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Exploring the Applicability of Artificial Intelligence in Recruitment and Selection Processes: A Focus on the Recruitment Phase

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Abstract

This study explores the use of artificial intelligence (AI) in recruitment and selection (RS) within the context of Human Resource Management (HRM). Contrast to past studies, this study makes a valuable theoretical contribution of a conceptual model to understand the effective use of AI in recruitment & selection processes by investigating the underexplored impact of the recruitment phase and the critical perspective of recruitment professionals. In so doing it builds on and extends technology adoption theory within the information systems by integrating HRM literature. The findings of this qualitative study indicate that AI is suitable for use in specific recruitment phases such as sourcing, pre-screening/pre-selection, and candidate engagement. However, there is a reluctance to use AI in the recruitment pre-planning and interview stages. It contributes valuable insights to inform HRM practitioners and organizations seeking to integrate AI into their recruitment processes.

Keywords

Artificial Intelligence, Human Resource Management, Technology Adoption Theory, Recruitment and Selection, AI Integration in Recruitment Processes, Artificial Intelligence in Recruitment and Selection

1. Introduction

The recruitment and selection process plays a crucial role in organizational success. According to a study by Arif et al. (2021), the recruitment process significantly impacts employee retention, job satisfaction, and organizational performance. By attracting and selecting suitable candidates, organizations can improve productivity, customer satisfaction, and profitability. Additionally, an effective recruitment and selection process can enhance the employer's brand and attract top talent. Thus, organizations are keen on adopting emerging technologies in the RS to gain benefits (Abbas, Liu, & Khushnood, 2022).

One of the emerging trends in recruitment and selection is the use of artificial intelligence (AI). AI can streamline the recruitment process by automating routine tasks, such as resume screening, scheduling interviews, and sending progression updates to candidates. It can also analyze data from candidate assessments and job performance to identify patterns and insights that can help organizations make better hiring decisions. According to a report by Deloitte (2021), AI technologies can reduce time-to-hire, improve candidate experience, and enhance the quality of hires which generally is appealing to many organizational leaders.

Thus, organizations are increasingly considering the adoption of artificial intelligence (AI) in various stages of recruitment and selection (RS) to leverage its benefits while mitigating the associated risks. However, the process of AI adoption in recruitment phases (RP) is complex because it involves multiple stakeholders with diverse perspectives, and their adoption of AI may differ (Bovet & Makridakis, 2019). While organizations may perceive AI as a means of achieving cost-effective strategic goals, recruiters, hiring managers, and other stakeholders associated with RS may have different perceptions of AI (Yao et al., 2010).

Despite strong support from HR leadership, AI adoption in RS is challenging and complex due to the intricacies of RS and the challenges presented by AI. For example, using AI in recruitment and selection raises concerns about potential biases and ethical issues thus triggering trust issues (Prakash, Joshi, Nim, & Das, 2023; Troshani, Hill, Sherman, & Arthur, 2020). AI algorithms may be trained on biased data, perpetuating existing biases in the hiring process (Dastin, 2018). Therefore, leaders and practitioners in HR and RS must use AI responsibly and ensure that AI algorithms are transparent, fair, and unbiased for use in business applications like RS. The World Economic Forum (2020) emphasizes the need for organizations to establish clear guidelines and governance frameworks to mitigate the risks of bias and discrimination in AI-based recruitment and selection processes. Therefore, the selection of AI and its applications in business requires careful consideration.

Therefore, the adoption of AI in RP cannot be solely driven by its capabilities or strategic leadership push. It requires the involvement and collaboration of various stakeholders in the decision-making process. In other words, the adoption of AI in RP should be based on a shared understanding and acceptance of its potential benefits and limitations by all stakeholders involved.

