovered that some interviewees were willing to trust AI under specific conditions, such as conducting prior testing of AI results. For instance, R1, R13, HRE1, HRE2, HM1, R2, R5, R6, R8, R12, and R13 mentioned that they would trust AI if it and HR departments had tested it. This suggests a link between facilitating conditions and the acceptance of AI on a smaller scale. These findings imply that organizations should consider initially testing AI in low-scale environments to gain the trust and confidence of RS professionals before implementing it on a larger scale.

Another theme that emerged is the selective trust in AI for specific recruitment phases, such as candidate engagement, sourcing, and pre-selection. Nearly all the interviewees lacked trust in AI during the interview phase. This sentiment was reinforced by R11, who stated, "*Even if AI is 100% accurate and I can trust it, I don't want to hire someone without any personal connection*." This suggests that beyond AI accuracy, other factors impact AI adoption, such as providing a better candidate experience. These findings also suggest that trust in AI is contingent upon various factors, such as past experiences, negative encounters, facilitating conditions, the volume of hiring, and recruitment phases.

6.6.8 HR outcomes outcome expectations from AI

In this section, the investigation aimed to elicit the perspectives of the research participants on the impact of AI on the HR outcome of time to hire, cost of hire, quality of hire, and retention rates, as exhibited next.

6.6.8.1 Time to hire.

All participants, from recruiters to hiring managers in the study, shared a common belief that AI could potentially reduce the time to hire in the RS. R4 and R10 explained that they already had reduced time to hire, especially in the high volume they were managing. More specifically repetitive, time-consuming work like sourcing and pre-screening have been automated using AI, thus has helped them to reduce the time to hire.

Based on these findings, it can be inferred that recruitment professionals have high expectations for AI to reduce hiring time in the RS process. The use of AI automation is likely to provide organizations with a significant advantage in attracting top talent, reducing the time it takes to fill open positions, and ultimately improving the overall efficiency of the recruitment process. It also provides insights into how this outcome applies to high-volume hiring.

6.6.8.2 Cost of hire

Two themes emerged: AI will reduce the cost of hire, and AI will not. R1, R4, R6, R8, R13, R14, HM1, and HRE2 believed that AI could contribute to reducing the cost of hiring, others such as R2, R3. HRE1 perceived that AI would not contribute to reducing the cost of hiring.

R2 said that implementing AI in their organization helped reduce the cost of hiring by decreasing the human workforce in RS in his organization. However, R3 cautioned that the benefits of AI might only apply to companies with high recruitment volumes, and it may not be effective in reducing costs for low-volume hiring. On the other hand, HRE2 supported the idea of AI reducing the cost of hire, emphasizing that it can only be achieved if the recruitment partners she hires utilize AI. By using AI, these partners could lower agency fees, which would ultimately lead to cost reduction for HRE2. Antwerp (1997) highlights the considerable expenses of hiring companies when engaging external recruitment agencies. This highlights that various factors influence the cost of hire, and all parties involved need to adopt AI to optimize cost savings.

Some recruiters, like R2 and R3, argue that investing in AI research and customization for business may not reduce the cost of hire. As a result, there are conflicting opinions among research participants regarding the effectiveness of AI in reducing hiring costs. These differing views underline the importance of additional research and consideration of factors such as organizational size, recruitment process complexity, implementation costs of AI systems, and hiring volumes.

6.6.8.3 Quality of hire

Regarding the quality of hire, there were divergent perceptions among interviewers. Some believed that AI had the potential to enhance the quality of hire, while others did not share this belief.

HRE1, R4, and R5 believed that AI improves the quality of hire by mitigating human bias in the recruitment process. This perspective aligns with existing literature, including studies by Dastin (2018) indicating that AI can minimize unconscious bias by eliminating identifiable information from resumes. Additionally, Joy et al., (2020) emphasize the significance of combining AI with human decision-making to ensure the mitigation, rather than amplification, of biases. For example, R5 mentioned:

> *We get a lot of information about candidates. We as humans cannot process such a large amount of data within a shorter period. But AI can process such massive volumes of data and provide us the informed decisions where we can use for our decision making. Hence it will increase the quality of hire.*

However, R2, R3, R14, and HRE1 held contrasting views and expressed concerns that AI algorithms may incorporate human bias, resulting in similar issues as those found in human-driven recruitment processes. The literature also supports these concerns, with Aguinis et al., (2017) and Birnbaum et al., (2020) suggesting that using AI in hiring may not necessarily lead to improved outcomes and could even introduce new biases.

Moreover, the quality of hire concept remains ambiguous for certain participants, including R2, R3, and R14, who have questioned the methods for measuring it. R10 provides insight by referring to the quality of hire as a "poorly defined measure," indicating that quantifying it accurately using AI or other approaches can be challenging. This suggests that measuring the quality of hire is a complex and multifaceted aspect that requires further statistical validation.

6.6.8.4 Retention rates

Most interviewees (R1, R7, R9, R11, R13, and HRE1) believed that incorporating AI in the recruitment process could contribute to higher employee retention rates. They argued that leveraging AI to gather and analyze more data during the sourcing phase would help identify the most suitable candidates for specific roles, ultimately improving retention rates. HRE1, for example, said:

> *"Human recruiters in RS cannot gather all the necessary information from candidates that would aid in predicting their retention rates. However, AI can accomplish this by gathering data from various sources within a shorter timeframe. Utilizing AI in this manner can assist in predicting the retention rates of candidates."*

It is important to note that the majority of RS participants who expressed that the HR outcomes mentioned above can be achieved through AI are those who have less experience. For instance, R11, R7, and R8 stated that all these outcomes are attainable, whereas R10 and R14 were more selective. This suggests that less experienced RS professionals have higher expectations regarding achieving HR outcomes through AI compared to those with more experience.

6.6.9 Behavioral intentions of AI in RS

This section examines the influence of job groups and industry on the considerations of research participants regarding AI adoption in RS. The subsequent findings will be discussed below.

6.6.9.1 Hiring job groups

The study found that certain job categories, such as blue-collar workers, vocational workers, pivotal roles, and senior executive roles, were not considered suitable for recruitment through AI-based RSs as per the rational explained next.

6.6.9.1.1 Blue collar workers

Several interviewees, including R1, R6, R7, R11, and HRE2, who had experience in industries such as manufacturing, transport and logistics, retail, agriculture, farming, construction, and hospitality, expressed doubts about the effectiveness of AI in hiring blue-collar workers. They highlighted challenges such as the unavailability of candidate data in AI-compatible formats (such as resumes) and the complexity of assessing skills in blue-collar roles. For example, R7 explained that blue-collar workers often do not have traditional resumes and are usually recruited through referrals or word of mouth. HRE2 provided an example: "*A mechanic may not be able to explain how they fix an engine issue;*

they simply open the engine and resolve it without uttering a single word. Therefore, AI would lack the necessary data to assess such skills." These findings suggest that the methods used to evaluate job skills may vary depending on the job type and industry, leading participants to express skepticism about AI's ability to assess these skills accurately.

6.6.9.1.2 Executive and senior-level roles

R3 and R14 raised concerns about the effectiveness of AI in executive hiring within the recruitment system. They emphasized the need for personal connections and human engagement in this process. R14 stated, "*In executive hiring, most of the people are passive candidates; they need personal connection; hence throughout the candidate engagement it needs human connection*." R3 further noted that "*C-level hiring needs deeper understanding of the roles which demands different assessments*". These insights indicate that AI may have limited application in executive hiring due to the importance of human interaction and personalized assessments.

Regarding senior-level roles, R10 and R12 expressed reservations about using AI in senior management recruitment. R12 mentioned the scarcity of qualified professionals in Australia and highlighted the risk of disqualifying candidates who meet specific qualifications. R10 raised the issue of legal obligations in certain countries, such as the UK, where explicit reasons for candidate disqualification must be provided. They questioned AI's ability to provide logical explanations for disqualification, especially in cases involving government or public service positions. He further said:

> *"It is not only about selection. It is also about deselecting as well. In the UK, there are regulatory requirements that we should be able to showcase why a candidate is deselected in the recruitment process, especially in the cases where a candidate makes a discrimination case or in government contractual roles. Sometimes it may even lead to legal cases, where the deselection process is demanded justifying how the candidate is disqualified". Thus, R10 emphasized the importance of justifying disqualification to avoid legal repercussions.*

Furthermore, R10 pointed out concerns about misleading claims made by AI developers regarding their products' capabilities. He stated, "*AI developers and entrepreneurs would say they use neural networks and this and that. But at the backend of their product, they use the AI framework our company developed, and we know that the product is not using any neural networks*."

This lack of transparency and trustworthiness in AI products for roles with high associated risks further contributes to the reluctance of RS professionals to utilize AI in senior executive recruitment.

In summary, these findings suggest that RS professionals, particularly experienced ones, are unlikely to rely on AI for recruiting senior executives. The concerns revolve around the need for personal connections, human engagement, transparency, explainability, and legal compliance in the hiring process for such roles. Further research is warranted to explore the issue of candidate disqualification and the potential legal implications in more depth.

6.6.9.1.3 Pivotal roles

R14, R10, HER1, R1, and R2 suggested that utilizing AI for sourcing candidates for "pivotal roles" may not be effective and explained pivotal as "*significant roles which are crucial to the organization's sustainability and growth and can exist at any level within the organization*". Literature also suggests that pivotal roles are different from executive or senior roles, crucial to an organization's sustainable competitive advantage, and occupied by high performers or high-potential employees (Yang & Vaiman, 2009, p. 306).

Interviewees emphasized that more complex assessments are required to evaluate pivotal roles, and R1 said, "*Pivotal roles require more assessments compared to non-pivotal roles, and the presence of data in resumes is not just sufficient to assess them*." R6 echoed this sentiment by mentioning that "*more complex assessments are required to assess such 'key' roles*." R4 and HM1 also supported these views. Therefore, it can be suggested that using AI in the RS to recruit candidates for pivotal positions is unlikely to receive positive reception from RS professionals.

Vocational or Special skilled workers

Certain RS professionals, including R1, R7, R11, HRM1, HRE1, and HRE2, expressed skepticism about the effectiveness of AI in recruiting candidates for roles that require special skills or vocational training. They highlighted the challenges associated with the specific assessments required for these positions. Vocational jobs, encompassing occupations like mechanics, carpenters, healthcare workers, and electricians, demand specialized education and training but lack a clear metric for evaluation during the interview process (Bureau of Labor Statistics, 2022).

The concerns were further emphasized by R1, R2, R7, R9, R13, and HRE2, who have experience hiring vocational workers, as they pointed out the difficulties in assessing certain skills and the limitations of AI in evaluating candidates' capabilities for these roles. These reservations indicate that RS professionals are cautious about using AI in the recruitment process for job groups requiring specialized skills and assessments, where human judgment and interaction play a crucial role.

6.6.9.2 Industry

The research participants in this study represented multiple industries, as exhibited in Figure 12 below.

Figure 12: Industry representation of the research participants

The study revealed that participants held different views on the suitability of AI in various industries, influencing their intentions regarding its use. Some participants, such as R2, R3, and R7, believed that AI is suitable only in certain industries and expressed their reluctance to use it in those industries. R2 specifically stated that the finance industry is a good fit for AI in recruitment, as it can automate candidate selection and evaluate skills like financial literacy using AI. Similarly, R3 and R7 argued that the hospitality industry is well-suited for AI, particularly for behavioral assessments using facial recognition. R2's view was supported by the statement, "*The finance industry is a good fit for the use of AI in recruitment, as candidate selection procedures are straightforward and skills such as financial literacy and statistical proficiency can be automated using AI*". Additionally, HRE2, R4, R7, and R8 believed that the IT industry is the most suitable for AI use in recruitment, as AI can automate the assessment of skills like coding practices for software engineers.

Contrastingly, HRE2, R13, R1, R4, R7, R8, R9, and R11 expressed the belief that AI cannot be applied in any industry. They pointed out limitations in data availability and access in industries such as automotive and construction. R13 emphasized this by stating, construction workers do not even have resumes and access to the Internet; hence their data which AI needs are not existing and cannot be used in those industries and those roles." HRE1 also added that AI could not be utilized in the aviation industry, despite R9's disagreement based on their aviation industry experience. Furthermore, R10 mentioned that trade unions might interfere with the use of AI in the recruitment system, suggesting concerns over job losses as a possible reason. R10 highlighted this by stating, "*Trade unions may interfere with the use of AI in the RS*."

While limitations were identified in certain industries, most participants believed that AI could be utilized in any industry within the recruitment system. The majority opinion was summed up by R2's statement, "AI can be used in any industry. It just depends on how you tailor it." However, considering the differing views and limitations of various industries, further research is needed, particularly in industries with trade unions, to understand better the potential use of AI in the recruitment system.

6.7 Findings relevant to moderating factors.

In the following subsections, the researcher presents the findings demonstrating the moderating effects of interviewees' experience and the hiring volume they managed on the relationships between main constructs and behavioral intentions.

6.7.1 Experience of the RS professionals

The findings suggest a connection between the consideration of AI adoption and the professional experience of RS professionals. Specifically, the results indicate that more experienced RS participants tend to adopt a discerning approach towards AI, while less experienced professionals exhibit a more open-minded perspective, indicating their inclination towards AI adoption in multiple areas of RS.

For example, R13, with two years of experience, showed interest in utilizing AI in many phases of RS compared to more experienced professionals and anticipated greater benefits from AI use. In contrast, R14 and R10, with 15 and 16 years of experience respectively, did not endorse the use of AI in every RS phase and advocated for selective implementation in RS. Therefore, it can be inferred that experienced professionals are more critical when evaluating the suitability of AI, as demonstrated by R13, who emphasized the importance of experience in making informed decisions about the utilization of AI technologies. He explained:

> *"If I did not have experience, I would be eager to jump start with all AI technologies in every phase of the RS. But my experience now is helping me to be decisive on whether I want to use AI or not in certain recruitment phases."*

The experienced professionals identified various requirements that need to be fulfilled before adopting AI in RS. Notably, professionals with extensive experiences, such as R10 with 16 years of experience, emphasized the need for AI governance frameworks as a prerequisite for AI implementation. Similarly, professionals with over 10 years of experience, including R9, expressed caution and were not inclined to adopt AI everywhere, even if it proved accurate. This sentiment was shared by other experienced professionals (with more than 5 years of experience) in RS. In contrast, less experienced professionals exhibited a higher intention to adopt AI in RS, reflecting a more open mindset. These findings highlight the divergent perspectives between experienced professionals, who stress specific requirements and exercise caution, and less experienced professionals, who demonstrate a greater willingness to embrace AI in RS. The results emphasize the influence of professional experience on perceptions and intentions regarding AI adoption in the recruitment domain.

6.7.2 Hiring volume

The findings present two distinct perspectives regarding the impact of AI usage based on the hiring volume. One group of participants who were hiring a large volume of candidates demonstrated a greater willingness to employ AI, However, another group of participants who were hiring a low volume exhibited hesitation and required convincing regarding AI's effectiveness before adopting it for their specific needs. This suggests that the latter group may be more inclined to try out AI for smaller-scale hiring initiatives until they are more confident using AI on a larger scale.

For instance, R4, responsible for hiring over 200 positions monthly, has already incorporated AI into their prescreening process, acknowledging that it is indispensable given the scale of their hiring requirement and said, "*given the scale of our hiring, it would be impossible to manage without the use of AI*". However, it is important to note that these professionals work for large corporations with high hiring volumes.

On the contrary, HRM1, who hires only 2-3 candidates annually, expresses less enthusiasm towards AI and states that it may be more suitable for high-volume hiring, indicating a reluctance to use AI for low-volume hiring needs and said, "*it may be more* *suitable for high-volume hiring, and I would not use AI for my low volume hiring needs"*. Similarly, R11 suggests conducting pilot programs with AI for low-volume hiring before implementing them in the recruitment process. R9 also mentions receiving very few candidates for specialized executive and senior positions and displays no inclination to use AI for those positions. This suggests that the relationship between behavioral intention and other factors, such as benefits, facilitating conditions, or recruitment phases, may be weaker for high-volume hiring. However, this aspect will be statistically examined in the quantitative study.

6.8 Hypothesis updates

The findings reported above imply that modifications to the existing hypotheses are necessary, particularly when determining the strength of the influence of the main or moderating factors on AI adoption in RS. The predicted relationship column in Table 10 reflects the type of these relationships based on the findings reported above.

Hypothesis number	Independent Construct	Dependent construct	Moderator	Coding	Predicted Relationship
H1	Benefit Expectations	Behavioral Intentions		BE→BI	Positive
H1.1	Benefit Expectations	Behavioral Intentions	Experience	Exp x BE→BI	Less experience strengthens the relationship
H1.2	Benefit Expectations	Behavioral Intentions	Volume	Vol x BE→BI	Low Volume strengthens the association
H2	Social Influence	Behavioral Intentions		SI→BI	Positive

H2.1	Social Influence	Behavioral Intentions	Experience	Exp x SI→BI	Less experience strengthens the relationship
H2.2	Social Influence	Behavioral Intentions	Volume	Vol x SI→BI	More Volume strengthens the association
H3	Facilitation Conditions	Behavioral Intentions		FC→BI	Positive
H3.1	Facilitation Conditions	Behavioral Intentions	Experience	Exp x FC→BI	More experience strengthens the relationship
H3.2	Facilitation Conditions	Behavioral Intentions	Volume	Vol x FC->BI	Low Volume strengthens the association
H4	Recruitment Phase	Behavioral Intentions		RP→BI	Positive
H4.1	Recruitment Phase	Behavioral Intentions	Experience	Exp x RP→BI	Less experience strengthens the relationship
H4.2	Recruitment Phase	Behavioral Intentions	Volume	Vol x RP→BI	Low Volume strengthens the association
H5	Trust	Behavioral Intentions		TR→BI	Negative
H5.1	Trust	Behavioral Intentions	Experience	Exp x TR→BI	Negative but Less experience strengthens the relationship
H5.2	Trust	Behavioral Intentions	Volume	Vol x TR→BI	Low Volume strengthens the association
H6	Behavioral Intentions	Use Behavior		BI->UB	Positive
H6.1	Behavioral Intentions	Use Behavior	Experience	Exp x BI->UB	Less experience strengthens the association
H6.2	Behavioral Intentions	Use Behavior	Volume	Vol x BI->UB	Low hiring Volume strengthens the association
H7	Facilitation Conditions	Use Behavior		FC→UB	Positive

H8	Recruitment Phase	Use Behavior		RP→UB	Positive
H9	Trust	Use Behavior		TR→UB	Negative
H10	Use Behavior	Outcomes		UB→OC	Positive

Table 10: Hypothesis update

It should be noted that, while the qualitative research revealed some insights relevant to AI adoption in recruitment and selection (RS), and its applicability to certain roles such as blue-collar, specially skilled roles, executive roles, and vocational roles, the researcher decided that more focused research is needed to determine the applicability of AI in recruiting candidates for such roles. Additionally, there are other studies in the same domain, such as those by Luo, J., et al., (2023) and Raveendra, P. V., et al., (2020), regarding blue-collar workers and the applicability of AI in recruiting such roles. Thus, the researcher excluded that scope from the above hypothesis as it is outside the scope of the research.

6.9 Update to the construct's measurements

The findings presented above also provide insights into how the main constructs should be measured related to AI-RS. These measurement items specific to the RS in AI are listed in table 11 below.

Construct /Driver	Measurement input variables	Qualitative research reference section
Benefit Expectations (BE)	▪ Increasing candidate pool ▪ Increasing work-life balance ▪ Increasing career progress ▪ Standardizing recruitment process ▪ Increasing informed decision making	6.6.2.1

Social Influence	▪ Candidates ▪ Managers ▪ HR community ▪ Modern era ▪ Media, documentary, science fiction ▪ Customers ▪ Hiring managers	6.6.3
Facilitating Conditions	▪ Availability of AI tools ▪ Auditability of how decisions were made. ▪ Regulations like GDPR ▪ Compatibility with other phases ▪ Protection of data privacy (not hackable)	6.6.5
Recruitment Phase	▪ Pre-planning ▪ Pre-screening ▪ Sourcing ▪ Candidate engagement ▪ Interviews	6.6.1
Trust in AI	▪ Trust AI can provide human-like experience. ▪ Trust AI to conduct behavioral / culture fit assessments. ▪ Trust AI to make hiring decisions	6.6.7
Behavioral Intentions	▪ In high-volume hiring ▪ In low-volume hiring ▪ In white-collar hiring ▪ In blue-collar hiring ▪ Hire candidates for any industry	6.6.9, 6.7
Use Behavior	▪ Currently Using AI in all of the recruitment phases ▪ Currently Using AI to reduce admin work. ▪ Currently using AI in any of the recruitment phases ▪ Using AI tools as integrated platforms	6.5
HR outcomes	▪ Time to hire. ▪ Cost of hire ▪ Quality of hire ▪ Retention rates	6.6.8
Volume	▪ 1-50 candidates ▪ More than 50	6.7.2
Experience	▪ 1-5 years ▪ Above 5	6.7.1

Table 11: Main construct measurements identified from the qualitative results.

These findings provide the foundation for quantitative research, as it requires testing the hypotheses through statistical data that can use the measurement criteria identified in Table 11. The quantitative research and its approach are explained in Chapter 7.

CHAPTER 7

QUANTITATIVE RESEARCH OVERVIEW

7.1 Introduction

This chapter discusses the quantitative method used to test the AI-RS model developed in this study. It explains why surveys were chosen as the preferred data collection method and how they were designed and structured. The chapter also covers the data collection approach and the intended sample size. It provides an overview of the data analysis and validation approach and the methodology for testing the hypothesis and answering research questions.

This chapter, along with Chapter 9, represents the next steps of the research, as shown in the frame in Figure 13.

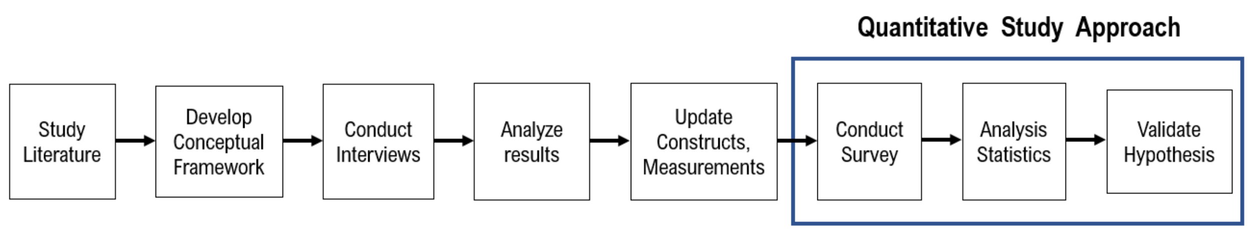

Figure 13: Quantitative study approach

7.2 Quantitative method: Survey

Quantitative research aims to collect and analyze numerical data to examine relationships, patterns, and differences in the data and draw conclusions based on statistical analysis (Creswell, 2017). This method is considered highly reliable and valid due to its structured and standardized data collection and analysis processes (Trochim, 2006). In this study, a structured survey is intended to collect data, which has several advantages in quantitative research.

Surveys are useful for collecting data from many participants in a short period, making it possible to gather data from a representative sample of the population being studied (Creswell, 2017). Furthermore, surveys use standardized questions and response options, allowing for data comparison across participants and controlling biases in the data collection process. It enables efficient data collection while minimizing inconsistencies in verbal communication, such as those that may arise during interviews or misunderstandings during observations (Mathers et al., 1998).

In addition to efficiently collecting data while minimizing communication inconsistencies, the survey can reach a broader range of sources and demographics. As noted by Babbie & Mouton (2011), the survey approach can be disseminated quickly to various sources and geographies, increasing the sample size within a shorter period and ultimately strengthening the statistical power of the study (Hair et al., 2017; Richey et al., 2016; Brown, 2015). Also, surveys can be administered in different settings and modes, such as online, by mail, or in person, allowing participants to reach different locations (Salkind, 2010).