Thus, this study aims to explore the suitability of adopting artificial intelligence (AI) in the recruitment and selection process in the recruitment phases, from the perspective of recruitment and selection practitioners such as recruiters, hiring managers, and HR executives. To achieve this goal, the study uses a new conceptual framework which integrates the recruitment phase into the well-known Unified Theory of Acceptance and Use of Technology (UTAUT) model. Because recent research has emphasized the need for new theoretical models to understand emerging phenomena such as AI (Venkatesh et al., 2003). Scholars have responded to this call by developing new theoretical frameworks, such as the UTATU-OM (Operations Management) model, to address the complexities of AI applications.

By adopting this contextualized theoretical framework, the study provides a more comprehensive understanding of the complexities and applicability of AI in the recruitment and selection process. Thus, this study contributes to the literature by proposing a novel theoretical framework that can guide future research and practice in AI in recruitment and selection. Additionally, the study provides managerial insights into the suitability of recruitment phases for adopting AI.

This research paper is structured into several sections. The initial section offers an in-depth examination of the recruitment and selection process, encompassing an overview of its fundamental principles and functions. Subsequently, an investigation of AI applications in the recruitment and selection process is presented, drawing upon insights from diverse literature studies. Following this, the theoretical framework employed in this study, namely the Unified Theory of Acceptance and Use of Technology (UTAUT), is elucidated as the foundational basis for the development of the research's conceptual framework. The subsequent sections elaborate on the research design, outlining the data collection approach, and expounding on the chosen data analysis methods. A comprehensive account of the research findings and their implications is then provided, culminating in the concluding remarks that encapsulate the overall outcomes of the investigation.

1.1. Recruitment and Selection Process

The Recruitment and Selection Process (RSP) is critical in identifying suitable candidates to fulfill an organization's human capital needs, impacting organizational growth and performance (Azeem & Yasmin, 2016; Ekwoaba et al., 2015; van Esch et al., 2019). The RSP comprises various functions, including recruitment planning, sourcing, pre-selection, selection, communication, and engagement with candidates and other stakeholders (Barber, 1998; Holm, 2009). Armstrong and Taylor (2014) provide a detailed description of ten R&S stages, including defining requirements, attracting candidates, screening applicants, interviewing, testing, assessing candidates, obtaining references, checking applicants, offering employment, and following up. Given the multifaceted and complex nature of the RSP, it is essential to prioritize strategies to attract and identify the most suitable candidates for the organization. The next paraphs explain each of these phases in detail.

1.2. Preplanning

Recruitment pre-planning is a crucial aspect of the recruitment and selection process, which is essential in establishing a foundation for the efficient recruitment of candidates (Kanagavalli et al., 2019). This phase includes defining recruitment requirements, determining sourcing strategies, outlining job descriptions, and identifying financial benefits (Kanagavalli et al., 2019; Hallam, 2009a). According to Thebe (2014), this phase establishes a reciprocal relationship between the recruitment process and the organization's strategic objectives, ensuring the selection of suitable candidates for the appropriate roles within a specified timeline.

Kanagavalli et al. (2019) argue that recruitment pre-planning allows for the identification of skill gaps, analysis of turnover and retention rates, and evaluation of the effectiveness of sourcing channels, enabling informed recruitment-related decisions. By conducting a thorough pre-planning phase, organizations can effectively allocate resources and streamline their recruitment processes to achieve their desired goals. Therefore, recruitment pre-planning is a vital component that must be prioritized by organizations to ensure they recruit suitable candidates and achieve their strategic objectives.

1.3. Pre-Selection or Pre-Screening

The pre-selection or pre-screening process involves shortlisting a small number of candidates from a large pool of applicants. However, this process can be challenging and time-consuming due to the high volume of applications received for a single job (van Esch & Black, 2021). Traditional pre-screening methods, such as manual screening and ranking, can be error-prone and result in the deselection of potentially suitable candidates.

To address these challenges, new techniques such as e-recruitment-based filtering criteria have been introduced. However, inconsistent CV formats and a lack of contextual information in resumes limit their effectiveness (Black & van Esch, 2021). In contrast, 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 analyze resumes and identify relevant information such as skills and experience, and rank candidates based on their suitability for the job.

By automating the pre-screening process, recruiters can save time and resources and ensure that suitable candidates are not inadvertently overlooked (Li et al., 2021). Thus, the use of automated techniques in pre-screening processes can be a useful tool for recruiters in managing a large volume of job applications effectively.

1.4. Selection or Interview Phase

The selection or interview process is a critical step in the recruitment and selection process (RSP), where shortlisted candidates are evaluated based on multiple selection criteria to determine the final list of candidates for hiring (Hunter & Hunter, 1984). Interviews assess job-related and person-organizational fit by evaluating the communication, teamwork, and subject knowledge (Salgado, 1997). Different types of assessments like cognitive ability tests, personality assessments, situational judgment tests, and behavioural interviews are used for different job types and selection criteria (Dipboye & Johnson, 2013).

The interview process may include multiple tests and various rounds of interviews that differ based on the job type and selection criteria (Huffcutt et al., 2001). New types of interviews, like puzzle interviews and coding tests for software engineers, have emerged over time (Jackson & Schuler, 1995). The process involves coordination among interview panel members and candidates and can take a long time to complete. Different stakeholders are involved, such as subject matter experts, hiring managers, recruiters, HR managers, and senior executives, depending on the role (Vidal & Marques-Quinteiro, 2017). Having a structured approach to the interview process, including standardized assessments, and scoring criteria, is crucial to ensure objectivity and fairness.

1.5. Candidate Engagement and Communication

Effective communication and engagement with candidates are essential factors in the recruitment process and can significantly impact talent acquisition rates (Allen et al., 2010; Rose & Sandhya, 2022). The way recruiters communicate with candidates can influence their perceptions of the organization and affect their decision to accept or decline an offer (Harris & Fink, 1987; Taylor & Bergmann, 1987). As a result, organizations are increasingly prioritizing candidate communication and engagement as part of their recruitment efforts (Athanur et al., 2021).

However, providing the appropriate information to candidates at different stages of the recruitment process can be challenging since they expect a variety of details such as organizational information, job descriptions, interview process, assessment criteria, and interview updates (Palenius, 2021). Insufficient communication and engagement with candidates can result in negative consequences such as a damaged reputation, a limited pool of candidates, and prolonged recruitment cycles (Miles & McCamey, 2018). Therefore, it is essential to address the challenges associated with candidate communication and engagement to ensure a successful recruitment process.

To achieve this, organizations must develop effective communication strategies that will enable them to engage with candidates meaningfully and provide them with the information they need to make informed decisions about the job and organization. By doing so, organizations can improve their recruitment efforts, increase their talent acquisition rates, and positively impact their overall business outcomes.

1.6. Issues in RSP

Recruitment planning is a critical phase of the recruitment and selection process that can be complex and challenging, yet it is often overlooked by organizations (Zoller, 2018). Failure to pre-plan can negatively impact ongoing and future projects, making it difficult for organizations to achieve their goals (Hallam, 2009b). Sourcing and pre-screening candidates can also pose challenges, particularly when there is a shortage of HR professionals available to handle recruitment demands (Lutz, 2013; Torres, 2017). A high volume of applications in a limited time frame can lead to human bias in candidate pre-screening and selection, resulting in the wrong hire and a negative candidate experience (Clear, 2007; Lim et al., 2015).

Moreover, accurately assessing candidates can be challenging, resulting in the selection of the wrong person for the job. Some recruitment tests, such as psychometric tests, may not be scientifically sound (Piotrowski & Armstrong, 2006), and candidates may provide false information on their resumes, leading to the wrong hire and increased hiring costs (Const et al., 1995; Welch, 1999). As such, selecting the right candidates for the right job is an ongoing challenge for many RSP professionals, and the integration of emerging technologies in the recruitment process has become a topic of interest for HR leaders.

While technological advancements have impacted the recruitment process, their effectiveness remains a topic of debate (Lochner et al., 2021). AI and machine learning are being used to automate recruitment processes such as candidate screening and matching, reducing the burden on HR professionals. However, the use of these technologies can still be biased, and organizations must carefully consider their accuracy and fairness in the selection process. Thus, to address these challenges, organizational leaders are looking into various strategic interventions, including the integration of AI in RSP at a rapid pace.