In addition, surveys provide anonymity and confidentiality to participants, which can encourage more honest and accurate responses, especially on sensitive topics (Liao & Hsieh, 2017). The use of anonymous surveys can also reduce social desirability bias, where participants may respond in a way, they believe is socially acceptable rather than providing truthful answers (Salkind, 2010). Therefore, surveys are an effective tool for collecting quantitative data reliably and validly.

The significance of using a survey approach is particularly relevant in the context of AI, where the technology is being applied in diverse industries, countries, and companies, as indicated by Savola & Troqe (2019), Aljuaid & Abbod (2020), Nawaz (2019), Geetha & Bhanu (2018), Pal & Chabane (2018). Consequently, using a survey to collect data from these diverse sources and demographics is expected to increase the statistical power of the data analysis and provide more insightful information.

Thus, this research uses a quantitative survey approach to statistically test the list of hypotheses and answer research questions.

7.3 Survey design

An important decision when designing surveys is the number of questions or length of a survey (Rossi et al., 2004). Best practices suggest limiting the survey length to maintain participants' attention and interest (Groves, 2011). As such, the researcher limited the number of questions to those necessary to measure the constructs and moderation effects on the AI-RS. To ensure the reliability and validity of the constructs, multiple measures were used to assess each construct as per the granular level details gathered in the qualitative research. This approach ensures the construct has sufficient data or metrics to measure it, even if some indicators must be dropped due to errors, inconsistencies, or abnormalities (Mellinger & Hanson, 2020).

The survey questions were designed as closed-ended questions, where the respondents were provided with predefined response options to choose from. This approach has been shown to improve the response rate and reduce manual errors during data entry (Kitchenham & Pfleeger, 2002).

The survey was devised to obtain supplementary demographic data pertaining to the RS owner's professional designation (i.e., recruiter, hiring manager, HR executive), country of work, and industry they conduct recruitment for. Nonetheless, these demographic variables will be used only to provide descriptive statistics to understand the sample population.

7.4 The Survey Structure

The survey employed a structured design consisting of several sections. The first section provided an overview of the research, including the purpose, research institution, data collection process, storage policy, and the researcher's contact information. The second section outlined ethical considerations and data protection procedures, and the process for obtaining written consent was detailed. Participants had to provide written consent to proceed with the survey but were free to exit at any point and with any data collected deleted from storage.

The third section of the survey collected demographic information, while the fourth section collected data relevant to the research model's constructs. The Likert scale with seven points ranging from 1 to 7 was employed to measure the answers, based on empirical research suggesting that it has lower measurement errors than three or five-point scales (Munshi, 2014). Using Likert scales helped convert subjective data to objective data and increase the reliability and validity of the data collected.

Thus, the proposed survey consisted of a list of questions designed to collect data on the main constructs and their proposed answers, measured on a 1-7 Likert scale. The proposed answers to the multiple-choice questions in the survey were influenced by the qualitative research findings and the measurement criteria for each of the constructs listed in Table 11 in Chapter 6, Section 9. These questions and their answers are listed in Table 12 below.

Construct	Survey questions	Measurement input variables
Benefit Expectations	What benefits do you expect from AI in the recruitment and selection process?	▪ Increasing candidate pool ▪ Increasing work-life balance ▪ Increasing career progress ▪ Standardizing recruitment process ▪ Increasing informed decision making
Social Influence	Who inspires you to use AI in the recruitment process?	▪ Candidates ▪ Managers ▪ HR community ▪ Modern era ▪ Media, documentary, science fiction ▪ Customers ▪ Hiring managers
Facilitating Conditions	What facilitating conditions do you expect to use AI in the recruitment and selection process?	▪ Availability of AI tools ▪ Auditability of how decisions were made. ▪ Regulations like GDPR ▪ Compatibility with other phases ▪ Protection of data privacy (not hackable)
Recruitment Phase	In which recruitment phase would you use AI?	▪ Pre-planning ▪ Pre-screening ▪ Sourcing ▪ Candidate engagement ▪ Interviews
Trust in AI	How much do you trust in the areas below?	▪ Trust AI can provide human-like experience. ▪ Trust AI to conduct behavioral / culture fit assessments. ▪ Trust AI to make hiring decisions
Behavioral Intentions	In which area would you intend to use AI?	▪ In high-volume hiring ▪ In low-volume hiring ▪ In white-collar hiring ▪ In blue-collar hiring ▪ Hire candidates for any industry. ▪ Hire candidates for certain industries
Use Behavior	In which areas of RS do you use AI currently and why?	▪ Using AI in any of the recruitment phases ▪ Using AI to reduce admin work. ▪ Not using AI in any of the recruitment phases ▪ Using some AI tools

		▪ Using many AI tools
HR outcomes	What HR outcomes do you expect to achieve using AI in the recruitment process?	▪ Time to hire. ▪ Cost of hire ▪ Quality of hire ▪ Retention rates
Hiring Volume	How many numbers of candidates do you hire in a month?	▪ 1-10 employees ▪ 11-50 employees ▪ 51-100 employees ▪ More than 100 employees
Experience	How many years of experience do you have in the RS?	▪ 1-10 years ▪ Above 11 years

Table 12: Constructs and indicator variables mapping in the survey.

The survey was designed using Qualtrics software, a cloud-based platform allowing easy use on multiple channels such as web or mobile formats. Prior to distribution, the survey was tested with five qualified individuals to ensure readability, accessibility, and time to complete, and feedback was incorporated into the final survey, with their results excluded from the data sample. Participants who wished to receive a summary of the research after completion were given the option to provide their email addresses.

7.5 Sample size

The appropriate sample size in quantitative research has been a matter of ongoing debate (Adwok, 2015). Some scholars contend that adequate participant selection can produce a sufficient sample size, while others advocate for larger samples to achieve more precise statistical outcomes (Kish, 1965; DeVellis, 2017). However, despite these differing opinions, determining the exact number of participants required can be challenging (VanVoorhis, 1968).

For example, Various scholars have proposed different minimum sample sizes. For example, Green (1991) suggested a minimum of 50, Harris (1985) recommended exceeding the number of predictor variables plus 50, and Cohen and Cohen (1975) argued that the sample size depends on the number of independent and dependent variables. This variation in theories makes it difficult to establish an ideal sample size (Fowler & Lapp, 2019; Raudys & Jain, 1991). Thus, researchers aim to determine a sample size that is not too small or too large such that the right population of RS professionals, hiring volumes, and multiple geographies experiences are represented in this research.

Thus, rather than using random sampling, the researcher checked the LinkedIn profiles of each research participant to ensure that participants had the appropriate expertise in recruiting, hiring, or HR executive roles and at least one year of experience in the RS. Data collection occurred over two months, during which more than 400 participants were invited to participate. However, many participants lacked sufficient knowledge of AI in recruitment, leaving only 265 participants who attempted the survey. This will be further discussed in chapter 8.

7.5.1 Data collection method

The data collection process employed various approaches and channels, including professional networking sites such as LinkedIn and Facebook, and recruitment companies were approached via the Internet. This was informed by the qualitative research findings that indicated the frequent use of these platforms by research participants for sourcing candidates and keeping up to date with HR trends and technologies (Kaczmarek & Miller, 2015). It also used LinkedIn groups, as explained in Chapter 5, section 4 and additionally, potential participants were contacted through LinkedIn messages or email.

Furthermore, individuals who had expressed interest in participating further in qualitative research were included in the study. Overall, the data collection process ensured that participants had the requisite qualifications and experience to provide valuable insights into the research topic.

7.6 Data analysis approach

This chapter segment discusses the intended method for thoroughly analyzing the data set. The proposed approach comprises several phases, starting with data screening, then data cleaning and coding, as well as managing missing data, and finally, a validation process to ensure the reliability of the results. This process is illustrated in Figure 14 below.

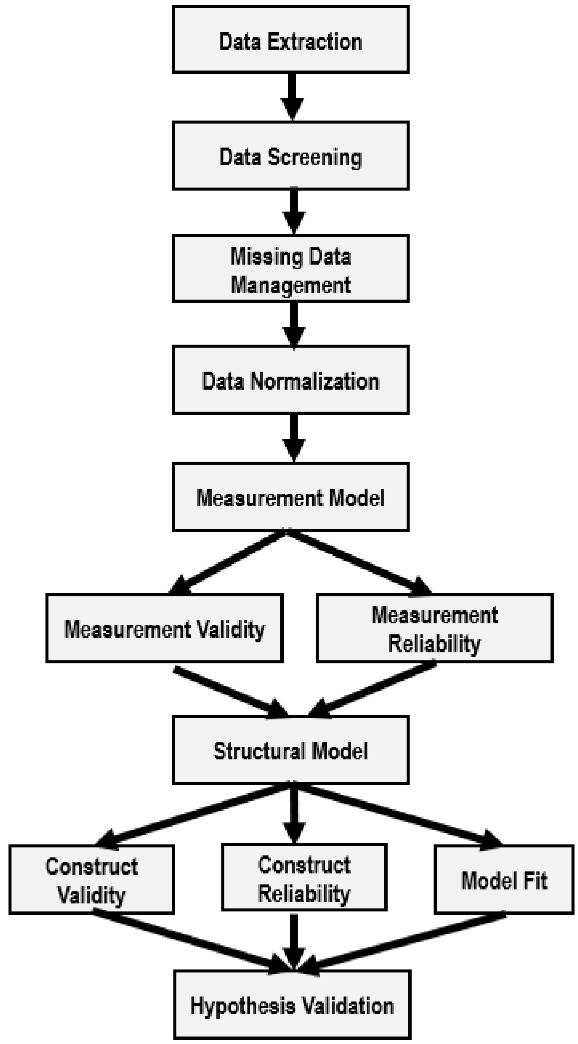

Figure 14: Data analysis approach

7.6.1 Data screening

The validity and reliability of research data are crucial components of scientific inquiry. Therefore, the research data will undergo several rigorous screening processes to ensure its accuracy and completeness. Firstly, the researcher will validate the data to ensure that participants have provided written consent for the survey in accordance with ethical standards (American Psychological Association, 2017). Any data lacking consent will be excluded from the sample to ensure its reliability and validity (Shillington, Lehman, Clary, & Blane, 2011).

Subsequently, the researcher will assess the completeness of the data and eliminate any data with less than a 90% completion rate from the sample. This criterion is essential as low completion rates can negatively affect the effectiveness of dependent variables on moderation factors (Hair, Black, Babin, & Anderson, 2019). Therefore, ensuring a high completion rate is necessary to ensure that the data collected is comprehensive and representative of the target population.

In the next step, the collected data will go through a coding exercise involving mapping the data to relevant construct measurements, giving them unique identification codes, and reverse coding when required, as Carter (1997) suggested. Reverse coding involves the reversal of the scoring of some variables to ensure that they align with the conceptualization of the construct under investigation. This technique ensures that the data collected is accurate, reliable, and consistent with the research objectives.

Lastly, the researcher will manage any missing and invalid data as it can affect the accuracy and reliability of the analysis. Various techniques, such as deletion, imputation, and substitution, can be employed for this purpose (Graham, 2009). These techniques ensure that the data used in the analysis is complete and valid, leading to more accurate and reliable results.

7.6.2 Managing missing data

Missing and invalid data can significantly impact the statistical results and reduce the statistical power (Little & Rubin, 2002). It can compromise the accuracy and reliability of statistical analyses; therefore, it is important to implement preventive measures to avoid such issues.

One way to do this is to recruit participants with relevant experience in research topics and industry. However, it is also possible for missing data to arise from systematic errors in the survey design, such as unclear wording, technical language, lengthy or confusing questions, or poor survey flow (data (Mellinger & Hanson, 2020). These factors can cause participants to skip questions and result in missing data. Thus, the survey was first evaluated with five participants to avoid such systematic errors, and feedback was collected and incorporated into the survey design. However, there may still be some missing data at random, requiring further assessment.

Literature suggests various ways to manage missing data and accepting less than 10% of missing data in the population is recommended to avoid losing statistical power (Hair et al., 2009). However, missing data may be difficult to overlook, particularly when the sample size is small (Allison, 2003). Therefore, the research will use preventive measures and management mechanisms such as listwise deletion, simple imputations, direct maximum likelihood (Direct ML), and multiple imputations to manage missing data, as explained in section 8 (Brown, 2015, p. 235).

7.6.3 Outliers

Outliers can significantly affect statistical analysis and hypothesis validation by producing inaccurate results (Dillon et al., 1987; West et al., 1995). The literature has identified two types of outliers: univariate and multivariate (Kline, 2005; Tabachnick & Fidell, 2001). Univariate outliers refer to cases with extreme values on a single variable, whereas multivariate outliers refer to cases with an unusual combination of values on two or more variables. Typically, extreme values are defined as scores that are more than 3.29 standard deviations away from the mean (Kline, 2005).

To minimize univariate outliers, the Likert scale was used to design each question with a range of 1-7 options to click on, while multiple-choice questions were designed to minimize the potential for invalid data entry, which could lead to univariate outliers (Mahdavinejad et al., 2018). However, multivariate analysis is more relevant to this research. Thus, Mahalanobis distance (D2) was used to identify multivariate outliers, measuring distance in standard deviation units between each observation and the mean of all observed variables (Byrne, 2001; Kline, 2005; Hair et al., 2006). A large D2 value indicates that the case is an extreme value on one or more variables. A conservative statistical significance test, such as $p < 0.001$, is recommended when using the D2 measure (Kline, 2005; Hair et al., 2006).

7.6.4 Normality

According to Hair et al. (2006), normality refers to the shape of the distribution of a metric variable and its correspondence to a normal distribution, which is a crucial factor in statistical analysis. Detecting deviations from normality is important since it can affect the interpretation of results and the estimation process. One method to detect normality is through a visual analysis of a histogram that represents the probability plot of the data set (Hair et al.,2006). Other techniques involve visually scanning the data for abnormalities.

In addition, skewness and kurtosis are also useful in identifying normality in a data set. Skewness measures the symmetry of distribution, while kurtosis refers to the heaviness of the tails in distribution compared to a normal distribution (Hair et al.,2006). In a normal distribution, skewness and kurtosis scores are zero, while they yield higher values in abnormal data. The threshold for identifying abnormalities varies. Hair et al. (2006) suggests skewness scores outside the -1 to +1 range indicate a skewed distribution. West et al. (1995) and Kline (2005) suggest that values of the skew index greater than 3.0 and a kurtosis index score from about 8.0 to over 20.0 describe extreme skewness and kurtosis, respectively. However, other researchers note that a skewness range of -2 to +2 or -7 to +7 is also acceptable, particularly when dealing with limited data (Byrne, 2010; Hair, 2010).

For this study, the researcher set the acceptable limit for observation values to ±2 for skewness and ±2 for kurtosis. The validated data will be used in structural equation modeling (SEM), which measures the reliability of scales, the validity of constructs, and the association among them.

7.7 Structural equation modeling (SEM)

Structural equation modeling (SEM) is a widely used statistical technique for analyzing relationships among multiple latent variables or constructs (Byrne, 2001). SEM has become a crucial method for data analysis in many academic research fields (Byrne, 2001; Kline, 2005; Hair et al., 2006), providing a framework to measure the model consisting of various constructs, including main constructs, mediating constructs, and moderating constructs, and assess the relationships between them (Gefen et al., 2000; Tabachnick & Fidell, 2001).

The process of SEM involves validating the constructs using the measurement model, which includes confirmatory factor analysis (CFA) and factor analysis, and examining the structural model, which assesses the relations between constructs (Bentler, 1995; Hoyle, 1995; Hair et al., 2006). SEM ultimately enables researchers to test hypotheses and answer research questions.

7.7.1 Factor Analysis (FA)

Factor analysis (FA) is a statistical technique employed to analyze the correlations among measurement items or variables. It identifies underlying dimensions and summarizes them into components or factors (Hair et al., 2006). FA aims to understand the structure of a set of variables, develop a questionnaire to measure underlying variables, reduce a data set to a manageable level, and ultimately understand the constructs (Field, 2006, p. 619). FA can be performed using either exploratory factor analysis or confirmatory factor analysis techniques. Exploratory factor analysis is often used when a researcher attempts to identify common patterns from measured variables that may lead to developing factors or constructs, which, in turn, may lead to developing a theory. Confirmatory factor analysis, on the other hand, is used when constructs are already defined based on a theory (Hair et al., 2006, p. 105). In this research, the researcher employed confirmatory factor analysis because factors were identified based on the UTAUT model and the results of qualitative research. These identified factors are then measured using the measurement model.

7.8 Measurement model

An important step of the measurement model is ensuring the reliability and validity of the identified constructs; thus, two main steps are performed. The first step involves evaluating the reliability and validity of the individual constructs. The second step is the overall model validity, measured through goodness of fit (GOF) indices. This process is explained in the next sub-sections.

7.8.1 Reliability of the scales

Reliability pertains to the consistency, stability, and reproducibility of the scales utilized in measuring the individual indicator variables and the constructs (Sekaran, 2000). It is considered one of the most significant determinants of an instrument's quality, as it aids in identifying any inconsistencies that the scales may possess and their influence on the measurement results. Internal reliability is crucial when there are multiple scalers for each construct, as Bryman & Cramer (2005) mentioned.

While there are several measurement criteria to assess the reliability of constructs, this research employs Cronbach's alpha and composite reliability measures to evaluate internal consistency.

7.8.1.1 Cronbach Alpha

Cronbach's alpha is a measure that evaluates the internal consistency of the scales of indicators and constructs, indicating the consistency of responses on a scale of 0 to 1, with values closer to 1 considered good and acceptable (Cronbach & Meehl, 1955). The Cronbach's alpha thresholds suggested by Taber (2016) are used in this research. This decision is based on the precautionary measures taken before data collection, including qualifying the survey participants and testing the survey to avoid systematic errors.

Additionally, the researcher chose to retain most of the data to avoid removing data that may be relevant, and composite reliability is also used to evaluate factor reliability.

Assessment	Cronbach alpha
Robust	0.81
Faily high	0.76-0.95
High	0.73-0.95
Good	0.71-0.91
Relatively high	0.70-0.77
Slightly low	0.68
Reasonable	0.67-0.87
Adequate	0.64-0.85
Moderate	0.61-0.85
Moderate	0.61-0.65
Satisfactory	0.58-0.97
Acceptable	0.45-0.96
Sufficient	0.45-0.96
Not satisfactory	0.4-0.55
Low	0.11

Table 13: Cronbach alpha baselines (Taber,2016)

However, the interpretation of Cronbach's alpha varies depending on the thresholds used. George & Mallery (2003) offer general guidelines for interpretation, while Taber (2016) proposes a different set of threshold values with some overlap. Various factors, including the number of questionnaire items, subject knowledge of the survey participants, and interpretation of questions, can affect Cronbach's alpha scores (Gliem & Gliem, 2003). Therefore, other reliability criteria, such as composite reliability, are used in conjunction with Cronbach's alpha.

7.8.1.2 Composite reliability (CR)

Cronbach's alpha assumes the unidirectionality of scales and that indicators are equally related to the construct (Serkan, 2017). In other words, it assumes that the factor loading is equal for each variable, although, in practice, some items may measure differently from the rest of the indicators. Therefore, composite reliability (CR) is an alternative to Cronbach's alpha because, unlike Cronbach's alpha, CR considers error covariances, making it a better approach in CFA.

CR is obtained by combining the true score variances and covariances of indicator variables and dividing them by the total variance of the construct. The formula for CR is as follows (Raykov, 1997):

$$\boxed{CR = (\sum \lambda^2) / (\sum \lambda^2 + \sum \varepsilon)}$$

In the formula, λ (lambda) represents the standardized factor loading for the item, and i and ε are the respective error variance for item i. The error variance (ε) is estimated based on the value of the standardized loading (λ), which is calculated as follows:

$$\boxed{\epsilon_i = 1 - \lambda_i^2}$$

Upon confirming the reliability, then the validity of the constructs is assessed as explained next.

7.9 Construct Validity

In structural equation modeling (SEM), the validity of a construct is measured in two ways: convergent validity and discriminant validity (Bagozzi & Yi, 1998). Both methods are crucial steps in a reflective measurement model, which is the foundation of this research.

7.9.1 Convergent validity

Convergent validity is a statistical concept employed to assess the extent to which various measures of a given construct are positively associated with one another, thereby providing evidence for the validity of the construct under examination. This concept plays a crucial role in the validation of tests and can be established using several statistical methods, including correlations and factor analysis (Campbell & Fiske, 1959). Specifically, convergent validity reflects the extent to which the observed variables of a particular construct share a considerable portion of the variance (Hair et al., 2006).

In assessing convergent validity, several measures are utilized, including factor loadings, average variance extracted (AVE), and construct reliability (CR) estimation (Hair et al., 2006). Moreover, Hair and colleagues (2006) proposed that ideal standardized loading estimates should be 0.7 or higher, AVE estimation should exceed 0.5, and reliability estimates should be above 0.7 to demonstrate adequate convergent validity.

Consequently, the current study adopts a minimum threshold of loadings >0.7, AVE >0.5, and reliability >0.7 as the cut-off criteria for assessing convergent validity.

7.9.2 Discriminant validity

Discriminant validity is a statistical concept that pertains to the ability of a measure to differentiate between conceptually distinct constructs (Hair et al., 2006). This property of a measure indicates the degree to which it measures a unique construct rather than other constructs. Thus, it demonstrates whether a given test or measurement tool measures what it is intended to measure and nothing else (Hair et al., 2006). Consequently, the correlation between the measure and other measures of different constructs should be low.

Various methods can be employed to assess discriminant validity. For instance, the Fornell-Larcker criterion compares the squared multiple correlations (R^2) of each indicator with the construct it represents to the R^2 of that indicator with all other constructs (Fornell & Larcker, 1981). Moreover, Hair et al. (2006) suggested that the average variance extracted (AVE) for each construct should be compared with the corresponding squared inter-construct correlations (SIC). The SIC denotes the correlations between two or more different constructs or measures and thus indicates the relationship between constructs that are conceptually distinct and should not be highly correlated. The magnitude of these correlations reflects the degree of discriminant validity of the measures used to assess these constructs. High inter-construct correlations imply that the measures do not measure distinct constructs, while low inter-construct correlations indicate that the measures measure distinct constructs. Furthermore, AVE estimates that are consistently larger than SIC estimates provide support for the discriminant validity of the construct (Chin, 1999). This procedure was employed in this research to assess the discriminant validity of the constructs.

Once the convergent and discriminant validity of the constructs meets the predetermined thresholds, they are used to validate the model fit, refine the model, and achieve goodness-of-fit criteria before using them to validate the hypotheses.

7.10 Construct's goodness of fit

The second step ensures all constructs meet the goodness of fit (GOF) criteria. GOF criteria test whether the model fits the data well and whether the measurement model is consistent with the conceptual model (Byrne, 2010).

To evaluate the goodness of fit of a structural equation model, fit indices such as the chi-square test, Root Mean Square Error of Approximation (RMSEA), Normed Fit Index (NFI), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI) can be used (Byrne, 2010; Hair et al., 2006). However, the chi-square test is affected by sample size and requires a large sample size to produce an acceptable result (Bryne, 1998; Levesque, Zuehlke, Stanek, & Ryan, 2004). Therefore, alternative methods such as Maximum Likelihood Estimation

(MLE), Bootstrapping, and the critical ratio or t-test can also be used to estimate model parameters and fit.

The thresholds for fit indices may vary depending on the situation, such as the sample size. For example, Holmes-Smith (2002) suggests that factor loading values should be greater than 0.7, although a value greater than 0.5 is also considered acceptable (Churchill, 1979). The critical ratio values should be above 1.96 (Hair et al., 1998; Byrne, 2001). Table 14 below summarizes the cutoff thresholds suggested by various scholars.