2. AI Applications in RSP

AI is being applied in various stages and functions of the recruitment and selection process, and it has been reported to provide various benefits such as automating manual functions like resume screening (Teixeira & Bruni, 2021), target job campaigns, answering candidate's questions and interviews (Galanaki & Papalexandris, 2020). The implementation of AI in the recruitment process is expected to reduce the manual workload of HR professionals. The application of these AI technologies in different recruitment phases is listed in **Table 1** below.

According to the literature, there is a wide range of AI platforms available for organizations to utilize (**Table 2**), and some companies have begun developing their own AI products for use within their HR departments and in RSP (Zhang et al., 2021). This trend towards developing in-house AI products reflects a growing need for organizations to tailor their HR practices to their specific needs and context (Zhang et al., 2021). For instance, IBM has started developing AI technologies for use in its HR department in the process of recruiting its human capital workforce (Guenole & Feinzig, 2018) (see **Table 2**).

As there is a wide range of Artificial Intelligence (AI) technologies that can be leveraged during the recruitment phases, it is essential to comprehend the viewpoints of Recruitment and Selection Process (RSP) professionals to determine

Table 1. AI applications in recruitment phases (Sources: as per the reference column)

Recruitment phase	AI technology	AI function	Reference
Workforce planning (pre-planning)	AI-based workforce predictions and forecasting tools	Predicting retention rates, turnover rates	(Guenole & Feinzig, 2018)
		Predicting resource requirements based on the organization's strategic forecasts	
	AI-based financial forecasts	Cost-benefit prediction of the RSP function	(Guenole & Feinzig, 2018)
Sourcing	Natural language processing	Job description generation and job campaigns	(Coombs et al., 2021)
Prescreening	AI algorithmic prescreening	Prescreening candidates from resumes	(Yin et al., 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	(Suen & Hon 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, 2018; Allal-Chérif et al., 2021; Leong, 2018; Savola & Troqe, 2019)
	AI-based virtual assistants	Scheduling interviews between candidates and interviewers	(Allal-Chérif et al., 2021; Zhou et al., 2019)
		Generating assessment reports after interviews	(Suen & Hon, 2019)
		Background and reference checks	(Allal-Chérif et al., 2021)

AI applications in recruitment phases (Sources: as per the reference column).

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

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. Additionally, automated email centres, robust analytical dashboards, team tracking, and individual performance metrics can be utilized to enhance recruitment processes and improve overall outcomes.	Sony Music, Velcro, Maersk, Getty images, Drone deploy, Lyft

Continued

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 behavioural 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, form stack, 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, faster, 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 though a human language processing.	Bank of America.
HireVue		AI virtual interviewer	Bank of America

AI platforms/products for RSP (Sources: Aljanabi et al., 2023).

the most suitable RSP phases for AI integration (Skrobotov, 2021). Consequently, this study aims to investigate the perceptions of RSP professionals, as elaborated in the subsequent section.

3. Technology Adoption

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, integrates eight technology acceptance models to provide a comprehensive approach to understanding technology adoption (Venkatesh et al., 2003). The framework is designed to explain the intention to use technology and actual technology usage from the end user's perspective and considers various factors that influence behavioural intentions and actual use, including performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT is recognized as the most effective framework for explaining up to 70% of the variance in technology adoption usage (Venkatesh et al., 2003), with a clear separation of behavioural intention and use behaviour, 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 1**.

3.1. Behavioural Intentions (BI)

Behavioural intentions (BI) refer to "the subjective probability that a person will perform a given behaviour" (Sheppard et al., 1998: p. 198). In the context of the Unified Theory of Acceptance and Use of Technology (UTAUT), BI is considered the strongest predictor of use behaviour (Venkatesh et al., 2003). However, intentions do not always translate into actual user behaviour, and other factors can influence the relationship between intentions and behaviour (Sheppard et al., 1998). Performance expectancy, which refers to an individual's perception of the degree to which using a system will improve job performance, has been identified as the strongest predictor of behavioural intentions and has been operationalized in various ways (Venkatesh et al., 2003). However, it may not

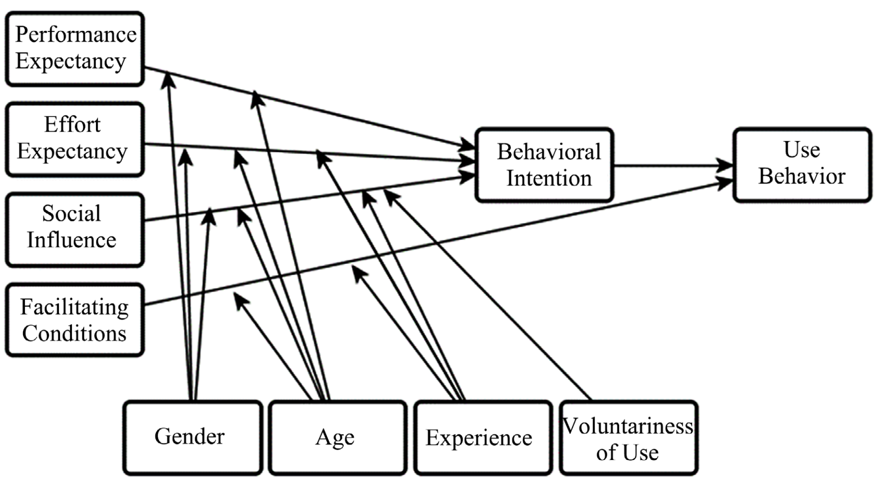

Figure 1. AI-RSP adoption model (Soruces: Venkatesh et al., 2003).

capture all expectations that individuals have of technology, especially in regulated sectors like healthcare where compliance with regulations may be critical (AlQudah et al., 2021). Therefore, the more comprehensive construct of perceived usefulness, which incorporates expectations of usefulness, applicability, and performance, may be more relevant in such contexts. To overcome the limitations of the performance expectancy construct in technology adoption research, AlQudah et al. (2021) proposed the use of benefit expectations (BE) as an alternative construct. BE encompasses various factors such as performance, usefulness, and applicability and better captures individuals' expectations of technology. Thus, BE may be more appropriate to use instead of PE in certain contexts. Considering the importance of understanding individuals' expectations and perceptions of technology adoption, this research will utilize the BE construct instead of PE to gain a more comprehensive understanding of individuals' expectations and perceptions of technology. By doing so, this research aims to contribute to the existing literature on technology adoption by providing a more nuanced understanding of the factors that influence actual user behaviour.

3.2. Social Influence (SI)

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

3.3. 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 et al., 2003). This construct is determined by considering the influence of perceived behavioural control on the system, compatibility, and facilitating conditions. In addition to predicting behavioural intentions, it has also been identified as a predictor of technology use behaviour within the context of the study. 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 et al., 2003).

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

3.4. Effort Expectancy (EE)

Effort expectancy is defined as the degree of ease associated with using the system (Venkatesh et al., 2003). 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 behavioural 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 et al., 2003). Thus, it can suggest that EE is not applicable at all times of the life cycle of the technology instead is applicable only during the early stages of the technology adoption.

3.5. Use Behaviour (Actual Use)

The UTAUT model defines use behaviour as the actual extent to which a technology or system is employed. Venkatesh et al. (2003) have identified that behavioural intention is the strongest predictor of user behaviour, 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 is specific user attributes Venkatesh et al. (2003).

The Unified Theory of Acceptance and Use of Technology (UTAUT) model can be extended by introducing recruitment phases as a conceptual framework to provide a more contextualized understanding of AI adoption in the recruitment process. The inclusion of recruitment phases in the conceptual framework can incorporate the specific requirements of the recruitment process, enabling recruitment specialists to gain a better understanding of AI adoption in the recruitment process. **Figure 2** illustrates this extended conceptual framework.