Estimate	Recommended value	Interpretation	Reference
Factor Loading	>0.5	Acceptable	Churchill, (1979); Holmes-Smith (2002)
	>0.7	Good	
Critical ratio (t-value)	>1.96	Acceptable	Hair et al. (2006); Byrne (2001)
Standard residuals	±2.8	Acceptable	Byrne (2001); Hair et al. (2006)

Table 14: Some of the model validation thresholds

After confirming the construct goodness of fit, the overall model is tested, as explained in the next sub section.

7.10.1 Model fit through Goodness of Fit (GOF)

The concept of model fit comes once all the constructs are individually evaluated for reliability and validity (Hair et al., 1998). The model's Goodness of fit (GOF) is a statistical concept that evaluates the degree of correspondence between a model and observed data.

GOF indices are used to assess the accuracy and reliability of the model (rather than the individual constructs) and to determine whether the model accurately represents the data. The choice of the GOF index depends on the research question and data structure, as different indices have varying assumptions and limitations. It is essential to note that a good fit of the model to the data does not necessarily imply that the model is a true representation of the underlying processes, but it is a necessary condition for valid inferences (Hair et al., 1998).

GOF indices fall into three categories: absolute, incremental, and parsimonious fit indices (Hair et al., 1998). The absolute fit indices evaluate the overall model fit and include indices such as the likelihood ratio statistic chi-square (χ2), Root Mean Square Error of Approximation (RMSEA), and Goodness of Fit Index (GFI) (Hair et al., 1998). The incremental fit indices compare the proposed model to a baseline model and assess the model's fit using the normed fit index (NFI) and the comparative fit index (CFI) (Hair et al., 1998; Hair et al., 2006). The parsimonious fit indices investigate whether the estimated model is simpler or can be improved with fewer estimated parameter paths and include the adjusted goodness of fit (AGFI) (Hair et al., 1998). The AGFI is an example of a parsimonious fit index. The recommended threshold values for each fit index are summarized in Table 15 below.

Index	Type of fit	Recommended criteria	Reference

Chi-square (X^2)	Model fit	$X^{2,}$ Degree of freedom (df), p>0.05	Joreskog and Sorbom (1988)
Normed Chi-square ($X^{2/}$df)	Absolute model fit and parsimony of the model	1.0< χ 2 /df <3.0	Hair et al. (1998); Bryne (2001); Hair et al. (2006) GIF >0.8 is also acceptable according to Baumgartner, H., Homburg (1996) And Doll, W.J., Xia, W., Torkzadeh, G (1994)
Goodness of fit (GIF)	Absolute model fit	1) >0.9 2) >0.8	
Root mean square of error approximation (RMSEA)	Absolute fit	<0.05 (good fit) <0.08 acceptable fit)	
Normed Fit Index (NFI)	Incremental fit	>0.09 or >0.8	Awang (2012), Forza & Filippini (1998);
Adjusted goodness-of-fit index (AGFI)	Parsimonious fit	>0.90 or >0.8	Dang, Nuberg, Bruwer, 1994

Table 15: The commonly used goodness of fit indices

A good-fit model will have a low RMSEA and high values for NFI, CFI, TLI, and R-squared. In this research, the commonly used goodness of fit indices was employed to assess the model fit to the data. Once the model fit is assessed and ensured, the finalized model is used to test the hypothesis.

7.11 Hypothesis testing using SEM.

After achieving a good model fit, the final step in the analysis process involves hypothesis testing to examine the relationships between variables. This can be accomplished by comparing the standardized regression coefficients to a critical ratio (t-test) or by testing the significance of the path coefficients in the structural model. Two commonly used thresholds in hypothesis testing using the t-test are the p-value and confidence interval thresholds (Hair et al., 1998). The p-value represents the probability of observing a t-statistic as extreme or more extreme than the one calculated from the sample, assuming the null hypothesis is true (Emmert-Streib & Dehmer, 2019). If the p-value is less than the alpha level, the null hypothesis is rejected, and the difference between the means is considered statistically significant.

The confidence interval is a range of values expected to contain the true population mean with a certain level of confidence (Sullivan & Feinn, 2012). If the confidence interval does not contain the value of zero, the null hypothesis is rejected, and the difference between the means is considered statistically significant. The most used alpha level in hypothesis testing is 0.05, corresponding to a 5% chance of a Type 1 error (Kline, 2013).

Type 1 error concludes that there is a significant effect or difference between two groups when there is not (Cohen, 1994). The probability of making a Type 1 error is denoted by the alpha level, which is typically set at 0.05 in many fields. A Type 1 error can be costly in certain contexts, such as in medical research or in legal cases, where it can lead to incorrect conclusions or decisions being made based on faulty evidence. Therefore, it is important to carefully consider the consequences of making a Type 1 error when choosing the appropriate alpha level for a study (Cohen, 1994).

This research uses an alpha level of 0.05 as the threshold to minimize the risk of a Type 1 error. Once the hypotheses are validated, the results are assessed and interpreted to answer the research questions.

7.12 Chapter Summary

This chapter provides an overview of the quantitative research design approach, data analysis, and hypothesis validation process. The quantitative research was designed to confirm the factors identified in the qualitative research and the conceptual model developed using UTAUT. A survey-based approach was chosen to collect sample data from recruiters, hiring managers, and HR executives with experience in AI recruitment processes. The data processing method included managing missing data, normalizing data, and validating data using multiple scales, such as Cronbach alpha and composite reliability. The validated data samples were then used in a structural model to validate the constructs and their relationships and to test the 23 hypotheses developed. The results of the analysis process are explained in the next chapter.

CHAPTER 8

QUANTITATIVE ANALYSIS

8.1 INTRODUCTION

This chapter presents the results of the statistical analysis undertaken to examine the quantitative data. It elucidates the various steps involved in structural equation modeling, including the measurement and structural models, and then reports the outcomes of the measurement model. It comprises the constructs that define the model, the reliability and validity results, and the final measurement model fit results.

The chapter also explains the structural model, outlines the valid and invalid paths, and reports the model fit results. Then the chapter reports the results of the hypothesis testing. It should be noted that this chapter does not offer an interpretation of the results. Instead, it provides a statistical foundation for interpreting the results, which will be undertaken in Chapter 9.

8.2 Response rate, missing data, and outliers

In finalizing the data for analysis, the researcher first measures the response rate, missing data, and outliers of the data set collected from the survey, as explained in the next subsection.

8.2.1 Response rate and non-response bias

In this study, the initial target group comprised 400 individuals, resulting in 265 recorded responses (Although the final data sample ended up as 215 after treatment for missing data, normalization, etc., which will be explained in subsequent sections), reflecting a response rate of 66% during the eight-week data collection period. The response rate of 66% indicates that approximately one-third of the targeted individuals did not participate, which may lead to possible non-response bias. Non-response sample bias can be a concern when conducting surveys because it occurs when individuals who choose not to participate in the study may systematically be different from those who do participate (Groves & Peytcheva, 2008). However, the selection of research participants in this study was conducted with meticulous care to ensure representation from all relevant recruitment and selection (RS) groups, including individuals with prior experience in RS. As a result, it is anticipated that the impact of non-response bias will be minimal. Although the response rate was only 66%, the rigorous participant selection process is expected to mitigate any potential non-response bias. This approach strengthens the generalizability and validity of the study findings, as the sample is more likely to be representative of the target population.

8.2.2 Missing data

When conducting statistical analysis, missing data in the sample can be a problem. To prevent bias in their study, the researcher took steps to minimize potential sources of bias, such as pre-testing the survey, adjusting question length, and conducting quality checks. These measures were suggested by experts in the field, including Chen (2010), Dillman et al. (2014), and Groves et al. (2011).

39 participants out of 265 responses abandoned the survey, providing partial answers and skipping some questions leading to some missing data. Additionally, six respondents did not complete relevant questions on business impact, trust, current use, and recruitment phases. Table 16 exhibits the missing data profile because of this.

Variable	N	Mean	Std. Deviation	Missing		No. of Extremes	
				Count	Percent	Low	High
Role	232	1.78	.891	0	.0	0	0
Vol	232	2.86	1.286	0	.0	0	0
EXP	228	1.86	1.047	4	1.7	0	28
PST	228	2.98	1.257	4	1.7	0	0
UB2	232	3.92	1.182	0	.0	0	0
UB3	227	5.51	1.210	5	2.2	16	0
UB4	231	5.98	1.028	1	.4	14	0
BE1	231	6.08	1.160	1	.4	4	0
BE2	229	5.76	1.116	3	1.3	4	0
BE3	230	5.73	1.203	2	.9	5	0
BE4	230	5.62	1.278	2	.9	19	0
BE5	231	5.69	1.137	1	.4	10	0
SI1	231	4.88	1.472	1	.4	5	0
SI2	230	5.33	1.223	2	.9	15	0
SI3	230	5.40	1.249	2	.9	15	0
SI4	230	5.29	1.297	2	.9	28	0
SI5	228	4.74	1.582	4	1.7	5	0
SI6	228	4.86	1.489	4	1.7	4	0
SI7	229	4.36	1.736	3	1.3	0	0
FC1	230	5.30	1.257	2	.9	22	0
FC2	230	5.40	1.120	2	.9	11	0
FC3	230	5.46	1.150	2	.9	14	0
FC4	230	5.63	1.073	2	.9	7	0
FC5	230	5.65	1.179	2	.9	10	0
TR1	226	5.21	1.420	6	2.6	28	0

TR2	228	4.95	1.529	4	1.7	6	0
TR3	225	5.03	1.558	7	3.0	7	0
INT1	229	5.86	1.074	3	1.3	3	0
INT2	229	5.25	1.303	3	1.3	29	0
INT3	228	5.51	1.101	4	1.7	11	0
INT4	229	4.92	1.467	3	1.3	9	0
INT5	230	5.12	1.468	2	.9	41	0
PH1	228	5.72	1.118	4	1.7	5	0
PH2	227	5.78	1.134	5	2.2	4	0
PH3	226	5.89	1.122	6	2.6	4	0
PH4	226	5.46	1.226	6	2.6	14	0
PH5	226	5.14	1.534	6	2.6	34	0
UB1	231	5.70	1.010	1	.4	7	0
EE2	229	5.33	1.240	3	1.3	26	0
EE3	225	5.39	1.224	7	3.0	14	0
EE4	228	4.80	1.502	4	1.7	5	0
OC1	230	5.57	.990	2	.9	5	0
OC2	228	5.41	1.105	4	1.7	13	0
OC3	229	5.42	1.080	3	1.3	10	0
OC4	228	5.17	1.311	4	1.7	3	0

Table 16: Missing data profile of the same data

The Little's MCAR test for the dataset returned 0.378, indicating that there is no systematic missing data (Little & Rubin, 2014).

Managing missing data

To manage the missing data and reduce its impact on the study's results, the researcher employed a combination of listwise deletion and imputation techniques (Allison, 2002; Enders, 2010). Listwise deletion is used to maintain the integrity of the independent and dependent variables (Graham, 2009).

The use of listwise deletion resulted in the removal of 45 cases from the original dataset. This approach allowed the researcher to maximize the use of the remaining data that was consumable and applicable to the study's objectives. Overall, the researcher's precautions and management techniques effectively mitigate the impact of missing data on the study's findings (Schafer & Graham, 2002).

After that, the dataset under investigation comprised a sample of N=220, which displayed negligible missingness, amounting to less than 5% of the observations. This proportion falls below the commonly accepted threshold for ignorable missing data (Newman, 2014). Specifically, statistical analysis of the missing data pattern, as assessed through Little's MCAR test, revealed a significant deviation from the missing at random assumption (Chi-square = 830.087, Sig. = .000). In such cases to mitigate the damage, data imputation is a recommended method (Newman, 2014).

Therefore, mean substitution was chosen as the imputation method to maximize the available information (Newman, 2014). It should be noted that alternative methods, such as the expectation-maximization algorithm, have been suggested as more appropriate for dealing with data missing completely at random (MCAR) (Graham et al., 2013; Moon, 1996; Zhang et al., 2014).

Following the successful management of missing data with mean substitution, the data set was further observed for outliers, as explained in the next subsection.

8.2.3 Outliers

The current study employed univariate and multivariate outlier tests to identify potential outliers. Univariate outliers were detected by examining the frequency distribution of the Z-score of the observed variable, which enables the identification of extreme scores within a single variable (Kline, 2005). However, no univariate outliers were found in the present investigation. The researcher attributes this to using Likert-type measurements in the study, where responses are restricted to a finite range from 1 to 7. Such a limited range of responses may have contributed to the absence of univariate outliers in the data.

Multivariate outliers are observations in a dataset that deviate from the general pattern of the other observations in multiple dimensions rather than just one dimension, as is the case with univariate outliers. In other words, multivariate outliers are extreme values unusual not just in one variable but in combinations of variables. The current study utilized Mahalanobis Distance (D2) to detect multivariate outliers.

D2 measures the distance between the standard deviation of each variable and the means of all observed variables. A large D2 value indicates the presence of one or more variables significantly different from the others, thereby indicating the existence of potential outliers (Kline, 2005; Hair et al., 2006). It is worth noting that respondents who provide identical responses to all questions may also cause such anomalies (Hair et al., 2006). The study employed a D2 value cutoff of 70 to identify such outliers, and 3 records that exceeded the cutoff value were eliminated from the data file.

Additionally, a significance level of $p < 0.001$ was applied in conjunction with D2, as suggested by Kline et al. (2005). However, the researchers exercised caution and did not remove all records, as this could affect the generalizability of the data (Hair et al., 2006). As a result, the final sample size which was used for the remaining analysis was 217. The dataset's skewness was tested to assess its normality, and another two records were removed from the 217 initial data set as part of the composite reliability improvement process explained in Chapter 7, section 8. Thus, the final sample data set consisted of 215 valid data records.

8.2.4 Data normalization

The normality of the data (N=215) was assessed through the utilization of the thresholds of ±2 and ±2 for skewness and kurtosis, respectively, as recommended by Byrne (2010) and Hair (2010). The results showed that none of the variables reported values outside these thresholds. Therefore, it was concluded that the data were normally distributed, and normalization techniques were deemed unnecessary at this analysis stage.

8.2.5 Sample size adequacy

To ascertain the adequacy of the sample size for data analysis, the researcher employed KMO and Bartlett's test of sphericity as these are commonly used methods for the purpose (Kaiser, 1974; Bartlett,1954). The KMO measure is a statistic that measures the degree of common variance among the variables in a dataset. A KMO value of 0.6 or higher is considered acceptable for factor analysis, indicating that the sample size is adequate for EFA. Bartlett's test of sphericity is a statistical test that evaluates the null hypothesis that the correlation matrix is an identity matrix, meaning that there is no relationship between the variables. A significant result indicates that the variables are not independent, and that the correlation matrix is not an identity matrix. In other words, the data are suitable for factor analysis.

The researcher conducted the test using Maximum Likelihood, and the results revealed a sampling adequacy of 0.858 and a significant P value of 0.000, which confirmed the adequacy of the sample size and factor analysis could be meaningfully performed.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.858
Bartlett's Test of Sphericity	Approx. Chi-Square	3871.934
	df	820
	Sig.	.000

Table 17: KMO and Bartlett's test of sample size adequacy of the data

8.3 Descriptive statistics

This section presents the descriptive statistics of the sample of 217 research participants, and data was collected for further analysis.

8.3.1 Geographies

Table 18 lists the geographical distribution of the respondents (N=217). It indicates a noticeable concentration in the Philippines, where most respondents were recruiters. This concentration may be ascribed to outsourcing recruitment services to nations such as the Philippines, as noted in previous research (Lockwood et al., 2008). Furthermore, a comparatively greater representation of respondents is observed in Australia, Nigeria, Pakistan, India, and the USA relative to other countries in the sample population.

Frequency	Percen t	Valid Percent	Cumulative Percent	
Australia	17	7.8	7.8	7.8
Brazil	1	.5	.5	8.3
Canada	1	.5	.5	8.8
China	9	4.1	4.1	12.9
Costa Rica	2	.9	.9	13.8
Egypt	1	.5	.5	14.3
Germany	1	.5	.5	14.7
Hungary	1	.5	.5	15.2
India	7	3.2	3.2	18.4
KSA	1	.5	.5	18.9
Malaysia	1	.5	.5	19.4
Nepal	1	.5	.5	19.8
Netherlands	1	.5	.5	20.3
Nigeria	12	5.5	5.5	25.8
Pakistan	18	8.3	8.3	34.1
Philippines	120	55.3	55.3	89.4

Singapore	4	1.8	1.8	91.2
UAE	2	.9	.9	92.2
UK	4	1.8	1.8	94.0
USA	13	6.0	6.0	100.0
Total	217	100.0	100.0	

Table 18: Country representation of the validated data sample

8.3.2 Hiring Industries

About 75% of the participants, particularly recruiters, serviced multiple industries rather than one. Figure 15 displays the distribution of participants across different industries. Notably, a considerable proportion of participants were in the Administrative & Supportive Services, Professional, Scientific, Technical Services, Financial Services, and Information and Communication Technology (ICT) industries. The high concentration of participants in these industries may suggest an elevated demand for recruitment services in various sectors, such as healthcare, professional services, financial services, and IT.

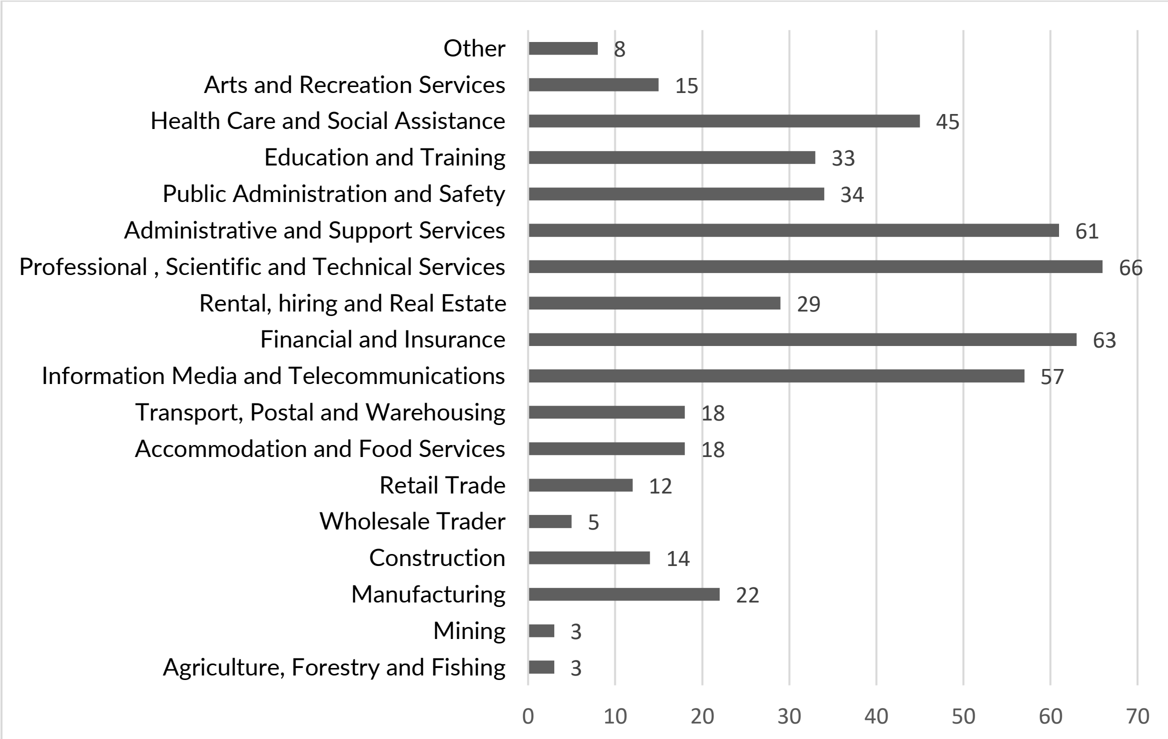

Figure 15: Hiring industries survey respondents catered for

Participants' experiences were grouped into four categories: 1-5 years, 6-10 years, 11-15 years, and over 15 years. The distribution of participants is summarized in Table 19. Most participants (approximately 60%) had less than five years of experience, while only 10% had over 15 years of experience.

Years	Frequency	Percent
0-5 years	109	50.7
6-10 years	57	26.3
11- 15 years	26	12.0
Above 15 years	23	10.6
Total	217	100.0

Table 19: Research participant’s experience categorization

The experience of the participants captured in the dataset did not pertain to the length of time they had been employed in their current position as a recruiter, hiring manager, or HR manager. Rather, it referred to the overall duration of their professional experience since the commencement of their career.

8.3.3 Participant's job group

Respondents represented three roles of recruiter, hiring manager, and HR executive. Their representations among the survey respondents are exhibited in Table 20.

Frequency	Count	Percent
Recruiter	112	51.6
Hiring Manager	39	18.0
Human Resource Executive	66	30.4
Total	217	100.0

Table 20: Job group classification of research participants

The rationale behind the deliberate choice of a larger cohort of recruiters stemmed from their comparatively more pronounced engagement in the recruitment whereby recruiters recommended the involvement of other recruiters within their respective organizations. Despite an equivalent outreach toward hiring managers, the research encountered resistance from the hiring managers, who declined participation in the study and attested to lacking familiarity with the implementation of AI in the recruitment and selection process.

8.4 Normality of Factors

In this section, the normality of the constructs was assessed using skewness and kurtosis, as explained next.

8.4.1 Main constructs

Descriptive statistics were utilized to analyze the normality of data of benefit expectations (BE) construct, which indicated that the data fell within the acceptable range of ± 2 and ± 2 for skewness and kurtosis, respectively (see Appendix table 48), in accordance with Brown's (2006) and Brown's (2015) recommendations for Structural Equation Modeling (SEM).

The assessment of facilitating conditions (FC) was conducted by applying a five-indicator measurement approach utilizing a Likert scale of 1-7. The indicators exhibited a normal distribution, as confirmed by the acceptable levels of skewness and kurtosis (see Appendix Table 49). Descriptive statistics for the indicators are presented in the table below.

The measurement of social influence (SI) incorporated the use of a Likert scale of 1-7 and involved the utilization of seven indicators. Descriptive statistics demonstrated that the variables exhibited normal distribution (See Appendix Table 50), as indicated by the satisfactory levels of skewness and kurtosis. To ensure the dependability and validity of the indicators, constructs, and overall model, some of the indicators may be eliminated during the measurement phase.

The recruitment phase (RP) assessment was conducted using a set of five indicators evaluated on a Likert scale ranging from 1 to 7. Descriptive statistics were computed for the variables, indicating that they conform to a normal distribution, as demonstrated by the skewness and kurtosis values within acceptable ranges (see Appendix Table 51).

The evaluation of trust in AI was conducted using three indicator variables evaluated on a Likert scale ranging from 1 to 7. The examination of the data demonstrated that the variables exhibited a normal distribution, as corroborated by the skewness and kurtosis values presented in the table below (see Appendix Table 52).

The assessment of behavioral intentions (BI) to consider employing AI in the RS was conducted by utilizing a set of five indicator variables evaluated on a Likert scale ranging from 1 to 7. The data analysis exhibited a normal distribution, as demonstrated by the skewness and kurtosis values presented in the table below (see Appendix Table 53).

The evaluation of user behavior (UB) was conducted using four indicator variables evaluated on a Likert scale ranging from 1 to 7. The data analysis demonstrated that the variables exhibited a normal distribution (see Appendix Table 54), as corroborated by the skewness and kurtosis values.

The assessment of HR outcomes was conducted utilizing a set of four indicators measured on a Likert scale ranging from 1 to 7. The examination of the data demonstrated a normal distribution of the variables, as confirmed by the skewness and kurtosis values within +/-2 (Appendix: Table 55).