3.6. Qualitative Research Design

This research used qualitative methods using semi-structured interviews. Qualitative research methods offer advantages such as providing an in-depth

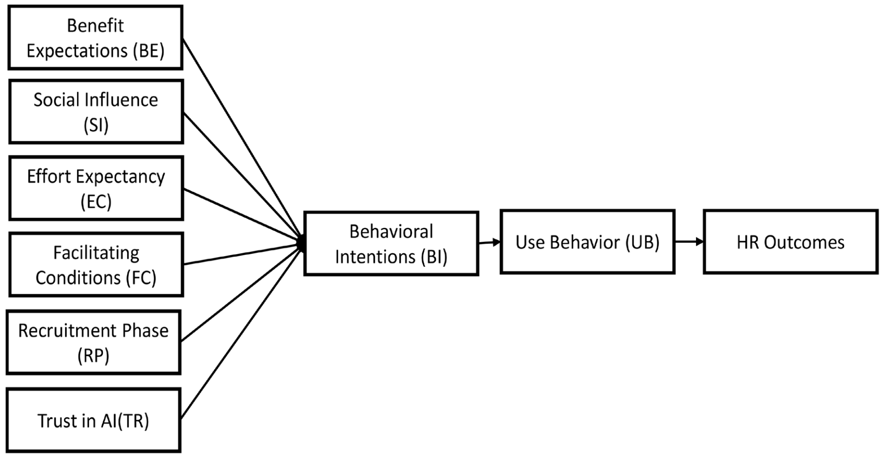

Figure 2. Conceptual framework (Source: Author).

understanding of experiences and perspectives (Creswell, 2014), an understanding of context, which allows for a more nuanced understanding of the issue (Maxwell, 2013), flexibility to allow for adjustments as research progresses (Denzin & Lincoln, 2011), and data richness, which can be used to generate theory and advance our understanding of a phenomenon (Creswell, 2014).

This study utilized semi-structured interviews to collect data, as they offer the advantages of both structured and unstructured interviews (Fylan, 2005). Structured interviews provide a framework for answering the research question by focusing on the necessary information (McGraw & Harbison-Briggs, 1989), while unstructured interviews allow for flexibility and exploration of data beyond the framework, potentially revealing valuable insights not initially considered (Carruthers, 1990). Given the researcher's limited knowledge of the RSP in HRM, the exploratory nature of the interviews was essential, enabling the gathering of information necessary to answer the research question while also exploring broader perspectives from experienced professionals.

The study was conducted in accordance with the ethical standards set forth by the University Ethics Approval Committee, and informed consent was obtained from all participants prior to participating in the interviews. To protect the participants' privacy and confidentiality, confidentiality and anonymity were maintained throughout the study.

3.6.1. Data Collection Approach

The current study utilized two distinct recruitment methodologies to ensure a diverse and representative sample of individuals with varying backgrounds and experiences from RSP professionals. One approach employed was the utilization of online professional networking sites, such as LinkedIn, to access a larger pool of potential participants who may have knowledge of recruitment and selection processes. This approach increased the researcher's ability to engage a wider audience and secure suitable interviewees who fulfill the study's eligibility criteria (Crawford et al., 2020).

In addition to online networking, the study also employed offline professional networking strategies, such as communities like university alumni associations. This approach was beneficial in obtaining access to working professionals who may not be as active on online networking sites. Moreover, the use of alumni groups from renowned universities ensured that participants had a certain level of experience and expertise in their field (Hagenauer et al., 2016).

Remote interviews were conducted using online meeting tools like Zoom and Microsoft Teams due to the geographical dispersion of the participants. The interviews lasted for 60 minutes and followed a general structure outlined in **Table 3**. They provided flexibility within the framework and an opportunity to explore participants' areas of expertise, thus enriching the research data (Fontana & Frey, 1998). The interviews were also structured to encourage participants to share

Table 3. Interview outline (Source: Author)

Theme	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 the recruitment process?
	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 do you educate yourself on the topic?
Benefit expectations	What benefits do you expect from using AI in the recruitment process, 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	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 do you think you can 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?