8.4.2 Moderating variables

This study employed two moderators, namely the RS professional's experience and hiring volume, to explore potential relationships between the main independent and dependent variables, as elaborated in Chapter 4, section 3. The subsequent paragraphs provide details on the descriptive statistics and coding procedures utilized for the moderating variables.

8.4.2.1 Experience of the RS professional

As the data obtained for the experience of recruitment professionals was categorical in nature, the use of skewness and kurtosis was not relevant (Hair et al., 2014). This is because categorical variables do not have an inherent numerical scale and, thus, do not possess a mean or variance that can be used to calculate skewness and kurtosis. Hence, the distribution of data within each category was examined. The results indicated that the highest representation was observed in the 1-5 years of experience category, while the other three categories exhibited lower representation.

Considering the low representation of the 6-10, 11-15, and over 15 years of experience categories, a decision was made to regroup the categories to enhance statistical power. Thus, the categories were combined into two groups, with the 1-5 years of experience category remaining unchanged. The resulting groups were named junior (1-5 years of experience) and senior (above 6 years of experience). The distribution of participants across each group is presented in Table 21 below.

Experience Category	Frequency	Percent
Junior	109	50.7
Senior	106	49.3
Total	215	100

Table 21: Categorical distribution of two age groups

8.4.2.2 Hiring volume

During the preliminary data analysis, the hiring volume was classified into four categories based on the monthly hiring volume: 1-10 employees, 11-50 employees, 51-100 employees, and more than 100 employees. The descriptive statistics of the hiring volume are demonstrated in table22 presented below.

Monthly Hiring	Frequency	Percent
1-10	54	24.9
11-50	29	13.4
51-100	20	9.2
Above 100	114	52.5

Table 22: Frequency representation of monthly hiring volume

To improve the statistical power of each group, the original hiring volume categories were combined into two larger groups: low hiring and high hiring volumes.

The monthly hiring of 100 or less was classified as low hiring while hiring volumes above 100 were classified as high hiring. As a result, the frequency distribution of the hiring volume data changed, as shown in Table 23 below.

Monthly Hiring	Frequency	Percent
Low (Below 100)	99	46.0
High (Above 100	116	54

Table 23: Frequency of two hiring groups

After the data was analyzed for normality, as indicated previously, then the data was analyzed for reliability and validity, as explained next.

8.5 Scale reliability

To ensure the accuracy of the constructs measured in the study, it is imperative to assess the reliability of the scales utilized to measure the individual indicators (Gardner, 1995). One common method to test for scale reliability is using Cronbach's alpha. A value greater than 0.7 for Cronbach's alpha indicates a reliable scale for the indicator (George & Mallery, 2003). This section describes the evaluation of scale reliability for each construct using Cronbach's alpha. The researcher employed IBM SPSS version 28 to calculate Cronbach's alpha for each construct.

8.5.1 Scale reliability -Benefit expectations (BE)

The measurement of the construct of BE was carried out utilizing a 5-item scale rated on a range of 1 to 7. The obtained value for the Cronbach alpha coefficient was

0.772, which is indicative of an acceptable level of internal consistency reliability. This finding suggests that the reliability of the scale was satisfactory, and as such, no further adjustments to the scale were deemed necessary. It should be noted that when the Cronbach alpha coefficient falls below the acceptable threshold, further instrument refinement may be necessary. However, in the present study, this criterion was met.

8.5.2 Scale reliability -Facilitating Conditions (FC)

The construct of Facilitating Conditions was assessed using a five-item scale, with responses ranging from 1 to 7. The internal consistency of the scale was evaluated using Cronbach's alpha coefficient, which yielded a value of 0.704. This finding indicates that the scale is reliable, as it exceeds the minimum threshold of 0.7 for internal consistency reliability. As a result, there is no need for further adjustments to be made to the scale at this stage.

8.5.3 Scale reliability -Social Influence (SI)

The construct of Social Influence (SI), measured using seven items on a scale of 1-7, resulted in a Cronbach's alpha of 0.784. This value is above the acceptable threshold of 0.7, indicating a reliable scale for the indicators. Therefore, no further improvements were considered to enhance Cronbach’s alpha.

8.5.4 Scale reliability -Recruitment phase (RP)

The recruitment phase was assessed through the utilization of a five-item scale. The reliability of this measurement was evaluated using the Cronbach alpha coefficient, which yielded a value of 0.715. This finding indicates a satisfactory level of internal consistency, as the obtained value surpasses the acceptable range of 0.7 for the Cronbach alpha coefficient. Therefore, no further reductions or enhancements were deemed necessary at this stage, as the obtained value suggests that the measurement instrument is reliable for assessing the recruitment phase.

8.5.5 Scale reliability -Trust

Trust in AI was measured using a three-item instrument, with responses rated on a 1-7 Likert scale. The internal consistency reliability of this measurement tool was assessed using the Cronbach alpha coefficient, which yielded a value of 0.840. This value exceeds the widely accepted threshold of 0.7 for internal consistency reliability, indicating that the instrument is reliable for measuring the construct of trust. As a result, no additional measures were taken to enhance the Cronbach alpha value, as the obtained value suggests a satisfactory level of internal consistency.

8.5.6 Scale reliability -Behavioral Intentions (BI)

The construct of BI was measured through a five-item Likert scale with responses ranging from 1 to 7. However, the Cronbach alpha coefficient for this measurement tool was 0.567, which falls below the widely accepted threshold of 0.7 for reliable internal consistency. In response, the researcher took measures to enhance the scale's reliability. Specifically, the researcher ensured that all items were measured in the same orientation and the scales were consistent.

Further analysis of Cronbach alpha informed that Cronbach alpha would improve to 0.602 if INT4 was removed, as depicted in Table 24. Hence the researcher decided to remove INT4 from the construct, which resulted in the increased Cronbach alpha of 0.602.

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
INT1	20.60	11.203	.422	.291	.473
INT2	21.29	10.533	.337	.159	.506
INT3	20.98	9.852	.575	.392	.382
INT4	21.56	11.321	.183	.069	.602
INT5	21.35	11.033	.219	.077	.581

Table 24: Cronbach alpha improvements by deleting items.

According to Taber (2018), an alpha value of 0.7 is considered the optimum level, while a value ranging from 0.6 to 0.7 is deemed acceptable and reliable. Therefore, no further reduction of items was undertaken.

8.5.7 Scale reliability -Use Behavior (UB)

The measurement of use behavior was evaluated using four items, resulting in a Cronbach alpha coefficient of 0.643, which is below the recommended threshold of 0.7.

However, it falls within the acceptable and reliable range of 0.6 to 0.7, as Brown (2005) suggested.

To improve the measurement's reliability, the researcher conducted a further analysis utilizing the "if deleted" option in AMOS. This analysis demonstrated that removing UB1 would increase the Cronbach alpha coefficient to 0.651. Nonetheless, the improvement was minor, and the removal of an indicator for such a small improvement was unwarranted. As a result, the researcher retained all four indicators, maintaining the Cronbach alpha coefficient of 0.643, which remains acceptable and reliable, as it exceeds the minimum threshold of 0.6.

Variable	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
UB1	16.91	6.982	.354	.651
UB2	15.57	7.599	.450	.555
UB3	14.87	8.493	.483	.552
UB4	15.35	9.905	.461	.551

Table 25: The Cronbach alpha of individual indicator items of Use Behavior (if deleted)

8.5.8 HR Outcomes

The measurement of HR outcomes was conducted by employing four individual items on a Likert scale with a range of 1 to 7. The resulting Cronbach alpha coefficient was 0.735, exceeding the acceptable threshold, indicating good internal consistency among the items. Therefore, no further measures were taken to enhance the Cronbach alpha value as the measurement instrument demonstrated adequate reliability.

8.5.9 Summary- Cronbach Alpha scale reliability of Constructs

The Cronbach alpha coefficient was utilized to evaluate the reliability of the finalized scales for the individual variables that reflected the constructs. The results indicated that, with the exception of Use behavior and Behavioral intentions, all constructs demonstrated a Cronbach alpha value above the recommended threshold of 0.7, indicating good and acceptable reliability. However, Use behavior and Behavioral intentions also achieved a valid and acceptable threshold of 0.6. A table summarizing the scale reliability of each construct is presented below in Table 26.

Construct name	Variables (Before Improvements)	Cronbach alpha (Before Improvements)	Improvements	Variables (After improvements)	Cronbach alpha (After Improvements)	Threshold achieved (above 0.6)
Benefit Expectations -BE	BE1 BE2 BE3 BE4 BE5	0.772	No	BE1 BE2 BE3 BE4 BE5	0.772	yes
Facilitating Conditions -FC	FC1 FC2 FC3 FC4 FC5	0.704	No	FC1 FC2 FC3 FC4 FC5	0.704	yes
Social Influence -SI	SI1 SI2 SI3 SI4 SI5 SI6 SI7	0.784	No	SI1 SI2 SI3 SI4 SI5 SI6 SI7	0.784	yes

Recruitment Phase-RP	RP1 RP2 RP3 RP4 RP5	0.715	No	RP1 RP2 RP3 RP4 RP5	0.715	yes
Trust - TR	TR1 TR2 TR3	0.840	No	TR1 TR2 TR3	0.840	yes
Behavioral Intentions -BI	INT1 INT2 INT3 INT4 INT5	0.567	INT4 was removed to improve Cronbach's alpha	INT1 INT2 INT3 INT5	0.602	yes
Use Behavior – UB	UB1 UB2 UB3 UB4	0.643	No	UB1 UB2 UB3 UB4	0.643	yes
HR Outcomes – OC	OC1 OC2 OC3 OC4	0.735	No	OC1 OC2 OC3 OC4	0.735	yes

Table 26: Summary of Cronbach alpha validity of construct indicators

In the subsequent phase, the reliability and validity of the constructs will be further evaluated utilizing structural equation modeling, as elaborated in the following section.

8.6 Structural equation modeling

The current study employed a two-step process for conducting structural equation modeling. The scale validation, which utilized Cronbach Alpha, as indicated in section 8.4, was utilized as input for the measurement model of SEM.

Next, a measurement model was constructed to evaluate the reliability and validity of the constructs in terms of composite reliability and divergent validity (Campbell & Fiske, 1959). Composite reliability was used to assess the reliability of the indicators of the entire construct, utilizing CR indices (Hair et al..2006). This step was iterated multiple times until the construct reliability and validity met the desired indices of composite reliability (CR) and average variance extracted (AVE). The steps were then repeated to achieve model-fit thresholds, which were evaluated through goodness-of-fit indices (GFI), adjusted goodness-of-fit indices (AGFI), root-mean-square error of approximation (RMSEA), and comparative fit index (CFI).

The model was a good fit once the desired thresholds for each index were met. The finalized and well-fitting model was then used to generate the latent variables and conduct a structural analysis in the second step. The subsequent sections delineate the assessments for both the measurement model and the structural model of the constructs.

8.6.1 Measurement model before model fit

The measurement model encompassed 36 indicators measuring the individual constructs and their correlations. Each indicator was derived from the qualitative research results and included 5 indicator variables for BE, 7 indicator items for SI, 5 indicator items for FC, 3 indicator items for Trust, 4 indicator items for BI, 4 indicator items for UB, 4 indicator items for Outcomes and 4 indicator items for RP (see Appendix figure 17).

The model underwent several iterations until each scale reached the desired thresholds for reliability and validity. Once the individual constructs met the reliability and validity criteria, the measurement model was then evaluated using confirmatory factor analysis (CFA) and assessed based on model fit criteria recommended for assessing constructs. These criteria included the chi-square (χ^2) statistic, degrees of freedom (df), goodness-of-fit index (GFI), root mean square error of approximation (RMSEA), normed fit index (NFI), comparative fit index (CFI), and adjusted goodness of fit index (AGFI). It is essential to meet the thresholds (refer to Table 27) for these indices to achieve model fit and ensure the validity of the constructs, as explained in the previous section.

Type of measure			Absolute fit measures			Incremental fit measures		Parsimony fit measure
Criteria	X^2	df	$X^{2/}$df	GFI	RMSEA	NFI	CFI	AGFI
Threshold			1< $X^{2/}$df<3	≥0.80	<0.05	≥0.80	≥0.90	≥0.80

Table 27: Goodness of fit criteria thresholds

Despite efforts, the initial measurement model failed to meet the necessary thresholds, as illustrated in Table 28. Consequently, it became apparent that refinement was necessary to achieve the desired level of composite reliability for each construct.

Type of measure			Absolute fit measures			Incremental fit measures		Parsimony fit measure
Criteria	X2	df	X2/df	GFI	RMSEA	NFI	CFI	AGFI
Threshold			1< X2/df<3	≥0.80	<0.05	≥0.80	≥0.90	≥0.80
Value archived	783.164	436	1.796	0.817	0.061	0.752	0.870	0.778
Accepted?			Yes	Yes	No	No	No	Yes

Table 28: Model fit indices before any improvements

To achieve construct reliability, validity, and model fit, researchers can use various techniques such as examining the data for abnormalities and outliers, treating the data to attain normality, eliminating problematic data or indicators, or removing constructs from the measurement model (Ghorbani, 2019). In this study, the researcher employed the Mahalanobis test to identify two abnormal records with D2 values exceeding 70 and subsequently removed them. As a result, the sample size was reduced from 217 to 215.

Despite the deletion, the composite reliability of the UB construct marginally improved to 0.698, which is almost the threshold of 0.7 when applying rounding up. However, a two-step normalization process was implemented involving fractional mean ranking of the variable followed by normal transformation, as suggested by Templeton and Burney (2017). Subsequently, the composite reliability of the UB construct improved beyond the 0.7 threshold, as presented in Table 29.

Construct code	Composite reliability (CR)	AVE	MSV	MaxR(H)
OC	0.756	0.510	0.573	0.765
BE	0.752	0.385	0.401	0.776
SI	0.849	0.483	0.518	0.850
FC	0.724	0.353	0.567	0.760
TR	0.855	0.666	0.137	0.890
INT	0.727	0.583	0.346	0.845
PH	0.777	0.478	0.349	0.832
UB	0.702	0.439	0.338	0.782

Table 29: Model fit indices before any improvements

However, the convergent validity, which refers to the extent to which the indicators within a construct measure the same underlying construct and is typically assessed using average variance extracted (AVE), was below the recommended threshold of 0.5. Therefore, further improvement was required to enhance the convergent validity of the constructs (Fornell & Larcker, 1981). To address this issue, the researcher employed the approach of eliminating indicators with lower regression weights. This approach is a commonly used technique to enhance constructs' convergent and divergent validity (Hair et al., 2006). The elimination process was iteratively performed until the overall model fit was deemed satisfactory.

In the final iteration of the measurement model, the researcher retained 23 out of the 36 variables with standard regression weights exceeding 0.7, as per the recommendation of Hair Jr et al. (2021).

One of the variables retained in the study was INT3, which measures behavioral intentions. Although its factor loading of 0.57 was below the recommended threshold, the researcher decided to keep it due to its positive impact on the composite reliability, AVE, and overall model fit, as indicated by the CFI and GFI. Removing INT3 would compromise the integrity of the model, suggesting that INT3 is an essential variable for the overall analysis, despite falling under the recommended threshold.

Hair Jr. et al. (2017) and Wieland & Vollenbroek-Gunnink (2017) both emphasize the importance of considering the overall model fit when deciding whether to drop variables in partial least squares (PLS) path modeling. According to these authors, dropping variables can lead to a decrease in model fit and compromise the integrity of the analysis, particularly if the variable in question significantly impacts the composite reliability and AVE, as well as the overall model fit. Therefore, removing a variable like INT3, which significantly impacts the model fit despite falling below the recommended threshold, could compromise the overall integrity of the analysis and should not be dropped. Furthermore, according to Wieland et al. (2017), when a construct contains only two variables, it is advised not to drop any variables to ensure the construct is accurately measured. This iterative process enabled the study to achieve both convergent and divergent validity of the constructs and the model fit.

8.6.2 Measurement model after the model fit.

The final measurement model, which was constructed to assess the individual indicator variable scales, attained the recommended thresholds for all model fit indices. It included the chi-square (χ^2) statistic, degrees of freedom (df), goodness-of-fit index (GFI), root mean square error of approximation (RMSEA), normed fit index (NFI), comparative fit index (CFI), and adjusted goodness of fit index (AGFI) (Hair, 2009). The composite reliability of all constructs was above the recommended threshold of 0.7, while the AVE values ranged from 0.5 to 0.8, indicating high convergent validity. The results are explained in the subsequent sections.

The final measurement model consisted of eight constructs which were measured using 23 indicator variables. This composition of the constructs and the indicator variables are represented in the Appendix, figure 18. The regression weights of each of the indicator variables of the constructs are exhibited in Table 30 below.

Variable belonging Construct	Indicator/ Variable	Regression weights
Benefit Expectations	BE4	.707
Benefit Expectations	BE3	.667
Benefit Expectations	BE2	.652
Trust	TR3	.842
Trust	TR2	.911
Trust	TR1	.677
Outcomes	OC3	.836
Outcomes	OC2	.651
Outcomes	OC1	.797
Social Influence	SI5	.851
Social Influence	SI6	.726
Social Influence	SI4	.611
Facilitating Conditions	FC3	.806
Facilitating Conditions	FC2	.844
Facilitating Conditions	FC5	.445
Behavioral Intentions	INT3	.573
Behavioral Intentions	INT1	.922
Recruitment Phase	RP3	.808
Recruitment Phase	RP2	.843
Recruitment Phase	RP1	.594
Use Behavior	UB2	.800
Use Behavior	UB4	.604
Use Behavior	UB3	.802

Table 30: Regression weights of all variables after the model fit.

Upon confirming the validity of each indicator variable or its scale, the reliability of each indicator variable is assessed using composite reliability, as explained next.

8.6.3 Composite reliability

Composite reliability assesses the internal consistency of a scale or survey instrument of an indicator variable. It is commonly used in research to determine the extent to which a set of survey questions or items measure the same underlying construct or dimension (Nunnally (1978). The calculation of composite reliability involved using the formula proposed by Fornell & Larcker (1981) and Hair et al. (2006) to determine the overall reliability of each latent construct. A threshold of 0.7 was set for composite reliability, as it is considered necessary to demonstrate good reliability. The obtained results indicated that all constructs met the 0.7 thresholds for composite reliability, indicating their reliability had been ensured, as depicted in Table 31 below.

Construct Name	Composite Reliability	Threshold (0.7) passed?
Trust	0.846	Yes
Benefit Expectations	0.722	Yes
Social Influence	0.750	Yes
Facilitating Conditions	0.748	Yes
Behavioral Intentions	0.731	Yes
HR Outcomes	0.806	Yes
Recruitment Phase	0.797	Yes
Use Behavior	0.783	Yes

Table 31: Composite Reliability of constructs after the model fit.

Construct validity pertains to the extent to which the measuring instrument utilized in the study effectively measures the intended construct (Mellinger & Hanson, 2020). Two commonly used types of validity are assessed to evaluate construct validity: convergent validity (CR) and discriminant validity (AVE).

8.6.4 Convergent validity

Convergent validity is evaluated using the average variance extracted (AVE), which should exceed the minimum threshold of 0.5 to satisfy the convergent validity criterion (Hair et al., 2010). However, if the convergent validity (AVE) falls below 0.5, the composite reliability (CR) should be considered. If the CR is above 0.7, then AVE below 0.5 value is deemed acceptable and fulfills the convergent validity criterion (Hair et al., 2010).

Table 32 presents each construct's AVE and CR values in the measurement model. Although the AVE of behavioral expectations falls below the threshold of 0.5, its CR value surpasses the threshold of 0.7, which indicates that it satisfies the convergent validity criterion.

Construct Name	CR	AVE
Trust	0.846	0.650
Benefit Expectations	0.722	0.465
Social Influence	0.750	0.505
Facilitation Conditions	0.748	0.513
Behavioral Intentions	0.731	0.590
HR Outcomes	0.806	0.583
Recruitment Phase	0.797	0.572
User Behavior	0.783	0.550

Table 32: Construct validity through convergent (CR) and discriminant (AVE) validity thresholds

8.6.5 Discriminant validity

Discriminant validity, which refers to the degree to which measures of different constructs are distinct and not measuring the same underlying construct, was measured by comparing the AVE of each construct with its corresponding squared inter-construct correlation (SIC). The value of AVE needs to be higher than the SIC to meet the construct validity criteria (Hair et al., 2006). Table 33 below presents each construct and shows that the AVE values are higher than the corresponding SIC values, indicating that the constructs meet the discriminant validity criterion.

	CR	AVE	MSV	MaxR(H)	Trust	BE	SI	FC	BI	OC	RP	UB
Trust	0.846	0.650	0.132	0.874	**0.806**							
Benefit Expectations	0.722	0.465	0.386	0.725	-0.161	**0.682**						
Social Influence	0.750	0.505	0.391	0.779	-0.217	0.535	**0.710**					
Facilitation Conditions	0.748	0.513	0.399	0.812	-0.241	0.597	0.625	**0.716**				
Behavioral Intentions	0.731	0.590	0.343	0.862	-0.130	0.492	0.314	0.364	**0.768**			
HR Outcomes	0.806	0.583	0.399	0.824	-0.364	0.621	0.564	0.632	0.321	**0.764**		
Recruitment Phase	0.797	0.572	0.343	0.830	-0.118	0.585	0.298	0.490	0.586	0.388	**0.756**	
User Behavior	0.783	0.550	0.399	0.807	-0.307	0.592	0.559	0.609	0.378	0.632	0.549	**0.741**

Table 33 : Construct validity through convergent (CR) and divergent (AVE) validity thresholds

8.7 The final construct model fit results

After ensuring that each construct achieved its reliability and validity thresholds individually as well as collectively, the overall model fit criteria were assessed and compared against the predefined thresholds. The results are presented in Table 34.

Type of measure	Chi-Square	Degree of Freedom	Absolute fit measures			Incremental fit measures		Parsimony fit measure
Criteria	X2	df	X2/df	GFI	RMSEA	NFI	CFI	AGFI
Threshold			1< X2/df<3	≥0.80	0.06 and 0.08	≥0.80	≥0.90	≥0.80
Value archived	317.050	198	1.601	0.891	0.053	0.812	0.936	0.848
Accepted?			Yes	Yes	Yes	Yes	Yes	Yes

Table 34: Goodness of fit indices of the finalized model

The model's goodness-of-fit index (GFI) had a value of 0.891, which is above 0.8, as recommended by Baumgartner and Homburg (1995) and Doll et al.,1994). Additionally, the model was validated using the AMOS integrated tool developed by James Gaskin et al. (2022) and passed the model fit criteria specified by Hu and Bentler (1999), as presented in Table 35 below (Extract from James Gaskin AMOS Plugins).

Measure	Estimate	Threshold	Interpretation
CMIN	331.114	--	--
DF	199.00	--	--
CMIN/DF	1.664	Between 1 and 3	Excellent
CFI	0.930	>0.95	Acceptable
SRMR	0.060	>0.08	Excellent
RMSEA	0.053	<0.06	Excellent
PClose	0.193	>0.05	Excellent
Congratulations, your model fit is excellent!			

Table 35: Final Model fit (Gaskin, J., Lim, J., & Steed, J. (2022)

The above model fit criteria used Hu & Bentler's (1999) model fit threshold, as depicted in Table 36 below.

Measure	Terrible	Acceptable	Excellent
CMIN/DF	>0.5	>3	>1
CFI	<0.90	<0.95	>0.95
SRMR	>0.10	>0.08	<0.08
RMSEA	>0.08	>0.06	<0.06
PClose	<0.01	<0.05	>0.05

Table 36: Model fit criteria suggested by Hu and Bentler (1999)

8.8 The structural model validation

8.8.1 Validation approach

While validating the hypothesis, a structural model was created using the measurement model validated in the previous step (see 7.5). The structural model comprised five exogenous variables (BE, SI, FC, RP, TR) and three endogenous variables (BI, UB, OC) and the relationships between those constructs. The nature of the relations was determined based on the list of hypotheses developed previously (see Chapter 4, section 2) and the qualitative research designed in Chapter 6.

Various model fit criteria were employed to assess the goodness of fit of the structural model, including the chi-square to the degree of freedom ratio, GFI, RMSEA, NFI, CFI, and AGFI. These criteria are well-established in the literature (Hair et al., 1998; Baumgartner & Homburg, 1996; Xia et al., 1994; MacCallum et al., 1996; Bentler & Bonett, 1980) and are commonly used in research to evaluate the adequacy of a model. The model is considered to fit the data if it satisfies all the criteria.

After achieving the model fit, the relationships between the variables were further examined for any moderation effects based on the list of hypotheses presented in Table 36 above. The subsequent section explains the outcomes of this validation.

8.8.2 Structural Model Fit

Multiple iterations were conducted to ensure the model adequately fits the data and satisfies the requisite threshold criteria. To improve the model fit, weaker relationships were evaluated for potential removal. However, this was ultimately unnecessary in this model, as the initial model already demonstrated a good fit for the data.

The results of the model fit analysis indicate a chi-square/df ratio of 1.871, which falls within the recommended range of 1 to 3. The GFI value of 0.870 exceeds the threshold of 0.8, indicating a good fit (Forza & Filippini (1998). The RMSEA value of 0.064 is below the maximum acceptable level of 0.08, indicating a good fit (Awang ,2012). The NFI value of 0.813, which is above 0.08, indicates a good fit (Forza & Filippini ,1998), and the CFI value of 0.901 which is above the threshold of 0.9, indicates a good model fit (Hair et al. (2010); Forza & Filippini ,1998). Additionally, the AGFI value of 0.829 is between 0.9 and 0.8, recommended as marginal and acceptable (Byrne & Campbell, 1999). Overall, these findings suggest that the model fits well with the data. A summary of these results is presented in Table 37 below.

Type of measure			Absolute fit measures			Incremental fit measures		Parsimony fit measure
Criteria	X2	df	X2/df	GFI	RMSEA	NFI	CFI	AGFI
Threshold			1< X2/df<3	≥0.80	<0.08	≥0.80	≥0.90	≥0.80
Model results	392.904	210	1.871	0.870	0.064	0.813	0.901	0.829
Did the threshold meet?			Yes	Yes	Yes	Yes	Yes	Yes

Table 37: Structural Model fit results summary

The squared multiple correlations for each construct were calculated as part of the model validation process. The results revealed that the squared multiple correlations for behavioral intentions were 0.952, indicating that 95% of the variance in behavioral intentions was accounted for by the exogenous variables of benefit expectations, social influence, facilitating conditions, trust, and recruitment phase. Similarly, the squared multiple correlations of use behavior (UB) were 0.867, indicating that the endogenous variables of behavioral intentions, recruitment phase, and trust accounted for 86% of the variance in user behavior. Lastly, the squared multiple correlations of HR outcomes (OC) were 0.807, indicating that the user behavior construct accounted for 80% of the variance in HR outcomes.

Apart from assessing the model fit thresholds, the researcher also evaluated the coefficient parameter estimates to ensure their validity and reliability. Such evaluation enables the identification of potential areas for refinement or revision to improve the model's overall explanatory power.

8.8.2.1 Coefficient parameter estimates.

The coefficient parameter estimates derived from a structural equation model are important in establishing the population covariance matrix of the model, which represents the strength of relationships between the various constructs. It serves to validate the study's hypotheses. The current validated model comprised a total of 23 parameters that defined the individual constructs and their relationships.

The significance of each parameter coefficient was determined using a critical ratio obtained by dividing the regression weight by the standard error of the estimate (Swain et al., 2019). Specifically, a parameter coefficient was considered statistically significant at the 0.05 level if the critical ratio exceeded 1.96 or was less than -1.96 for a given estimate, as Hair et al. (2006) recommended. By establishing the significance of the parameter estimates, this approach helps to identify any influential relationships between constructs and can assist researchers in refining or revising the model to improve its overall explanatory power.

This study examined nine causal pathways within the model to identify any significant relationships between constructs. All the nine pathways evaluated were statistically significant, with a p-value of 0.05 and a critical ratio (CR) above 1.96 or below -1.96. Thus, pathways were declared significant at the above threshold values. These values are reported in Table 38 below.

Path			Estimate	S.E.	C.R.	P Value
Behavioral Intentions	<---	Benefit Expectations	.271	.006	43.518	***
Behavioral Intentions	<---	Trust	-.028	.002	-16.067	***
Behavioral Intentions	<---	Social Influence	.146	.005	30.953	***
Behavioral Intentions	<---	Facilitation Conditions	.125	.004	30.901	***
Behavioral Intentions	<---	Recruitment Phase	.512	.006	87.715	***
Use Behavior	<---	Behavioral Intentions	1.253	.059	21.134	***
Use Behavior	<---	Facilitation Conditions	-.065	.022	-2.904	.004
Use Behavior	<---	Recruitment Phase	-.251	.044	-5.713	***
Outcomes	<---	Use Behavior	1.155	.036	31.742	***
Abbreviations > Estimate: Regression weights, C.R. -Critical Ratio (t value), SE: Standard Error, P : P value The convention is: * = p < .05 ** = p < .01 *** = p < .001						

Table 38: Regression weights of the hypothesized relationships

The validated data model and structural model were then used to test the hypothesis list explained in Chapter 6, section 8, and listed in Table 10. The results of the hypothesis testing are explained in the next subsection.

8.8.3 Main constructs

Upon validating the significance of each path, the standard regression weights (β) were employed to examine the strength or weakness of the relationships as projected in the hypotheses. The results of the hypothesis validation are presented in Table 39 below.

Hypothesis number	Coding	Predicted Relationship	Standardized regression weights (β)	Hypothesis supported?
H1	BE→BI	Positive	.294	Supported
H2	SI→BI	Positive	.189	Supported
H3	FC→BI	Positive	.192	Supported
H4	RP→BI	Positive	.485	Supported
H5	TR→BI	Negative	-.064	Supported
H6	BI→UB	Positive	1.132	Supported

H7	FC→UB	Positive	-.076	Not Supported
H8	RP→UB	Positive	-.161	Not Supported
H9	TR→UB	Negative	-.128	Supported
H10	UB→OC	Positive	.908	Supported

Table 39: Hypothesis validation

The results suggested that all hypotheses except H7 and H8 were supported. The hypothesis of Facilitating conditions and recruitment phases influencing use behavior is not supported.

A visual representation of the supported and unsupported hypotheses is presented in Figure 16 below, where the tick mark indicates the supported hypotheses, and the cross mark depicts the unsupported hypotheses.

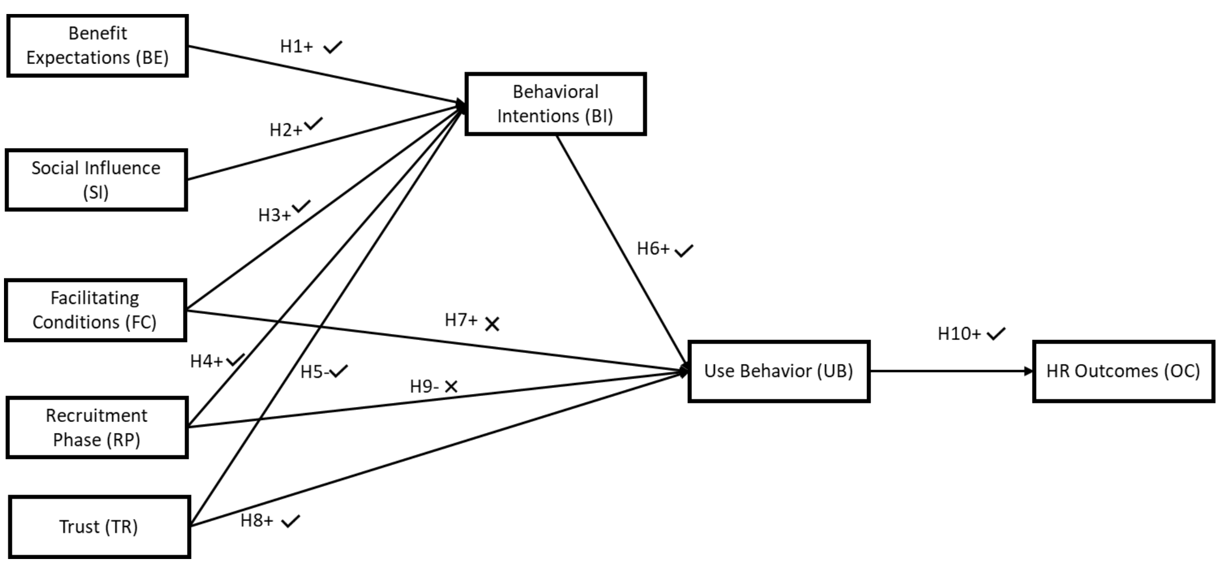

Figure 16: The list of supported and unsupported main hypotheses.

8.8.4 Moderations

The researcher hypothesized that the relationship between the main constructs would be moderated by the RS owner's experience and the hiring volume. A multi-group categorical analysis was conducted using IBM AMOS software to test these moderation effects. The process involved two steps.

In the first step, multiple models were created, each representing a moderator category. The models were then compared to determine if they had a significant difference. The significance was determined by the chi-square difference and p-value (Kline, 2011). If the difference was below 0.05, further investigation was conducted to identify the type of moderation predicted in the hypothesis, such as higher moderation or lower moderation. The results of the moderation are listed next.

8.8.4.1 Moderation by the RS professional's experience

The current study employed a moderation analysis to investigate whether the relationship between the main constructs was influenced by the RS owner's experience and hiring volume. Specifically, two categories of experience were utilized: Junior (up to 5 years of experience) and Senior (more than 6 years of experience) RS professionals. The chi-square difference between the constrained and unconstrained models was 18.323, with a p-value of 0.05, indicating a significant difference between the models, thus prompting a further examination of the moderation effect.

The findings revealed that experience had a moderation effect on all the associations specified in the structural model. A detailed discussion of the results will be provided in the subsequent paragraphs.

8.8.4.1.1 Moderation by experience on BE and BI (H1.1)

This study compared two models, one with a constraint on the relationship between benefit expectations (BE) and behavioral intentions (BI), for two groups of professionals with different experience levels. The resulting p-value of 0.019 was found to be below the threshold of 0.05, indicating a significant difference between the models. The analysis of the standardized regression weights revealed that the group with less experience had a slightly higher influence between BE and BI, with values of 0.297 and 0.294, respectively. While this difference is small, it is statistically significant and supports the hypothesis (H1.1) that professionals with less experience have a stronger association between BE and BI.

8.8.4.1.2 Moderation by experience in SI and BI (H2.1)

Upon comparing two models, one with a constraint on the relationship between Social Influence (SI) and Behavioral Intention (BI) for junior and senior professional groups, a significant difference was found with a p-value of 0.039, below the 0.05 threshold. The standardized regression weights between the two groups on SI and BI were 0.209 and 0.186, respectively. Regression weights can generally be interpreted as the standardized effect size of a variable on the outcome variable (Cohen et al., 2003). A regression weight of 0.2 or higher is often considered a moderate effect size, while a weight of 0.5 or higher is considered a strong effect size (Ghai & Ghai, 2019).

These results suggest that professionals with less experience exhibit a stronger association between SI and BI compared to their more experienced counterparts. Hence, the hypothesis (H2.1) that less experienced professionals have a stronger association between SI and BI is statistically supported.

8.8.4.1.3 Moderation by experience on FC and BI (H3.1)

The statistical analysis conducted through multi-group categorical analysis showed that the two models, one with a constraint on FC and BI with two group settings of junior and senior, were significantly different, with a P value of 0.001 below the 0.05 threshold. This finding supports the hypothesis that the experience level moderates the association between FC and BI. The standardized regression weights between less and more experienced groups on FC and BI were 0.185 and 0.193, respectively. The results suggest that professionals with more experience have a stronger relationship between FC and BI than those with less experience.

8.8.4.1.4 Moderation by experience on RP and BI (H4.1)

The study involved two distinct models, one of which was characterized by a constraint on RP and BI. These models were evaluated in two group settings, namely junior and senior. The findings indicate a notable difference between the two groups, as reflected by the computed P value of 0.019, which fell below the threshold of 0.05. The standardized regression weights between the two groups on RP and BI were 0.533 and 0.466, respectively, suggesting that the group with less experience exhibited a stronger association with RP and BI. This result is consistent with the researcher's hypothesis, which posited a stronger relationship between RP and BI among less experienced professionals. Thus, the hypothesis is supported by statistical evidence.

8.8.4.1.5 Moderation by experience on Trust and BI (H5.1)

The two models, one with a constraint on Trust and BI, with two group settings of junior and senior, were found to be significantly different, as evidenced by their P value of 0.008 being below the 0.06 threshold. The standardized regression weights between the two groups on Trust and BI were -0.055(higher experience) and -0.067 (less experience), respectively, indicating a negative influence. This finding suggests that the higher experience group negatively impacts the association between Trust and BI. Since the association is negative, professionals with less experience have higher trust levels than those with more experience. Thus, the hypothesis (H5.1) that less experienced professionals strengthen the association between Trust and BI is statistically supported by the study's findings.

8.8.4.1.6 Moderation by experience on UB and BI (H6.1)

The study explored two models, one of which incorporated a constraint on the UB and OC, and these models were evaluated in two distinct group settings, namely junior and senior. The results revealed significant differences between the two groups, with a computed P value of 0.037 that fell below the established threshold of 0.05. The standardized regression weights between the two groups on BI and UB were 0.932 and 0.857, respectively. These outcomes demonstrate that professionals with less experience exhibited a stronger association with BI and UB, thereby supporting the research hypothesis.

The above results are summarized in Table 40 below.

Experience	Relationship	DF	CMIN	P	Std Regression weights	
					Junior	Senior
	BE->BI (H1.1)	9	12.437	0.019	.297	.294
	SI->BI(H2.1)	9	15.322	0.039	.209	.186
	Trust->BI(H5.1)	9	9.470	0.008	-.067	-0.055
	RP->BI(H4.1)	9	12.320	0.019	.533	.466
	FC->BI(H3.1)	9	14.361	0.011	.185	.193
	BI->UB (H6.1)	9	17.870	0.037	.932	.857

Table 40: The effect of RS professionals' experience on construct relationships

8.8.4.2 Moderation by the hiring volume

The monthly hiring volume for RS owners was classified into two groups based on the number of hires per annum: low hiring volume and high hiring volume. A volume of fewer than 50 hires per annum was classified as low hiring volume, while a volume above 50 was classified as high volume. The chi-square difference between the constrained and unconstrained models was 294.796, with a P value of 0.000, indicating that the two models are significantly different. A p-value of 0.000 indicates that the probability of obtaining such a difference by chance is very low, which suggests that the difference is likely to be real and not due to random variation (Agresti, 2007). Therefore, the moderation effect on the hypothesized associations was further examined.

8.8.4.2.1 Moderation by hiring volume on BE and BI (H1.2)

In this study, two models were compared to examine the relationship between BE and BI, with one model incorporating a constraint on their association. The study also explored the impact of low and high monthly hiring volumes on the relationship between BE and BI. The results showed a significant difference between the two models, as evidenced by a p-value of 0.001, below the threshold of 0.06. Furthermore, the standardized regression weights for the low-volume and high-volume groups on BE and BI were 0.408 and 0.370, respectively, indicating that the low-volume hiring group had a stronger association with BE and BI. The researcher posited that low hiring volumes would increase the strength of the relationship; thus, the hypothesis is statistically supported.

8.8.4.2.2 Moderation by hiring volume on SI and BI (H2.2)

The study examined two models, one imposing a constraint on the SI and BI, with two distinct group settings of low and high monthly hiring volumes. The findings indicated a significant difference between the two models, with a p-value of 0.000. The standardized regression weights for SI and BI between the low-volume and high-volume groups were 0.125 and 0.253, respectively. These results indicate that the association between SI and BI is stronger in the low-volume hiring group as compared to the high-volume group.

The researcher had initially hypothesized that higher hiring volumes would result in a stronger association between SI and BI. Thus, the study's results suggest that this hypothesis is statistically supported.

8.8.4.2.3 Moderation by hiring volume on FC and BI (H3.2)

This study aimed to explore the relationship between Facilitating Conditions (FC) and Behavioral Intentions (BI) in two distinct group settings with varying monthly hiring volumes, using a model that placed constraints on these variables.

The results indicated significant differences between the two groups, like the p-value of 0.001. The standardized regression weights for FC and BI were computed for the low-volume and high-volume groups, yielding values of 0.296 and 0.233, respectively. These results suggest that the group with high-volume hiring has a stronger association with FC and BI than the low-volume hiring group. The statistical analysis supported the researcher's hypothesis that low hiring volumes would increase the strength of the relationship between FC and BI.

8.8.4.2.4 Moderation by hiring volume on RP and BI (H4.2)

The two models, one with a constraint on RP and BI and two group settings of low and high monthly hiring volumes, were found to be significantly different, as indicated by a p-value of 0.001.

The standardized regression weights on RP and BI between the low-volume and high-volume groups were 0.183 and 0.163, respectively. These findings reveal that the group with low-volume hiring has a stronger association with RP and BI. The researcher hypothesized that low hiring volumes would increase the strength of the association between RP and BI. Thus, the hypothesis is supported by the data.

8.8.4.2.5 Moderation by hiring volume on Trust and BI (H5.2)

The study aimed to investigate the relationship between trust and business intelligence (BI) within two distinct settings of monthly hiring volumes, using a model that placed constraints on these variables. The results revealed significant differences between the two groups, as evidenced by a p-value of 0.001. Standardized regression weights were computed for the low-volume and high-volume groups, yielding values of -0.064 and -0.053 for trust and BI, respectively. These results suggest that the group with low-volume hiring exhibits a stronger association between trust and BI than the high-volume group. The hypothesis posited by the researcher, namely that low hiring volumes would increase the strength of the association between trust and BI, was supported by the statistical findings.

8.8.4.2.6 Moderation by hiring volume on BI and UB (H6.2)

The two models, one with a constraint on the UB and BI, with two group settings of low and high monthly hiring volumes, were found to be significantly different, as indicated by their P value of 0.001. The standardized regression weights between the low-volume and high-volume groups on UB and BI were 1.078 and 1.052, respectively. The findings suggest that the group with low-volume hiring has strengthened the association. Thus, the hypothesis is supported by the data.

The summary of the group difference is listed in Table 41 below.

	Path	DF	CMIN	P	Std Regression weights	
					Low hiring volume	High hiring volume
Hiring Volume	BE->BI (H1.2)	9	292.927	0.001	.408	.370
	SI->BI (H2.2)	9	244.034	0.000	.125	. 253
	Trust->BI (H5.2)	9	294.713	0.001	-.064	-.053
	RP->BI (R4.2)	9	290.618	0.001	.183	.163
	FC->BI (H3.2)	9	273.098	0.001	.296	.233
	BI->UB	9	278.703	0.001	1.078	1.052

Table 41: The standard regression weights of two hiring volumes

8.9 Chapter Summary

This chapter presents the quantitative research conducted on 215 survey respondents, comprising recruiters, hiring managers, and HR executives. The data analysis involved four steps. Firstly, the data was prepared and managed through missing data management and normalization techniques. Secondly, the individual variables of the constructs were validated for their measures using Cronbach's alpha and composite reliability. The initial measurement model comprised 33 variables but was reduced to 23 variables by removing items that caused issues with the measurement model fit.

In the third step, the measurement model was subjected to factor analysis and structural model analysis to evaluate the component validity, reliability, and relationships among the constructs to determine the overall model fit. All constructs met the model fit criteria.

Finally, in the fourth step, the hypotheses were tested, and the results revealed that 21 out of 23 hypotheses were statistically supported. The study also showed that the experience of RS professionals and hiring volumes affect the relationships between the constructs. The results of these hypotheses are presented in Table 42 and are interpreted and discussed in Chapter 8.

Hypothesis number	Independent Construct	Dependent construct	Moderator	Coding	Predicted Relationship	Supported?
H1	Benefit Expectations	Behavioral Intentions		BE→BI	Positive	Yes
H1.1	Benefit Expectations	Behavioral Intentions	Experience	Exp x BE→BI	Less experience strengthens the relationship	Yes
H1.2	Benefit Expectations	Behavioral Intentions	Volume	Vol x BE→BI	Low Volume strengthens the association	Yes
H2	Social Influence	Behavioral Intentions		SI→BI	Positive	Yes
H2.1	Social Influence	Behavioral Intentions	Experience	Exp x SI→BI	Less experience	Yes

					strengthens the relationship	
H2.2	Social Influence	Behavioral Intentions	Volume	Vol x SI→BI	More Volume strengthens the association	Yes
H3	Facilitation Conditions	Behavioral Intentions		FC→BI	Positive	Yes
H3.1	Facilitation Conditions	Behavioral Intentions	Experience	Exp x FC→BI	More experience strengthens the relationship	Yes
H3.2	Facilitation Conditions	Behavioral Intentions	Volume	Vol x FC->BI	Low Volume strengthens the association	Yes
H4	Recruitment Phase	Behavioral Intentions		RP→BI	Positive	Yes
H4.1	Recruitment Phase	Behavioral Intentions	Experience	Exp x RP→BI	Less experience strengthens the relationship	Yes
H4.2	Recruitment Phase	Behavioral Intentions	Volume	Vol x RP→BI	Low Volume strengthens the association	Yes

H5	Trust	Behavioral Intentions		TR→BI	Negative	Yes
H5.2	Trust	Behavioral Intentions	Volume	Vol x TR→BI	Low Volume strengthens the association	Yes
H5.1	Trust	Behavioral Intentions	Experience	Exp x TR→BI	Negative but Less experience strengthens the relationship	Yes
H6	Behavioral Intentions	Use Behavior		BI->UB	Positive	Yes
H6.1	Behavioral Intentions	Use Behavior	Experience	Exp x BI->UB	Less experience strengthens the association	Yes
H6.2	Behavioral Intentions	Use Behavior	Volume	Vol x BI->UB	Low Volume strengthens the association	Yes
H7	Facilitation Conditions	Use Behavior		FC→UB	Positive	No
H8	Recruitment Phase	Use Behavior		RP→UB	Positive	No
H9	Trust	Use Behavior		TR→UB	Negative	Yes
H10	Use Behavior	Outcomes		UB→OC	Positive	Yes

Table 42: Summary of Hypothesis validations

CHAPTER 9

RESEARCH DISCUSSION & CONCLUSION

9.1 Discussion and Conclusion

This chapter discusses the results of the research undertaken and concludes the thesis. It begins by explaining how the thesis meets its research objectives and answers the research questions, leading to the theoretical contribution of the thesis to the R&S HRM literature by providing a valuable model to drive AI use in R&S in HR. It also offers managerial implications and presents the study's limitations and directions for future research.

9.2 Answering research questions and discussion

The primary aim of this research was to investigate the use of AI in the recruitment and selection process to attain strategic HR outcomes. To this end, the research posed three key research questions, namely:

1. What factors drive AI adoption in RS, and what do recruitment professionals perceive are AI's potential benefits and drawbacks?
2. Under what conditions are the adoption drivers applicable in the adoption of AI in RS?
3. How and under what circumstances does the use of AI in RS affect strategic HR outcomes?