Interview outline (Source: Author).

their thoughts and experiences openly (Kvale, 1996), resulting in a more in-depth understanding of the research topic.

The interviews were structured based on the UTAUT constructs but it was customized to fit the research objectives, research participants and the research domain of RSP.

3.6.2. Data Analysis Approach

The data analysis process involved three steps: data transcription, encoding data, and thematic analysis. The first step involved multiple listens of the audio recordings, followed by generating transcripts using online software and cross-checking transcripts with the recordings to ensure accuracy. In the second step, personal information was encoded in accordance with research ethics guidelines to maintain confidentiality. Finally, the third step involved utilizing thematic content analysis (TCA) to comprehend the data gathered from the interviews. TCA was deemed necessary due to the diverse range of industries, demographics, and experiences represented by the three participant groups in this study (Holton, 1975; Jørgensen, 2001; Vaismoradi et al., 2013).

TCA is a deductive approach that can interpret qualitative and descriptive data, such as verbal conversations or expressions, and extract concepts to provide a more profound explanation of the data. It 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). By utilizing TCA, the study was able to analyze the data in a systematic manner to identify patterns and themes, which provided a more in-depth understanding of the research question.

The sample size of 17 human participants in our study has been determined based on previous research studies that have examined similar research questions related to the impact of AI in different business applications. Sample size in a qualitative study is often determined based on saturation, meaning that data collection and analysis continue until new information and themes no longer emerge from the data (Curty et al., 2023; Baghlaf, 2023). In this research after the 17th participant, data collection was stopped as the saturation point was reached.

4. Findings

4.1. Demographic Data

17 participants participated in the interview, and they represented the roles of a recruiter, hiring manager, or HR executive. The demographic profile of the interviewees is presented in **Table 4**.

Most of the participants in this study were from regions such as Oceania, Europe, and the Middle East. This trend can be attributed to the fact that data collection primarily took place through LinkedIn and UK-based alumni networks, both of which are predominantly populated by individuals from these regions. However, it is worth noting that the LinkedIn connections and members reached during data collection were representative of a diverse global population.

Table 4. Demographic data of the interviewees (Sorted by RSP role) (Source: Author).

Number	Country	Experience (years)	Industry	RSP Role
14	Australia	15	Natural resources	Hiring Manager
11	India	8	Banking & Financial	HR Executive
12	India	13	IT and Telecom	HR Executive
2	Australia	10	IT and Telecom	Recruiter
5	Philippines	10	HR and Admin Services	Recruiter
6	Philippines	4	Business process outsourcing (BPO)	Recruiter
7	India	4	Transportation and logistics	Recruiter
8	Pakistan	12	IT and Telecom	Recruiter
10	United Kingdom	16	IT and Telecom	Recruiter
13	Australia	13	Professional Services	Recruiter
15	Australia	3	HR and Admin services	Recruiter
1	Saudi Arabia	13	Manufacturing	Recruiter
3	Pakistan	5	HR & Admin services	Recruiter
4	India	14	IT and Telecom	Recruiter
9	Nigeria	9	Aviation	Recruiter
16	Netherlands	2	Legal	Recruiter
17	Netherlands	15	IT and Telecom	Recruiter

Demographic data of the interviewees (Sorted by RSP role) (Source: Author).

4.2. Participant Profile

The participants represented a wider industry representation as depicted in Figure 3 below.

The participants in this study possessed extensive experience in RSP and had recruited for a diverse range of job groups, ranging from small-scale hiring to large-scale recruitment efforts. A detailed breakdown of each participant's experience and profile is provided in the Table 5 below.

4.3. Main Findings

This study has centred on AI use in recruitment phases like recruitment pre-planning, sourcing, candidate engagement, pre-selection, and selection (interviews). Nevertheless, two interviewees, namely R4 and R13, indicated that onboarding is another phase that could potentially benefit from the use of AI. However, this phase was not incorporated into the present study since it occurs after the recruitment process (Bradt, Check, & Pedraza, 2010), and denotes the

Table 5. Interviewee profile (Source: Author).