These research questions were formulated in response to the gaps, such as RS-specific AI adoption drivers, barriers, and similar identified in the literature review (see Chapter 2). While existing HR literature examines the perspective of candidates (Pandey et al.,2022), studies examining the perspectives of recruitment professionals on their uptake of AI have been limited. Furthermore, studies that have begun exploring AI use in HR (see Chapter 2, section 8) have largely ignored the impact of AI on HR outcomes and, importantly, in what circumstances AI most impacts these HR outcomes.

In doing so, this thesis makes a valuable theoretical contribution to the HRM literature of a model for the effective use of AI in RS to lead to strategic HR outcomes. It builds on and extends the UTAUT and UTAUT- Operations Management (OM) model by including key R&S moderators to explore the circumstances when AI is most effective. These are the recruitment volume, recruitment phase, and experience of RS professionals and the impact on HR outcomes.

A mixed-methods research design was utilized to address the research questions, incorporating both qualitative and quantitative data collection. The qualitative research phase involved in-depth interviews with 17 RS professionals, namely recruiters, hiring managers, and HR executives from IT, Telecommunications, transportation, aviation, manufacturing, and professional services (See Chapter 8, section 3). The quantitative research used a survey with 265 professionals, with 215 valid responses retained for statistical analysis. Structural equation modeling was employed to validate the hypotheses and answer the research questions outlined in the next section.

9.2.1 Research question 1

What factors drive AI adoption in RS, and what do recruitment professionals perceive its potential benefits and drawbacks?

A list of hypotheses of (H1 - H9) was tested to answer the first research question, as summarized in Table 43.

Hypothesis number	Independent Construct	Dependent construct	Coding	Predicted Relationship	Supported?
H1	Benefit Expectations	Behavioral Intentions	BE→BI	Positive	Yes
H2	Social Influence	Behavioral Intentions	SI→BI	Positive	Yes
H3	Facilitation Conditions	Behavioral Intentions	FC→BI	Positive	Yes
H4	Recruitment Phase	Behavioral Intentions	RP→BI	Positive	Yes
H5	Trust	Behavioral Intentions	TR→BI	Negative	Yes
H6	Behavioral Intentions	Use Behavior	BI->UB	Positive	Yes
H7	Facilitation Conditions	Use Behavior	FC→UB	Positive	No
H8	Recruitment Phase	Use Behavior	RP→UB	Positive	No
H9	Trust	Use Behavior	TR→UB	Negative	Yes

Table 43: Summary of hypothesis results leading to answers to research question 1

Regarding the factors which drive the intention to use AI, this research findings posit that benefit expectations, facilitating conditions, and recruitment phase are the positive influential factors or drivers. In terms of the current use of AI, statistical results reveal that behavioral intentions are the strongest driver influencing the current use of AI.

This novel finding regarding the influence of behavioral intentions in AI adoption in the RS context has not been previously explored to the knowledge of the researcher , although it aligns with prior multidisciplinary research investigating the application of AI in other domains. For instance, studies have examined AI voice assistants (Sun, Zhang, & Li, 2020), AI use by clinicians (Shin, 2019), and AI in healthcare more broadly (Lu & Zhang, 2019).

In contrast, relevant to the actual use of AI (beyond intentions), the findings indicate that neither facilitating conditions nor recruitment phases strongly influence the use of AI in RS. However, these factors strongly influence behavioral intentions or aspirations to use AI. This suggests that influencing behavioral intentions ~~is the only~~ may be the way to encourage the active use of AI in RS. It may also suggest that, in addition to governance frameworks and data protection regulations, there may be other factors contributing to driving AI adoption behaviors. These need to be tested and validated through empirical research.

Regarding the behavioral intentions (intent) or actual use of AI in RS, this research finds that benefit expectations, social influence, facilitating conditions, and recruitment phase directly and positively impact behavioral intentions, which in turn influence the active use of AI. Notably, benefit expectations were found to be the primary driver of behavioral intentions. Furthermore, when individuals perceive that their social environment supports the use of AI in recruitment, they are more inclined to have positive behavioral intentions toward using AI in the recruitment process. Similarly, when individuals perceive that the conditions for using AI in recruitment are favorable, they are more likely to develop positive behavioral intentions towards utilizing AI in recruitment. Finally, certain recruitment phases (sourcing, pre-screening, and candidate engagement) also influenced individuals' behavioral intentions towards using AI in recruitment.

A noteworthy finding is that trust in AI affects both behavioral intentions and actual user behavior within RS. The evidence demonstrates that factors like benefits, social influence, facilitating conditions, and recruitment phases are positive, however, the factors such as governance frameworks, transparency of AI algorithms, and end-to-end integration with other systems are impacting AI adoption in RS negatively. The findings contribute to the other multidisciplinary literature investigating how trust influences AI adoption and found that trust is a negative influencer (Kim et al., 2018; Komiak & Benbasat, 2006). These factors are discussed in detail next.

9.2.1.1 Benefits

The expected benefits drive behavioral intentions (intent) of AI amongst RS professionals. This is consistent with other multidisciplinary studies, where benefits are shown to be the biggest predictor of behavioral intentions (Ahn & Ryu,2018).

However, results of the quantitative phase reveal that **achieving work-life balance, increasing career prospects, and standardizing the recruitment process** are the most desired benefits compared to increasing the candidate pool and using AI for decision-making. Thus, these finding of this study differs from other empirical findings, such as improving efficiency (Agrawal et al.,2019), better decision-making (Mishra & Kumar, 2020), and enhancing customer experience using AI in business systems (Li & Li, 2018) as desired benefits.

Findings also reveal that RS professionals expect AI to support them by automating repetitive and administrative tasks, freeing RS professionals to invest more time in strategic and value-added activities. For example, using AI-based chatbots to answer and engage with candidates can operate 24/7, providing RS professionals with additional time that would have been otherwise spent addressing candidate queries (Gray & Kim,2021). This can lead to improved productivity and efficiency and the ability for RS professionals to focus on more strategic tasks that require their expertise and judgment (Kauppila & Laihonen, 2019).

Findings also suggest that RS professionals view AI as a benefit that has the potential to improve their job performance. Consequently, better hiring decisions, improved candidate experience, and increased productivity can be achieved (Pancholi et al., 2020). Ultimately, this can contribute to the career progression of RS professionals. For example, scheduling interviews and sending follow-up emails can free up recruitment professionals to focus on more strategic tasks such as employer branding and talent management. As a result, recruitment professionals can develop new skills and undertake more responsibilities, leading to career growth and advancement opportunities (Marler et al.,2012).

From an organizational perspective, AI-assisted automation can streamline the recruitment process and reduce manual workload, leading to improved accuracy and quality of hiring decisions. By automating tasks such as resume screening and candidate matching, AI can help RS professionals to identify the best-fit candidates for open positions, leading to better hiring outcomes (Kauppila & Laihonen,2019). This can increase job satisfaction for RSs and improve the retention of top talent within organizations.

Findings also suggest that AI tools can improve recruitment processes, allowing recruitment professionals to help their organizations save time and money while improving the quality of hires. Demonstrating the value of their work through these improvements can increase their chances of being promoted or given additional responsibilities within the organization (Campion & Campion, 2018).

In summary, findings from both qualitative and quantitative stages suggest that recruitment professionals perceive several significant benefits when utilizing artificial intelligence (AI) in the recruitment process. These benefits include enhancing work-life balance, improving career prospects, and standardizing recruitment.

9.2.1.2 Social Influence

Social influence was also shown to be a significant factor that drives behavioral intentions, influencing the active use of artificial intelligence (AI) in the RS process. Of all the external factors, such as the modern era, media, documentaries, and customers, identified in Chapter 7, Section 8, these are the most influential factors compared to managers, HR communities, candidates, and hiring managers. However, these findings contrast with other studies in the same field, which suggest that senior managers or peers play the most critical role in driving behavioral intentions (Aljumah & Alfawaz, 2020; Farooq et al., 2020; Huang et al., 2020; Zhang & Lu, 2020).

Therefore, the results of this study suggest that media and communication channels play a significant role in influencing behavioral intentions towards AI in the RS to the extent that they become major factors in driving behavioral intentions to use AI. The difference between the current study's findings and those of other studies may indicate that knowledge in this area is evolving, and thus, new studies are required to investigate how these influences are changing and to identify any other emerging factors.

9.2.1.3 Facilitating conditions

Quantitative evidence suggests that the facilitating conditions that drive behavioral intentions to use AI are evolving. Specifically, facilitating conditions such as tracking how AI makes decisions, securing privacy data, and integrating with other systems are the largest contributors driving the intention to adopt AI. These facilitating conditions appear to outweigh other hypothesized facilitating conditions, such as the availability of AI tools and regulatory compliance.

Additionally, the statistical findings of this research differ from other studies that suggest AI tool availability drives behavioral intentions (Zhang & Chen, 2020; Kim, Lee, & Lee, 2018). However, it should be noted that these other studies are in different disciplines, such as supply chain (Haider et al., 2020), financial services (Kwon & Shin, 2018), and healthcare services (Huang & Chen, 2019), compared to HRM. Therefore, this suggests that the facilitating conditions that drive the intention to use AI may differ depending on the industry sector or business function. Thus, further research on specific industries is needed to understand how and if facilitating conditions differ from industry to industry or if there are common factors facilitating conditions in all industries.

This research findings suggest that while the availability of certain facilities (such as end-to-end integration of AI, traceability of AI algorithms, and privacy protection of candidate data) positively influences RS professionals' intention to consider AI, but it does not necessarily drive actual usage of AI in RS. This suggests that facilitative conditions may encourage RS professionals to test and assess AI in RS. However, such conditions alone may not be sufficient to prompt them to apply these AI technologies in real-world situations. Other factors could contribute to their decision-making process, influencing whether they choose to apply AI in practical RS scenarios or incorporate it into their daily RS processes. Further studies are needed to identify other factors that may influence the active use of AI in RS.

9.2.1.4 Recruitment phase

The current study highlights the significant impact of the recruitment phase on the intention to adopt AI in the recruitment process. Specifically, pre-planning, sourcing, and pre-screening were found to have a strong positive statistical influence on behavioral intentions. In contrast, the results indicate that candidate engagement and interview phase have a negative impact on the intention to use AI in recruitment. These negative impacts on candidate engagement include the absence of human interaction, which job candidates (as per RS professionals) found to be a significant drawback. RS professionals felt the lack of personal connection hindered their overall engagement and experience in the candidate engagement process. RS professionals also raised concerns about the fairness, accuracy, and potential biases of AI systems in assessing candidates. Moreover, the qualitative research highlighted AI's limitations in conducting complex skills assessments and providing human connection during interviewing phases. Candidates perceived that AI could not thoroughly evaluate intricate skills and failed to establish a human connection that they deemed important in the interviewing process (See Chapter 6, section 6.1.4).

However, it is important to note that qualitative research also suggests that some professionals are interested in using AI in candidate engagement while others are not. The opposing viewpoints were primarily due to the desire to provide a better candidate experience through personalization and establishing a human connection, which is perceived as challenging with the use of AI. While the statistical results presented in Chapter 8, section 8.3 support the idea that recruitment phases such as pre-planning, sourcing, and pre-screening are more amenable to using AI and candidate engagement is not, it is worth noting that there are conceptual studies suggesting that candidate engagement is a desired phase for implementing AI (Panchal & Gupta, 2019). However, empirical support remains scarce.

Therefore, the current findings suggest that recruitment phases such as pre-planning, sourcing, and pre-screening are perceived to be more suitable for AI adoption, whereas the implications of using AI in candidate engagement and interviewing require further empirical investigation to understand the managerial interventions required.

It is important to note that while the various recruitment phases positively impact the intention to use AI in RS, they negatively influence the actual use of AI. This suggests that the recruitment phase alone may not be a significant factor in driving the active use of AI in RS. Rather, it may be more effective to focus on facilitating conditions, such as implementing end-to-end integration of AI throughout all recruitment phases, to encourage AI adoption.

9.2.2 Research question 2:

Under what conditions are the drivers applicable in adopting AI in RS?

Results from the statistical analysis suggest that the AI adoption drivers, as delineated in Chapter 8 section 3, are applicable under certain conditions: the level of experience possessed by RS professionals and the hiring volume they support. The findings are detailed in the next section.

9.2.2.1 Experience of RS professionals

As summarized in Table 44 below, RS professionals' experience is a moderating factor that strengthens or weakens the relationship between the main construct and the behavioral intention (intent) of AI and the actual use of AI.

Hypothesis number	Independent Construct	Dependent construct	Moderator	Coding	Predicted Relationship	Supported ?
H1.1	Benefit Expectations	Behavioral Intentions	Experience	Exp x BE→BI	Less experience strengthens the association	Yes
H2.1	Social Influence	Behavioral Intentions	Experience	Exp x SI→BI	Less experience strengthens the association	Yes
H3.1	Facilitation Conditions	Behavioral Intentions	Experience	Exp x FC→BI	More experience strengthens the association	Yes
H4.1	Recruitment Phase	Behavioral Intentions	Experience	Exp x RP→BI	Less experience strengths the association	Yes
H5.1	Trust	Behavioral Intentions	Experience	Exp x TR→BI	Less experience strengthens the association	Yes
H6.1	Behavioral Intentions	Use Behavior	Experience	Exp x BI->UB	Less experience strengthens the association	Yes

Table 44: The influence experience

The results found that the less experienced professionals strengthen the associations in some cases, such as with benefit expectations and intentions to use AI, while more experienced professionals strengthen the relationships in some cases, like facilitating conditions and intentions to use AI. It can be assumed that less experienced professionals belong to the younger generation compared to more experienced professionals from older age groups.

When considering the relationship between benefit expectations and behavioral intentions the younger generation of RS professionals or less experienced professionals are expecting more benefits (such as work-life balance and career prospects) from AI compared to the older generation. This is in line with other multidisciplinary studies (Kossek et Al.,2006; Kim & DeLeire, 2012), which inform that the younger generation is expecting more benefits from using AI in the respective business processes.

Less experienced professionals are more motivated to consider AI than more experienced professionals (hypothesis H2.1), and qualitative findings indicate that their motivations are from media, the modern era, and customers, as explained in (section 8.4.1). That means the media and the modern era are impacting less experienced professionals to consider AI in the RS compared to their experienced counterparts. It may suggest an indirect link between technology use, exposure to modern technologies, and the digital savviness of the younger generation, who typically have less experience.

Numerous empirical research studies suggest that the younger generation, particularly millennials, are more technologically savvy than other age groups (D'Amico & Guastella, 2019). One aspect of this research revolves around digital literacy, which refers to effectively navigating and utilizing digital technologies. Studies consistently demonstrate that millennials possess higher levels of digital literacy than older generations. This proficiency is evident in their ability to search for information online efficiently, adapt to new digital tools and platforms, and engage in online communication and social media (Smale, 2018); Kim & Kwon, 2020); Angrave et al., 2016).

Moreover, technological adoption rates further validate the notion that millennials are more technology savvy. Research indicates that millennials are more likely to embrace and integrate new technologies into their daily lives compared to older generations (Rikard, Thompson & Headrick, 2018). This includes the rapid adoption of smartphones, social media platforms, and various digital applications. Millennials tend to be early adopters of new technologies, more willing to explore and adapt to technological advancements (Zainordin et al., 2021). Additionally, millennials exhibit greater proficiency in using digital devices and platforms. They tend to have a deeper understanding of the functionalities and features of technological devices such as smartphones, tablets, and laptops (Abidin & Mustaffa, 2020).

Similarly, the relationship between the recruitment phase, trust, and behavioral intentions is stronger with less experienced professionals. This may suggest that less experienced professionals may try to use AI in more recruitment phases, because they trust AI (except in the interview phase) compared to their experienced counterparts.

When examining the relationship between facilitating conditions and intentions to use AI, a shift in the trend becomes apparent, particularly when considering more experienced professionals. It is important to note that facilitating conditions in this context entails end-to-end system integrations, AI decision-making traceability, and governance frameworks, as outlined in Chapter 7, section 4. This suggests that experienced professionals tend to take a broader perspective that goes beyond simply automating manual work (RS).

Nonetheless, this statistical evidence indicates that the experience of RS professionals is an important factor that either strengthens or weakens the association between the main factors and the behavioral intentions of AI in RS, as explained above.

9.2.2.2 Hiring volume

As summarized in Table 45, it shows that hiring volume is one of the important drivers which strengthens or weakens the relationship between the main construct and the behavioral intention of AI or actual use of AI.

Hypothesis number	Independent Construct	Dependent construct	Moderator	Coding	Predicted Relationship	Supported?
H1.2	Benefit Expectations	Behavioral Intentions	Volume	Vol x BE→BI	Low Volume strengthens the association	Yes
H2.2	Social Influence	Behavioral Intentions	Volume	Vol x SI→BI	More Volume strengthens the association	Yes

H3.2	Facilitation Conditions	Behavioral Intentions	Volume	Vol x FC->BI	Low Volume strengthens the association	Yes
H4.2	Recruitment Phase	Behavioral Intentions	Volume	Vol x RP→BI	Low Volume strengthens the association	Yes
H5.2	Trust	Behavioral Intentions	Volume	Vol x TR→BI	Low Volume strengthens the association	Yes
H6.2	Behavioral Intentions	Use Behavior	Volume	Vol x BI->UB	Low Volume strengthens the association	Yes

Table 45: The influence of hiring volume.

Findings reveal that low hiring volumes significantly affect the strength of the relationships between behavioral intentions, benefit expectations, facilitating conditions, trust, and recruitment phases. These results provide a different perspective to existing literature highlighting higher hiring volumes as a driver for AI adoption (Aggarwal and Singh, 2019) and provide new insights into AI adoption at the individual level, with RS professionals keen to adopt first in the low hiring volumes. This finding and the qualitative research results suggest that RS professionals may be more likely to test, pilot, and analyze the AI in RS functions for low volumes before considering and applying that to large volumes.

This can be considered a conservative and risk-mitigating strategy as RS may be trying to reduce the damage AI may cause when applied in large hiring volumes. For example, a study conducted by Dery et al.,(2020) found that while AI can potentially improve recruitment and selection processes, it can also introduce new risks, such as bias, lack of transparency, and accountability. The study recommends that organizations start with a small pilot project to test and evaluate the effectiveness and potential risks of AI in recruitment and selection processes. Thus the current study provides statistical evidence that RS professionals are more risk-averse when considering AI in RS.

However, the relationship between social influence and behavioral intentions differs, with the association strengthened with larger hiring volumes. This suggests that RS professionals consider the use of AI in RS when they face high hiring demands and are influenced by external factors, such as customers, media, and the modern era, advocating for its use.

When faced with high hiring volumes, RS professionals may feel overwhelmed and seek ways to manage the influx of applicants efficiently and effectively. External influences, such as customer demands and media coverage, may also contribute to the perception that AI is a viable solution for handling large volumes of applicants. These influences may come in the form of success stories from other organizations that have implemented AI in their recruitment and selection processes or from experts in the field who advocate for its use.

It is important to note that while AI may offer benefits such as increased efficiency and accuracy, it is not a silver bullet solution for recruitment and selection challenges (Wakabayashi et al.,2020). RS professionals must carefully consider the potential risks and benefits of using AI in their processes and ensure that it aligns with their organization's values and goals. Piloting and testing AI functions for low volumes may be a conservative and risk-mitigating action before applying AI in RS for large volumes.

9.2.2.3 Other conditions

The qualitative research conducted in the present study provides evidence to suggest that additional conditions may impact the adoption drivers of AI in RS (see Chapter 6, section 6.6). The research revealed that RS professionals raised concerns about the suitability of AI for hiring certain job groups, such as blue-collar workers, vocational workers, and senior executives. Therefore, the results of this study suggest that organizations should carefully consider the conditions under which AI adoption drivers are applicable in RS, particularly when recruiting for certain job groups.

For example, research by Chan and Lee (2018) .

examines whether AI can contribute to fairer recruitment practices, specifically for blue-collar workers. The findings of their study suggest that the use of AI in recruitment does not necessarily lead to fairer outcomes for blue-collar workers because AI algorithms can perpetuate biases and discriminatory practices, with negative implications for the fairness of the recruitment process. Additionally, the study reveals that AI recruitment practices may not be suitable for all types of jobs and industries, including those with a high proportion of blue-collar workers. Overall, the research suggests that using AI in recruitment may not be the most effective or fair approach for recruiting blue-collar workers.

Similarly, research conducted by Pohler et al., (2020) explores the potential of artificial intelligence (AI) in human resource management (HRM), including its use in recruiting blue-collar workers. The authors suggest that although AI could benefit recruitment, its effectiveness is contingent on various factors, such as the type of job and industry, the quality and quantity of data used, and the ethical considerations of using AI in HRM. The urrent highlights the challenges of applying AI in recruiting blue-collar workers due to the lack of standardized job profiles and the complexity of assessing non-cognitive skills that are important for blue-collar jobs.

While the present study did not directly explore the suitability of using AI in RS for recruiting blue-collar workers, vocational staff, or senior executives, it offers valuable insights for future research endeavors in this domain. These insights can guide researchers in investigating the applicability of AI in RS for specific job groups and the conditions under which AI can be effectively utilized. Moreover, it highlights the importance of examining the feasibility and effectiveness of AI-based recruitment approaches for different job categories.

The study serves as a foundation for future research directions that aim to deepen our understanding of the applicability of AI in RS for recruitment practices. By building upon the findings and methodology of the present study, future researchers can explore and investigate the potential benefits, challenges, and ethical considerations associated with implementing AI in RS for recruiting blue-collar workers, vocational staff, and senior executives. This will provide valuable insights into the specific job groups for which AI-driven recommendations can be most advantageous and effective.

Furthermore, future studies can delve into the specific conditions and contextual factors that influence the applicability of AI in RS recruitment practices. By considering the unique characteristics and requirements of different job groups, researchers can identify the optimal scenarios and conditions in which AI-based recommendation systems can be successfully deployed in recruitment.

9.2.3 Research question 3:

How and under what circumstances does the use of AI in RS affect strategic HR outcomes?

9.2.3.1 Feasibility of HR outcome realization though AI-RS

This research question was designed to be answered using the hypothesis listed in Table 46.

Hypothesis number	Independent Construct	Dependent construct	Moderator	Coding	Predicted Relationship	Supported?
H10	Use Behavior	Outcomes	Not Applicable	UB→OC	Positive	Yes

Table 46: The list of hypotheses associated with AI use and HR outcome achievement.

The above hypothesis posited that the use of AI in RS processes would lead to the attainment of HR outcomes of time-to-hire (TTH), cost-of-hire (COH), quality-of-hire (QOH), and retention rates (RR). However, the statistics only support that TTH, COH, and QOH are achievable. When RR was part of the construct, the relationship did not support statistically. Thus, it suggests that RR may not be achievable by utilizing AI in RS. However, this aspect needs further research to understand what would be contributing to not achieving RR through the use of AI in RS. However, the qualitative data suggests that AI can contribute to the attainment of RR in other HR processes, such as employee engagement or onboarding processes, which are beyond the scope of this research.

The study results indicate that QOH is the most desirable outcome that can be achieved using AI in RS. The RS professionals in the research perceived that AI could standardize the recruitment process, remove human bias and anomalies, and thus assist in selecting the right candidate who meets the job criteria, leading to QOH.

Furthermore, quantitative evidence indicates the view that TTH can be reduced by using AI in RS. This finding is consistent with other empirical research studies that have explored the contribution of AI to reducing TTH through the AI-based automation of recruitment tasks that are time-consuming for human resources (Fang & Zhang, 2021; Alavi et al., 2020; Lee, 2019).

Finally, findings from quantitative and qualitative phases suggest that RS professionals believe that using AI in RS will help reduce COH. The belief is that increasing the candidate pool, reducing human bias and anomalies in the selection process, and selecting the right candidate for the job can reduce re-hiring costs. However, it should be noted that the outcomes predicted in this study are based on the other factors driving the AI adoption in RS and thus are subjected to meeting those criteria, as explained in the next paragraph.

9.2.3.2 Conditions of achieving HR outcome from AI use in RS

The study also investigated the conditions under which these outcomes are predicted to be achieved. As explained in the conceptual model (Figure 9), these outcomes are achieved if AI is used in the respective areas of the recruitment process and if the facilitating conditions are supported, as well as if the benefits expected by RS professionals are realized as explained in Chapter 6, section 6.2.

More specifically, results from the quantitative phase show that AI should be used in the recruitment phases of pre-planning, sourcing, and pre-screening to derive these predicted HR outcomes. Additionally, the facilitating conditions of end-to-end AI systems integration, the ability to track AI decision-making processes, and the protection of candidate privacy data supported by AI systems are required to achieve these outcomes. Furthermore, the professional’s benefit expectations of achieving work-life balance using

AI, standardizing the recruitment process through AI, and career progression using AI in RS should be supported by AI, which will then contribute to achieving these predicted outcomes.

It is also important to note that the AI adoption drivers identified in this research only apply in low volumes first and by less experienced RS professionals who would like to try AI in RS before using AI in the RS in practical situations. Additionally, as indicated above, adopting AI in recruiting blue-collar workers may not necessarily result in favorable HR outcomes. This is discussed further in future research (Section 6).

9.3 Theoretical Contribution of AI- RS

This study provides a theoretical contribution to HRM literature by developing and testing a model for the effective use of AI in RS to achieve strategic HR outcomes. It builds on and extends the UTAUT theory by including key R&S factors and moderators to explore the circumstances when which AI use is most effective. These factors include the recruitment phase, trust in AI, HR outcomes, the volume of recruitment, and the experience of R&S professionals.

Integrating AI in business processes, such as RS, has revealed gaps in existing theoretical frameworks (See Chapter 3, section 6) and suggests that research lags behind practice. As a result, the study extended existing frameworks to address better research questions related to AI adoption in the RS process. It utilized the UTAUT theory to understand the adoption of new technologies (See Chapter 3, section 5); and examined the unique circumstances when AI can be effectively applied in RS to achieve HR outcomes from the perspectives of recruitment professionals.

Thus, it addressed this gap by developing a model that contributes to the extant literature in the following ways: (1) incorporation of specific RS process phases as AI adoption drivers, (2) inclusion of trust in AI as a driving factor influencing AI adoption, (3) examining HR outcomes, and (4) the exclusion of effort expectations which distinguished from the UTAUT in favor of assessing AI adoption from the end-users perspective. These distinct features underscore the novelty and applicability of the developed conceptual framework in elucidating the complexities of AI adoption in RS processes.

Moreover, the AI-RS provides more specific contexts for RS. These contexts were developed based on insights generated from the qualitative study, thus increasing the relevance of studying AI phenomena in RS. This is explained in the next subsection.

9.3.1 The methodological contribution of AI in RS

The study adopted AI RS adoption measures so that they are more relevant to the AI context and can be used for future research examining the use of AI in HR. In that context of AI in RS, the main constructs, such as benefit expectations, were measured using RS-specific criteria that pertained to the RS instead of relying on generalized measures such as "I would find using AI beneficial" or "I would find AI easy to use". For example, the measurement criteria such as “achieving work-life balance using AI", "reducing manual work in RS by AI automation”, or “increasing career progress” of ‘benefit expectations’ in AI-RS were developed from the qualitative research results and as specific to AI-RS (see Chapter 6, section 6). Thus, measures were deemed more relevant and applicable in RS, as they aligned with the specific needs and challenges of the RS domain. Thus, measurement criteria in AI-RS can be utilized to measure benefit expectations in other emerging technologies like virtual reality, metaverse, cloud, and similar in HR. AI-RS contributed similarly to measuring other constructs of AI-RS as well.

The main construct of social influence in AI-RS measures the influence of media, including documentaries and science fiction, as well as communication channels like social media, on adopting emerging technologies. These measures were identified through qualitative research (See Chapter 6 Section 6.3), where most research participants indicated that the influence from such sources was much higher. The relevancy of these sources, such as media in technology adoption like AI, is applicable as AI technologies continue to evolve, and media has been shown to play a significant role in promoting their adoption. For instance, empirical studies demonstrate that YouTube plays a major role in promoting the adoption of artificial intelligence (AI) in various business applications (Kusumaningtyas & Santoso, 2020; Khan & Lee, 2020). The AI-RS thus provides statistically proven suggestions that influence from media and communication channels and the modern era are playing a bigger role in influencing end-users compared to other influences such as managers or peers as suggested in technology adoption models such as UTAUT (Venkatesh et al., 2003). These findings thus may have important implications for understanding the factors that influence the adoption of emerging technologies and for designing effective communication strategies to promote their adoption.

In terms of facilitating conditions, AI-RS stands out due to the distinct facilitating conditions it requires. Notably, the model highlights those end-to-end integrations of AI with other business systems, traceability of AI decision-making processes, and safeguarding the data protection and privacy of end-users are crucial facilitating conditions that strongly influence the acceptance of AI. Thus, it can suggests that FC is FC is crucial to the AI acceptance (i.e., UB) by strengthening intention (i.e., BI). This contrasts with other studies emphasizing the availability of technologies, training, and support as significant factors driving AI acceptance.

9.3.2 HR professional's perspective

This study contributes to the emerging literature on AI-RS by identifying the factors driving AI adoption in RS processes. The study reveals that integrating RS phases, trust in AI, and HR outcomes influence AI adoption in RS. This finding is novel and contrasts with other studies on technology adoption models, suggesting that AI adoption in RS differs from other forms of technology adoption.

The study further reveals that RS professionals are receptive to AI in pre-planning, sourcing, and pre-screening areas but not in candidate engagement and interviews. Qualitative research conducted as part of the study shows that refraining from using AI in the candidate engagement phase demonstrates respect for candidates. Empirical evidence supports this assertion, with a study conducted by the National Bureau of Economic Research revealing that job seekers generally prefer personal interaction in the hiring process, as the absence of such interaction may result in lower levels of trust and satisfaction with the employer (National Bureau of Economic Research, 2017). Moreover, research published in the Journal of Business and Psychology indicates that using AI in recruitment can create a sense of distance and a lack of transparency, contributing to negative perceptions of the hiring process among job seekers (Dery et al., 2019).

Thus, the study argues that factors such as candidate experience, ethics, and respect for candidates may be driving the adoption of AI in RS phases like candidate engagement. To ensure that candidates are treated fairly and respectfully throughout the recruitment process, organizations must consider a balanced approach incorporating AI with human interaction and implementing safeguards to minimize the potential for bias.

The study also reveals that trust in AI is an important factor driving acceptance and adoption of AI in the recruitment phases. The AI-RS framework suggests that negative trust in AI may be linked to the expected facilitating conditions such as algorithmic transparency, end-to-end integrations, and privacy data protection of candidates. Furthermore, the study provides a unique perspective by indicating that trust in AI is higher among less experienced professionals, suggesting that younger professionals may be more accepting and open to adopting AI compared to their more experienced counterparts.

Additionally, the impact of hiring volume, especially from the perspective of RS professionals, provides unique findings. The study revealed that RS professionals are more receptive to adopting AI in low hiring volumes, which contrasts with the organizational perspective, where higher hiring volumes have driven AI adoption (Huang et al., 2019; Kunc & Gartner, 2020).

These findings add an important aspect to the literature, which provides an evolving body of knowledge that is a possible linkage between AI or new emerging technology adoption and the age of end-users, specifically the generations. Moreover, the study finds stronger support to suggest that younger generations are more accepting of using AI, at least in the RS space. This finding suggests that the early adopters of AI will likely be younger and less experienced professionals with higher levels of trust in AI.

In conclusion, the study highlights the importance of considering the technical capabilities of AI and the social and ethical implications of its implementation in RS processes. These findings may trigger further studies in this area, as it suggests that there is a unique body of knowledge that drives AI adoption in RS processes. Ultimately, understanding these factors may help organizations implement AI to enhance the recruitment and selection process while still prioritizing candidate experience and ethical considerations.

9.3.3 Impact of AI adoption on HR outcomes.

Based on the researcher's knowledge, the AI-RS is the only model that explicitly measures the effectiveness or outcomes of AI adoption. Other technology adoption models, such as UTAUT, TAM, and Information Systems Success Model (ISSM) (DeLone, & McLean,2003), primarily focus on identifying the factors driving the actual use of technologies rather than measuring the predicted effectiveness or achievement of outcomes when such technologies are actively used. Instead, AI-RS can measure the strategic outcomes if the AI is adopted in the identified recruitment phases.

Thus, the AI-RS can be used as a theoretical framework to help businesses and organizations evaluate whether other emerging technologies, such as AI, would actively contribute to achieving the strategic outcomes of their respective divisions or organizations before making any investments. Therefore, the AI-RS model fills a critical gap in the existing technology adoption literature by providing a structured approach to assessing the effectiveness and impact of AI adoption.

9.4 Discussion

Various observations were made and analyzed in detail in both qualitative and quantitative research. These observations provide several discussion points, particularly regarding the emerging trends in business applications such as AI and the managerial actions necessary to maximize its benefits while also reducing potential risks.

9.4.1 Discussion based on general observations.

The observations from the qualitative research indicate that there is a growing interest among HR professionals regarding AI and its application in the realm of human resources. The participants showed positive engagement in the study, expressed interest in the research, and sought to involve their HR staff. Additionally, many participants requested to receive a summary of the research results, suggesting an emerging demand for information on AI. However, the study also found that over two-thirds of those who declined to participate in the research lacked experience or knowledge about AI. Because those individuals who claimed to lack familiarity with AI were active on LinkedIn using candidate recommendation features, which are LinkedIn products that employ AI in the background (Kim & Lee, 2021). Some of them also had a few job postings on LinkedIn that utilized AI in the background. That means they had been using AI indirectly, albeit unknowingly.

These findings highlight the need for more investigation and attention to be paid to the complexities of AI, particularly in terms of its general application and explainability. This implies that individuals might already be using applications integrated with AI without realizing it. Consequently, the data they input could unknowingly contribute to training machine learning models and shaping user patterns. Such approaches can foster mistrust, as end-users are often uninformed about how and when their data is utilized to develop AI models. Without sufficient clarity or transparency, users may become hesitant to engage with AI applications, leading to adoption challenges.

As noted in the studies of Soni et al. (2019), Metcalf et al. (2019), and (Borges et al., 2021), there is a lack of knowledge regarding AI applications and the benefits and damages that can result from their use. This further underscores the need for more research and education surrounding AI and its potential impact on society, particularly in the realm of human resources. For example, Greene et al. said: "Despite this wealth of output, research on counterfactual explanations is long on data, short on theory, and even shorter on practical recommendations on how to build effective XAI systems" (Greene et al.,2023). Therefore, researchers and AI developers must give more attention and investigations to the complexities, general application, and explainability of AI.

9.4.2 Managerial implications- Facilitation conditions of AI in RS

The research findings have managerial implications related to facilitation conditions, which are influenced by key factors such as expectations of benefits, social influence, and others. These implications call for specific managerial interventions, which will be further explained.

9.4.2.1 Managerial implications -benefit expectations from AI in RS

According to the findings of this study, the most desired benefits of AI use in RS include achieving work-life balance, increasing career prospects, and standardizing the recruitment process. This contrasts with other studies (Van den Broeck et al., 2020; Zehra and Bozkurt, 2020; Yang et al., 2019; Kargahi et al., 2019) that emphasize improved efficiency, reduced bias, improved candidate experience, better candidate matching, and improved decision-making as the primary benefits.

Furthermore, this research differs from the findings of Yang et al. (2019) and Zehra & Bozkurt (2020) as it reveals a shift in perspective regarding the fear of job losses. Specifically, this study presents a new perspective on RS, where AI is considered a career-boosting opportunity. Additionally, the benefits uncovered in this research expand on the findings of Aggarwal (2021), where RS professionals expect AI to standardize the recruitment process. Based on the presented findings, organizations can implement several facilitating conditions to leverage the benefits of AI in the recruitment process.

Firstly, organizations can prioritize implementing AI tools to promote the work-life balance of RS professionals. For instance, chatbots and virtual assistants can provide round-the-clock support to candidates, reducing recruiters' workload and promoting a positive candidate experience (Kulkarni & Kulkarni, 2018; Kshetri, 2018).

Secondly, organizations can implement standardized recruitment processes making them more objective and unbiased. Managers can use AI tools to screen resumes and evaluate candidates' skills, abilities, and suitability for a particular role. This can involve using predictive analytics and machine learning algorithms to assess candidate fit, enabling recruiters to make data-driven decisions based on candidate characteristics (Thota & Vemula, 2019).

Thirdly, managers can use AI to increase career prospects and identify areas of improvement for their RS professionals, which can help them develop new skills and increase their career prospects. AI can also be used to move RS professionals into a strategic leadership role that cannot be done by AI and utilize AI for repetitive administrative work.

Lastly, managers should monitor and address concerns about AI. While AI has potential benefits, some RS professionals may have concerns about its use. Managers should monitor these concerns and address them proactively to ensure RS professionals are comfortable using AI tools in the RS. This can be done by providing training and education about the benefits and limitations of AI and addressing any ethical concerns RS professionals and candidates may have.

9.4.2.2 Managerial implications- Social influence of AI in RS

The study found that the most significant influences on RS professionals were the modern era, media like documentaries, and customers. This may suggest that media and communication channels and the modern era are shaping the attitudes of RS professionals towards AI to the extent that they become the primary influences, specially for less experienced professionals. Thus, this finding differs from other studies in the same field, which suggest that senior managers or peers have the most significant influence on behavioral intentions (Aljumah & Alfawaz, 2020; Farooq et al., 2020; Huang et al., 2020; Zhang & Lu, 2020).

Thus, it may suggest that when organizations intend to use AI in the RS, these media channels, especially social media, can be leveraged to drive adoption. For instance, managers could collaborate with media outlets to raise awareness about the benefits of AI in recruitment or organize training programs for RS professionals to enhance their understanding of AI technologies (Aljumah & Alfawaz, 2020). The suggestion is supported by the qualitative research findings, where participants reported that they obtained a significant amount of their AI education from social media platforms like YouTube. This finding implies that social media, particularly YouTube, can serve as an effective platform for educating people on emerging technologies such as AI. Similarly, Hermann, I (2023) suggest that science fiction can influence people with less prior knowledge to educate and influence AI use.

On the other side, negative implications of AI can be projected by the media, especially social media, without any scientific or empirical evidence, which can influence RS professionals, especially those with less experience in RS. Thus, it may produce conflicting interests with the organizations' strategic goals. Thus, Corrigan et al. (2021) suggest that HR professionals should be aware of the potential impact of media coverage on stakeholder perceptions of AI and develop communication strategies that are transparent, informative, and responsive to stakeholder concerns as the impact from media on influencing AI is higher (Corrigan & Cheung, 2021).

Finally, strategic leaders should consider the influence of customers on RS professionals as they are positively influenced by customers (candidates and enterprise customers who RS professionals interact with) to use AI in the RS. Therefore, managerial interventions are required to understand customers' pressing needs and why customer demands are emerging. This may trigger a need to understand customer requests around using AI in the recruitment process in detail, especially the negative effects if those demands are not met. For example, Lee et al. (2018) argue that the future of recruitment is AI thus recruitment companies will be disadvantaged in the market if they do not adopt

AI in the recruitment process. Similarly, many empirical studies suggest that recruitment companies and HR departments that do not integrate AI may risk losing their business to competition (Cheema et al., 2020; Davenport & Kirby, 2015; Stone et al., 2015).

9.4.2.3 Managerial interventions – Facilitating conditions of AI in RS

This research revealed that providing ways to track how AI makes decisions, securing privacy data, and AI integration with other systems, are the main facilitating conditions RS professionals expect to adopt AI in the RS (See chapter 6, section 6.5) which suggests possible managerial interventions.

For instance, managers including AI developers could invest in developing AI tracking and auditing tools that enable RS professionals to monitor and analyze the decisions made by AI systems. This could help to build trust and transparency with customers and enhance the reliability and accuracy of the AI systems. Burrell (2016) suggests several ways to address concerns around opacity in machine learning algorithms. Those include making machine learning algorithms more transparent by explaining how the algorithms make decisions (Burrell, 2016). He suggested such actions can increase accountability for the use of machine learning algorithms by the AI developers as well as the AI adopters.

In addition, managers can prioritize the implementation of robust privacy policies and data protection measures to address the privacy concerns that RS professionals have.

This could involve implementing strict data access controls, data encryption, and data anonymization techniques to safeguard customer and employee data (Troncoso et al.,2021).

AI developers can also take precautions and mechanisms to address the concerns. For example, Chhabra et al. (2021) suggest privacy preservation mechanisms such as homomorphic encryption (the cryptographic technique that allows computations to be performed on encrypted data without requiring access to unencrypted data) and secure multi-party computation. Malin and Sweeney (2013) suggested that data de-identification methods, which balance the risk of re-identification against the usefulness of the de-identified data for its intended purpose, should be used by AI developers.

Finally, managers should facilitate the integration of AI systems with other RS systems, such as Application tracking systems (ATS) to enable seamless data sharing and processing (Tulu et al.,2021). This could help improve efficiency and accuracy in service delivery and enhance the overall customer experience as RS professionals expect from AI.

9.4.2.4 Managerial implications -Recruitment phases of AI in RS

The pre-planning, sourcing, and pre-screening are the recruitment phases most desired by RS professionals for considering AI use, while interviews and candidate engagement are the least desired, with a particular aversion towards interviews. This aversion is so strong that some RS professionals, as explained in qualitative research, are reluctant to use AI technology in interviews, even if the technology is 100% accurate. Thus, these findings trigger the need for various facilitating conditions.

Firstly, managerial interventions may require understanding the specific factors contributing to the desirability or undesirability of using AI in each of these recruitment phases. For example, providing a human-like treatment or "respecting" candidates are reasons why AI may not be used in interviews and candidate engagement, as explained by qualitative research and other empirical studies (Koc et al.,2019; Van Iddekingeet al., 2018). Therefore, it is recommended that AI developers and entrepreneurs explore the underlying reasons for this aversion and invest in areas where AI technology can address shortcomings in the recruitment process.

It is important to address RS professionals' concerns and fears about using AI in interviews, which can be achieved through effective communication and collaboration between HR professionals and AI experts (Taneja & Tohidinia, 2020). Collaboration can lead to the development of more customized AI solutions that better meet the needs of RS professionals and address their concerns, thus increasing acceptance and adoption of AI in the recruitment process.

Other interventions may include education and training programs to increase awareness and understanding of AI technologies and their benefits in recruitment (Gong, Zhang & Zhang,2021). Literature also suggests that the recruitment process to be redesigned by integrating AI into desired and feasible phases and using humans in other areas (Nguyen & Hoang, 2020). That suggestion leads to the discussion on hybrid RS process where humans and AI are used in RS. This concept also emerged during the qualitative research study.

This hybrid concept has been tested in other studies and suggested that the integration of AI and human intervention can lead to more efficient and effective recruitment processes, reducing the workload of recruiters and allowing them to focus on more strategic tasks such as candidate engagement and retention (Sharma and Sharma, 2020). The authors tested the effectiveness of their model by comparing it to a traditional recruitment process that did not use AI. They found that the hybrid model significantly improved the recruitment process in terms of time, cost, and accuracy. Specifically, the model reduced the recruitment time by 35%, decreased the recruitment cost by 25%, and improved the accuracy of shortlisting candidates by 90%. Yang et al., (2021) also suggested a hybrid model integrating human and AI resources into the recruitment process. Thus, leaders can exploit such models and conduct pilot projects to find the best hybrid models, where AI is used in areas that drive higher adoption and human resources are used in areas that have low AI adoption.

9.4.2.5 Managerial implications -Trust in AI and RS

As explained in Chapter 8, section 5.5, the statistical results suggest that trust has a positive effect on behavioral intention and use behavior. However, factors contributing to negative trust, such as algorithmic bias and a lack of transparency in AI algorithms, should be considered and addressed through measures to mitigate these concerns. Such measures could include explaining how AI algorithms operate, granting access to coding to increase transparency, and establishing limitations and conditions under which AI should be employed (Floridi & Cowls, 2019). By addressing these factors, stakeholders may be more likely to have greater confidence in using AI in the RS process and trust its capabilities.

Secondly, increasing awareness of how AI works, its limitations, how algorithms work, and how data are captured and used can be achieved through training programs, workshops, or information-sharing mechanisms like conferences. As explained in a previous section, media utilization may be beneficial as RS professionals show a higher influence from these media (Lee & See, 2004); Kang et al., 2019); Rashid & Asghar, 2018).

Furthermore, the results of the qualitative research suggest that involving RS professionals in AI pilot programs, utilizing early adopters in the testing of AI, and leveraging early adopters as influencers to address the concerns of those with negative perceptions could be effective strategies. By implementing AI pilot programs, RS professionals may assess the accuracy and business feasibility of AI prior to its deployment in the business environment, thereby enhancing trust in its capabilities.

Other empirical studies also suggest such interventions. For example, Klievink et al. (2019) suggest that pilot programs can help build trust in AI by allowing users to interact with the technology in a controlled environment and providing opportunities for feedback and improvement.

9.4.2.6 Managerial implications -HR outcomes from AI in RS

Based on the qualitative and quantitative research presented above and the predicted HR outcome achievement from AI use in RS (QOH, COH, TTH), several managerial interventions can be suggested to enhance the use of AI in the RS process.

Firstly, HR leadership should consider the conditions under which these HR outcomes are achievable. If these HR outcomes are desired as part of the strategic HR goals, then the conditions must be ensured, as this research proposes that attaining these outcomes is applicable within the specific conditions.

Furthermore, AI does not replace human judgment and decision-making (Parry & Wilson, 2020). Research suggests that reskilling to use AI is required, and therefore upskilling for RS professionals is necessary when intending to use AI in the RS to attain these outcomes (Turchin & Abdulla, 2021). It is also suggested that new jobs are emerging due to the adoption of AI, and thus users need upskilling and reskilling. For example, the

World Economic Forum suggested in the report "The Future of Jobs 2020" that "the adoption of AI is set to create 2.3 million new jobs by 2025, but at the same time displace 1.8 million jobs that are no longer relevant" (p. 20). The report emphasizes the need for upskilling and reskilling of the workforce to ensure that they are equipped with the skills needed to take on these new roles (World Economic Forum, 2020).

It is also suggested that organizations employ AI in other HR processes, such as onboarding, employee engagement, or training and development of employees, to improve retention rates (Dattaet al., 2021). By doing so, organizations can create more personalized and engaging experiences for their employees, which can increase their satisfaction and retention rates.

9.4.3 Managerial implications - Effort expectancy and AI-RS

The AI-RS framework offers a distinctive viewpoint on AI adoption, contending that the concept of effort expectancy (emphasized in other theories like UTAUT and TAM) does not apply to end-users in the context of AI. This may be because emerging technologies such as cloud computing, artificial intelligence (AI), and robotic process automation (RPA) and similar are integrated services that operate at the backend of end-user applications (Russell & Norvig, 2010) thus end-users such as RS professionals may not necessarily be in a position to comprehend or explain the efforts required to use backend technologies.

Empirical studies support the suggestion that AI is a backend system that employs complex algorithms and processes vast amounts of data to generate predictions or decisions that are subsequently used by front-end systems to enhance the user experience (Ng, 2017). For instance, AI may suggest products to users based on their browsing history or customize search results according to their previous searches. Nevertheless, users are typically unaware of the AI algorithms functioning behind the scenes to provide these recommendations or results (LeCun et al.,2015). In the RS context, candidate recommendation tools in LinkedIn, a platform most research participants utilize daily, function similarly (Hochberg & Yafeh, 2015).

Therefore, the onus of integrating and developing these backend processes lies with developers and integrators, rather than end-users. What matters to end-users such as RS professionals is ensuring the accuracy, transparency of algorithms, and availability of governance frameworks and seamless integrations as explained in the facilitating conditions, as opposed to the ease of use or efforts to use such technologies. For example, Sodhi and Soni (2021) discuss the ethical challenges and opportunities in HR analytics and emphasize the need for accuracy, transparency, and ethical considerations in implementing such technologies. Similarly, Ardabili et al., (2021) examine the ethical implications of AI in recruitment and selection, emphasizing the need to ensure fairness and minimize the potential for bias. Furthermore, the importance of accuracy and transparency of algorithms is emphasized by Martin (2021), who stresses the need for fair and transparent algorithms in recruitment and selection. Spitzmueller and Stanton (2020) also discuss the current opportunities and future directions of AI in personnel selection and assessment, highlighting the importance of accurate algorithms in ensuring reliable and valid results.

Thus, in the context of RS and its AI adoption and RS professionals' perspective, the qualitative results obtained by AI-RS in this research lead to removing the effort expectancy construct, making the framework more meaningful from the end-user's perspective in relation to AI adoption in RS. This is also highlighted by studies other than HR. For example, Khatri and Brown, (2010) in the research of designing and implementing emerging technologies from the perspective of healthcare workers, the authors argue that for emerging technologies like AI in healthcare, users may not have a clear understanding of what to expect from the technology and therefore may not be able to assess their perceived effort expectancy accurately. Instead, trust in technology and its ability to improve patient outcomes may be more important determinants of adoption. Additionally, Turel & Serenko (2012) who investigated Facebook adoption by users, the authors found that perceived ease of use, which is a criterion of assessing effort expectations, was not a significant predictor of Facebook usage, but rather enjoyment was the primary driver of adoption. Similar was found in the use of mobile banking, where effect expectancy is not a driver of the end users' actual use of the mobile banking technologies (Alalwan et al., 2017). However, unlike the current study, none of these studies are in the HR space.

Thus, the results of the AI-RS indicate that the construct of effort expectancy may be less significant in driving end-users' acceptance and adoption of emerging technologies (ETs) like AI. It suggests that managers may consider conditions driving AI adoption such as facilitating conditions may give more emphasis when implementing AI in the RS rather than focusing on EE.

9.5 Limitations of the study

While the mixed method research design has a number of advantages for this research study, some limitations also need to be acknowledged as explained next.

9.5.1 Experience of recruitment professionals

The present quantitative study has revealed a noticeable trend in the age distribution of the participants, with the majority falling within younger age groups which was assumed based on experience. Furthermore, analysis of the reported work experience revealed that a significant proportion of the participants had less than 10 years of experience, while those with over 15 years of experience were a minority. These findings suggest that younger generations may be more exposed to AI-based technologies, and therefore may possess a wider range of knowledge and expectations regarding AI compared to other age groups.

Thus, future research endeavors may benefit from incorporating the views of older age groups to obtain a more representative sample. This approach may help to elucidate potential differences in attitudes, beliefs, and perceptions regarding AI between different age cohorts, and may provide valuable insights for the development of AI-based recruitment processes that cater to the needs and expectations of a broader demographic.

9.5.2 Industries

Qualitative research findings have revealed that certain industries that predominantly hire blue-collar and vocational workers may not necessarily benefit from AI-based recruitment processes. These industries include transportation, manufacturing, and retail, among others. In the subsequent quantitative research, an effort was made to include representation from these industries. However, this study's sample size from these industries was comparatively smaller, possibly due to the utilization of LinkedIn and other professional networking sources for data sourcing.

Thus, future research endeavors may benefit from a more targeted focus on these specific industries, such as directly reaching out to companies in these sectors. This approach may be particularly relevant for remote and rural locations where these industries may not be as well-connected to the internet and online professional networks.

9.6 Future research suggestions

Based on the limitations of the research discussed in the previous section, the scope of the research explained in Chapter 1, section 7, the gaps in the literature identified in Chapter 2, section 10, and the conceptual framework AI-RS, the research can be further expanded as elaborated below.

9.6.1 Conceptual framework

The present research proposed the conceptual framework AI-RS. It measured the HR outcomes associated with the use of AI-based RS processes. As such, this framework may be a valuable tool to assess the outcomes achieved by other emerging technologies such as virtual realities, metaverse, cloud, and remote work, in related areas within the RS and HRM space.

Future research endeavors may benefit from utilizing AI-RS to evaluate the HR effectiveness of these other emerging technologies in the context of RS. This approach may enable researchers to compare the impacts of different technologies on HR outcomes, providing valuable insights for organizations seeking to leverage these technologies to improve their HR practices.

9.6.2 Perspectives of the candidates

Previous studies have explored the candidate's perspectives on AI in the RS, including their attitudes and concerns regarding its use. For example, research has shown that candidates may have concerns about the fairness and transparency of AI-based recruitment selection processes and potential biases in the algorithms used (Chen et al., 2019; Kostov et al., 2019). However, there is a lack of consensus on the effectiveness of AI in improving HR outcomes, including its impact on candidate experience and satisfaction.

To address this gap, the conceptual framework, AI-RS, developed in this research may be useful for measuring HR outcomes associated with AI-based recruitment selection processes from the candidate perspective. This approach may enable researchers to evaluate the impact of AI on candidate experience and satisfaction, as well as potential issues related to fairness and bias. Overall, this research may contribute to a better understanding of AI's potential benefits and drawbacks in the RS and inform the development of more effective and equitable HR practices.

9.6.3 Use of AI in the post recruitment and HR Outcomes

This study primarily focused on using AI in the recruitment phases of pre-planning, sourcing, candidate engagement, pre-screening, and interviewing. However, during the qualitative research phase, several participants suggested that AI could also be beneficial in the post-recruitment phases such as onboarding, employee engagement, training, and development. Thus, the same conceptual framework used in this study can be applied to analyze the effectiveness of AI technology on HR outcomes in the post-recruitment phases. The recruitment phases in the framework could be replaced with the phases of onboarding, training and development, and employee engagement. This would allow for a more comprehensive analysis of the impact of AI on HR outcomes across various stages of the employee lifecycle.

9.6.4 Retention rates and impact from AI adoption in RS

This study's findings indicate that incorporating AI into the recruitment and selection process may not always lead to improved retention rates, as perceived by professionals working in recruitment and selection (RS). However, participants in the qualitative study suggested that AI could be effectively utilized in onboarding new employees after completing the recruitment process. They predicted that this application of AI could potentially enhance retention rates.

Furthermore, the participants expressed that AI could be employed to evaluate employee engagement and subsequently predict their satisfaction or dissatisfaction with the organization. By identifying these issues beforehand, organizations can proactively address them, reducing the likelihood of employees resigning and ultimately leading to increased retention rates. Thus, this suggests future research.

9.6.5 Emerging Job Roles and Opportunities from AI in HR

The present research revealed that professionals in the RS hold a positive outlook regarding career progression using AI in recruitment processes. This contrasts with prior studies that predict job losses and negative impacts resulting from the implementation of AI (Cascio & Montealegre, 2016; Davenport & Kirby, 2015). Rather than viewing AI as a threat, the findings of this research suggest that RS professionals perceive it as a tool to reshape their profession. This indicates a trend in the transformation of the recruitment profession through the integration of AI. Consequently, future research may benefit from investigating the emergence of new job roles and functions within HRM resulting from the application of AI in recruitment processes.

9.7 Conclusion

This chapter presented and discussed the key findings of the research questions, limitations, and future research suggestions that emerged from this study. The primary objective of the research was to explain the factors driving AI adoption, conditions influencing those factors, and the HR outcomes of adopting AI in RS.

The study developed and tested a theory-driven conceptual framework, AI-RS, which extended the novel UTAUT and UTAUT OM models. By utilizing both qualitative and quantitative methods, this research adds unique knowledge to the emerging literature and provides applicable knowledge to business communities who seek to harness AI in recruitment and selection in HR. Overall, this study found that RS professionals perceive AI can contribute to achieving HR outcomes under certain circumstances.

These specific outcomes include increasing the hiring quality, reducing hiring time, and reducing hiring costs if AI is used in specific recruitment phases and within certain facilitating conditions to meet the benefits expectations of recruiters, hiring managers, and HR executives. The findings suggest RS professionals expected to reap several benefits by incorporating AI into their recruitment process. These benefits include improving work-life balance, enhancing the quality of recruitment, and advancing career progression. Furthermore, end-to-end AI integrations with other systems, the provision of data privacy, and the ability to track AI decision-making also encourage AI adoption in recruitment.

Factors influencing the adoption and use of AI in RS are primarily emerging technologies, documentaries, media, and customers. Specific recruitment phases also play a significant role in driving AI in RS, with recruitment pre-planning, sourcing, and pre-screenings being more suitable and inclined to adopt AI compared to interviews and candidate engagements.

A noteworthy finding of this research is the influence and acceptance of AI by less experienced professionals, suggesting that the younger generation of RS professionals may be more likely to adopt and use AI in RS, making them early adopters of AI.

Finally, it is worth noting that trust in AI still shows a negative influence to say Trust in AI in RS will be a barrier to adopting AI unless the factors contributing to low trust are eliminated.

This research contributes to the emerging body of knowledge on the use of AI in the RS by providing unique findings and a theoretical framework that can be applied to understand the HR outcomes of emerging technologies such as AI. This framework can also be extended and tested in other areas of HR and with other emerging technologies, such as cloud computing, virtual realities, remote working, and other digital technologies.

The research also offers useful insights for managers who want to use AI to achieve specific HR outcomes in RS. The results indicate that RS professionals are more willing to use AI in low hiring volumes before implementing it in larger ones. Thus, managers can consider and facilitate this approach to drive AI adoption in RS. Based on the research findings and the existing literature, these managerial interventions can be implemented to utilize AI and achieve optimal outcomes effectively. As a result, these interventions can assist HR leaders in making the most of AI technology.

Appendix

Reference Tables

List of hypotheses in the conceptual model

Hypothesis number	Independent Construct	Dependent construct	Moderator	Coding	Predicted Relationship
H1	Benefit Expectations	Behavioral Intentions		BE→BI	Positive
H1.1	Benefit Expectations	Behavioral Intentions	Experience	Exp x BE→BI	Less experience strengthens the relationship
H1.2	Benefit Expectations	Behavioral Intentions	Volume	Vol x BE→BI	Low Volume strengthens the association
H2	Social Influence	Behavioral Intentions		SI→BI	Positive
H2.1	Social Influence	Behavioral Intentions	Experience	Exp x SI→BI	Less experience strengthens the relationship
H2.2	Social Influence	Behavioral Intentions	Volume	Vol x SI→BI	More Volume strengthens the association
H3	Facilitation Conditions	Behavioral Intentions		FC→BI	Positive
H3.1	Facilitation Conditions	Behavioral Intentions	Experience	Exp x FC→BI	More experience strengthens the relationship
H3.2	Facilitation Conditions	Behavioral Intentions	Volume	Vol x FC->BI	Low Volume strengthens the association
H4	Recruitment Phase	Behavioral Intentions		RP→BI	Positive

H4.1	Recruitment Phase	Behavioral Intentions	Experience	Exp x RP→BI	Less experience strengthens the relationship
H4.2	Recruitment Phase	Behavioral Intentions	Volume	Vol x RP→BI	Low Volume strengthens the association
H5	Trust	Behavioral Intentions		TR→BI	Negative
H5.2	Trust	Behavioral Intentions	Volume	Vol x TR→BI	Low Volume strengthens the association
H5.1	Trust	Behavioral Intentions	Experience	Exp x TR→BI	Negative but Less experience strengthens the relationship
H6	Behavioral Intentions	Use Behavior		BI->UB	Positive
H6.1	Behavioral Intentions	Use Behavior	Experience	Exp x BI->UB	Less experience strengthens the association
H6.2	Behavioral Intentions	Use Behavior	Volume	Vol x BI->UB	Low Volume strengthens the association
H7	Facilitation Conditions	Use Behavior		FC→UB	Positive
H8	Recruitment Phase	Use Behavior		RP→UB	Positive
H9	Trust	Use Behavior		TR→UB	Negative
H10	Use Behavior	Outcomes		UB→OC	Positive

Table 47: List of hypotheses

Benefit Expectations: Data normality

Variable Name	No of Records	Min	Max	Mean	Std Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
BE1	215	1	7	6.04	1.080	-1.175	0.166	1.344	0.330
BE2	215	1	7	5.74	1.065	-0.784	0.166	0.639	0.330

BE3	215	1	7	5.76	1.058	-0.746	0.166	0.313	0.330
BE4	215	1	7	5.68	1.117	-1.047	0.166	1.152	0.330
BE5	215	1	7	5.64	1.080	-1.091	0.166	1.883	0.330

Table 48: Data normality of the indicators of Benefit Expectations

Facilitating Conditions: Data normality.

Variable Name	No of Records	Min	Max	Mean	Std. Dev	Skewness		Kurtosis	
					Statistic	Statistic	Std. Error	Statistic	Std. Error
FC1	215	1	7	5.34	1.169	-0.752	0.166	0.697	0.330
FC2	215	2	7	5.41	1.023	-0.531	0.166	0.356	0.330
FC3	215	1	7	5.45	1.092	-1.080	0.166	1.662	0.330
FC4	215	1	7	5.57	1.078	-1.079	0.166	1.901	0.330
FC5	215	1	7	5.60	1.159	-1.166	0.166	2.142	0.330

Table 49: Facilitating Conditions: Data normality.

Descriptive Statistics of Social Influence Indicators

Variable Name	No of Records	Min	Max	Mean	Std Deviation	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
SI1	215	1	7	4.93	1.348	-0.469	0.166	-0.297	0.330
SI2	215	2	7	5.29	1.189	-0.568	0.166	-0.088	0.330
SI3	215	2	7	5.39	1.138	-0.705	0.166	0.471	0.330
SI4	215	2	7	5.30	1.194	-0.610	0.166	-0.254	0.330
SI5	215	1	7	4.76	1.481	-0.343	0.166	-0.702	0.330
SI6	215	2	7	4.93	1.404	-0.366	0.166	-0.681	0.330
SI7	215	1	7	4.35	1.722	-0.420	0.166	-0.821	0.330

Table 50: Descriptive Statistics of Social Influence Indicators

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Variable Name	No of Records	Min	Max	Mean	Std Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PH1	215	2	7	5.79	1.022	-1.001	0.166	1.642	0.330
PH2	215	2	7	5.87	0.936	-0.815	0.166	1.121	0.330
PH3	215	3	7	5.99	0.896	-0.924	0.166	1.233	0.330
PH4	215	1	7	5.54	1.122	-1.442	0.166	3.347	0.330
PH5	215	1	7	5.19	1.448	-1.112	0.166	0.719	0.330

Table 51: Descriptive statists of Recruitment phase indicators

Descriptive statistics of indicator variables of Trust

Variable Name	No of Records	Min	Max	Mean	Std Dev	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
TR1	215	2	7	5.23	1.299	-0.898	0.166	0.414	0.330
TR2	215	1	7	4.96	1.466	-1.005	0.166	0.440	0.330
TR3	215	1	7	5.03	1.496	-1.012	0.166	0.396	0.330

Table 52: Descriptive statistics of indicators represented by Trust.

Descriptive statistics of indicators of behavioral indentations

Variable Name	No of Records	Min	Max	Mean	Std Dev	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
INT1	215	1	7	5.84	1.038	-1.222	0.166	3.239	0.330

INT2	215	1	7	5.15	1.336	-1.044	0.166	0.918	0.330
INT3	215	1	7	5.46	1.130	-1.155	0.166	2.472	0.330
INT4	215	1	7	4.88	1.457	-1.133	0.166	0.675	0.330
INT5	215	1	7	5.12	1.434	-0.638	0.166	-0.092	0.330

Table 53: Descriptive statistics of indicators of behavioral intentions latent construct

Descriptive statistics of indicators of use behavior

Variable Name	No of Records	Min	Max	Mean	Std Dev	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
UB1	215	1	7	3.99	1.555	.351	0.165	-.486	0.330
UB2	215	1	7	5.33	1.259	-0.972	0.165	1.063	0.330
UB3	215	1	7	6.03	1.000	-1.571	0.165	1.109	0.330
UB4	215	1	7	5.55	1.170	-1.386	0.165	1.774	0.330

Table 54: Descriptive statistics of indicator variable of Use Behavior construct

Data Normalization of HR Outcomes

Variable Name	No of Records	Min	Max	Mean	Std Dev	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
OC1	215	2	7	5.60	0.900	-0.531	0.166	0.862	0.330
OC2	215	2	7	5.41	1.064	-0.913	0.166	0.971	0.330
OC3	215	2	7	5.43	1.047	-0.707	0.166	0.617	0.330
OC4	215	1	7	5.16	1.289	-0.863	0.166	0.652	0.330

Table 55: Data Normalization: HR Outcomes

Reference Figures

Finalized measurement model before the model fit.

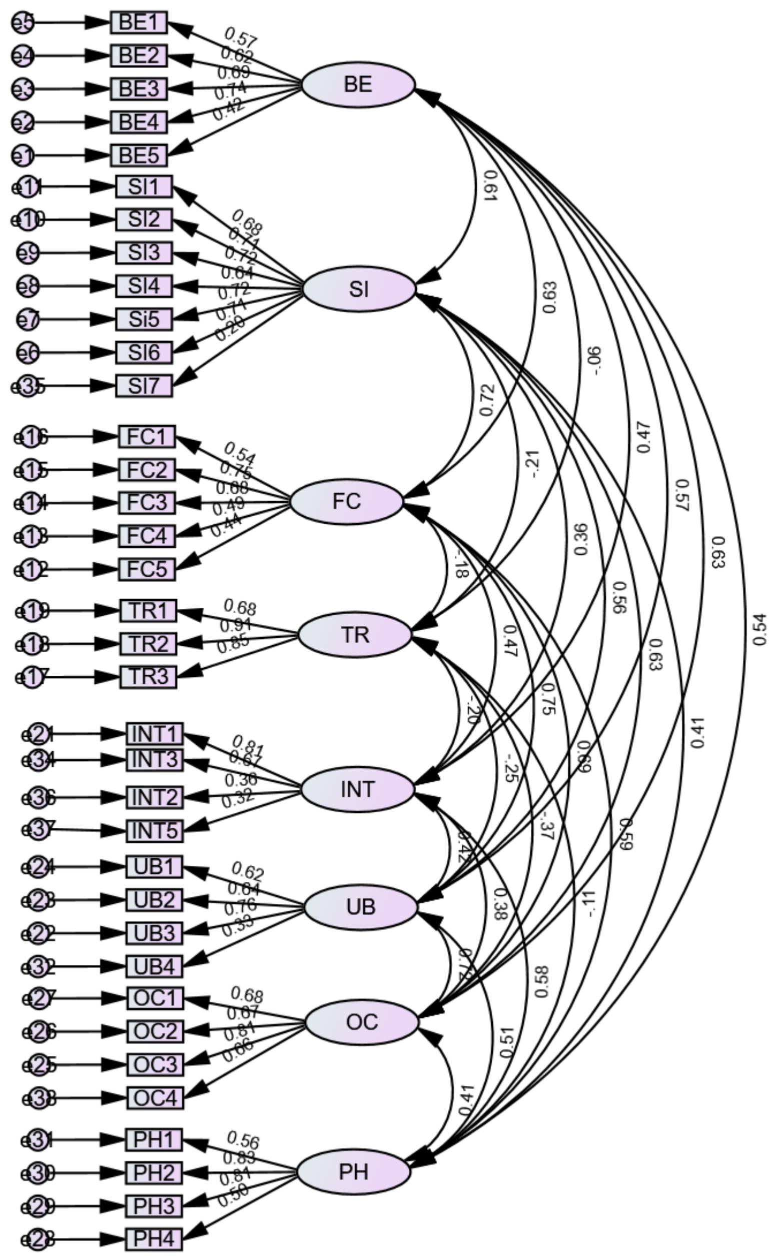

Figure 17: Finalized measurement model before model fit.

The results of the measurement model after model fit

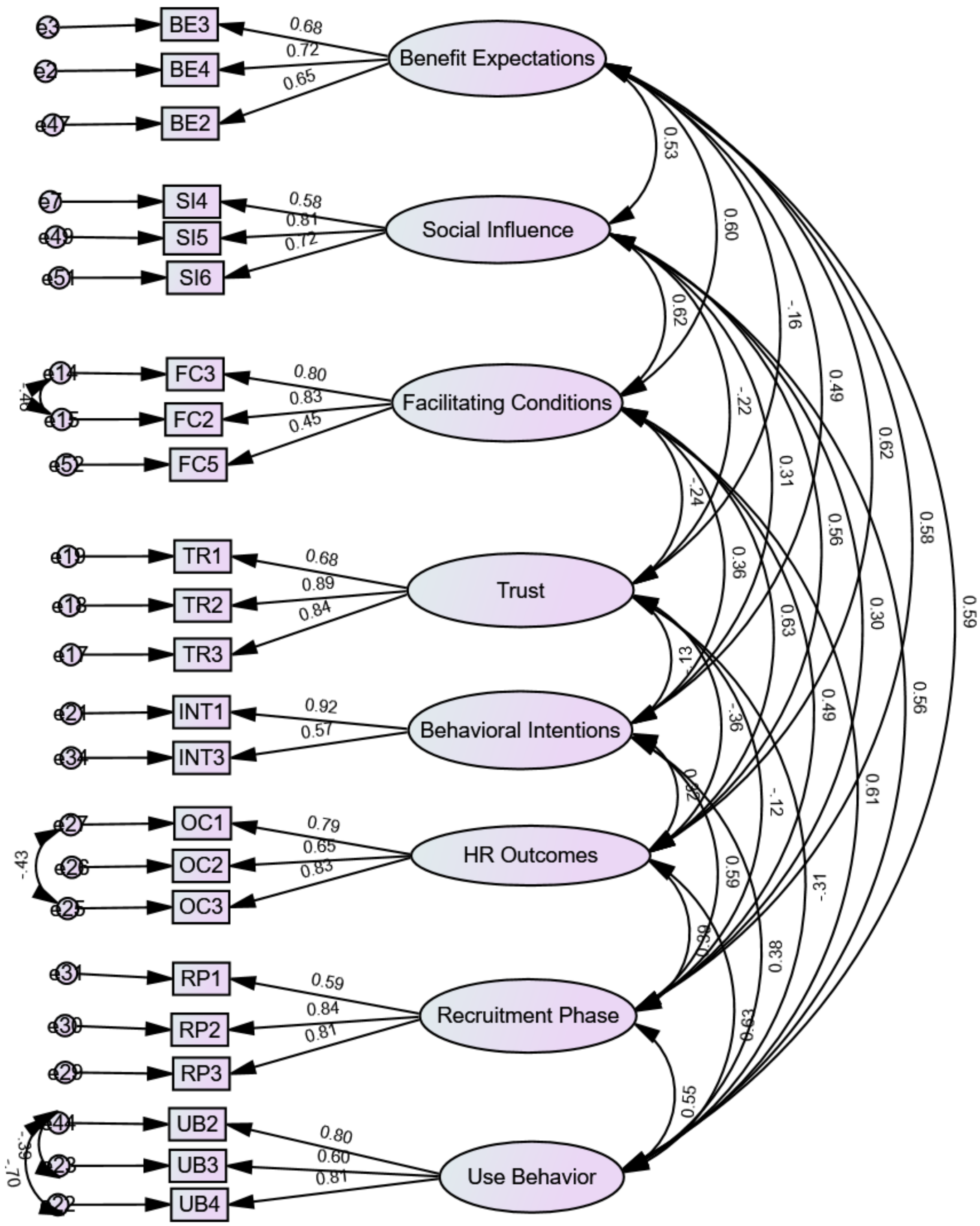

Figure 18: The finalized measurement model after model fit

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