Participant number	Role	Pseudo Code	Experience (In Years)	Candidate details
1	Recruiter	R1	13	R1 had extensive experience in recruitment, having worked as a national talent manager for a manufacturing company in Saudi Arabia, as well as in a retail company in the same region. With a total of 13 years of experience in recruitment, R1 was responsible for all aspects of the recruitment process, from candidate engagement to hiring manager collaboration, and focused on recruiting for middle to senior-level positions. Notably, R1 did not utilize external recruitment firms as part of the sourcing process.
2	Recruiter	R2	10	R2 was a talent acquisition partner for an IT company in Australia and was responsible for managing various HRM activities, including recruitment and strategic planning. He had a total of 10 years of experience in the RSP, focusing on recruiting for IT companies. R2 was involved in all phases of the recruitment process and did not rely on external recruitment companies for candidate sourcing. However, for middle to senior positions, he searched for potential candidates in other countries who were open to relocating to Australia if the recruitment process was successful.
3	Recruiter	R3	5	R3's professional experience is characterized by his dual roles as a Human Resource Manager and Operations Manager, which also encompass recruitment responsibilities. As an external recruiter, he managed his own recruitment agency and provided recruitment services to clients. While involved in all aspects of the RSP, he was not responsible for the final hiring decision, which was made by the hiring manager of the client company. R3 has worked in different industries, including IT, hospitality, and facilities management, where he primarily focused on recruiting junior blue-collar workers. R3's tenure in the RSP industry spans five years.
4	Recruiter	R4	14	R4 worked as an internal recruiter, assuming the role of HR business partner, with an experience of 14 years in recruitment, primarily in the IT sector. She was associated with a global IT consulting company, which has a workforce of over 2.5 million employees. During her tenure, she was actively involved in all phases of the RSP, recruiting junior to mid-level experienced candidates. R4's recruitment workload was high, with a volume of 250 candidates per month, which necessitated her to compete with other IT consulting companies in attracting and hiring top talent. She also led the hiring of MBA graduates from prestigious Indian universities, which she considers a successful strategy for attracting young talent to the organization.
5	Recruiter	R5	10	R5 had the official designation of Human Resources Specialist and worked as a recruiter in the Philippines for a total of ten years. During this time, he gained experience in recruiting for various junior to mid-level roles. Further details regarding his involvement in different recruitment processes, industries, or organizations are not available.

Continued

6	Recruiter	R6	4	R6 worked as a recruitment specialist in the Philippines, and all four years of her career involved hiring for junior to mid-level roles. Her primary focus was on business process outsourcing (BPO) roles, where most of her clients were based in the USA and had call centres or administrative services established in the Philippines. She had an average monthly fulfilment target of 65, which refers to the number of positions she was required to fill in each month.
7	Recruiter	R7	4	R7 worked as an internal recruiter for four years in India in the transportation and logistics industry, holding the official title of Recruitment and Payroll Manager. During his tenure, he was primarily involved in recruiting blue-collar workers, specifically drivers, for the organization. R7 was responsible for all phases of the recruitment process, including sourcing, screening, interviewing, and onboarding new hires. His average monthly fulfilment target was 28.
8	Recruiter	R8	12	R8 held the position of Technical Recruitment Specialist and worked as an internal recruiter with a focus on middle to senior-experienced candidates. He worked in Pakistan and hired an average of 20 candidates per month. In addition to his work as an internal recruiter, he was also an external recruiter for IT and startup firms and established his own recruitment agency.
9	Recruiter	R9	9	R9 served as a Talent Acquisition Manager in the aviation industry and was primarily involved in the recruitment of skilled and senior positions, such as pilots, cabin crew, and airport security agents for a Nigerian airline company. Having nine years of experience as an internal recruiter, R9 held the responsibility of overseeing the entire recruitment process for the company, from sourcing potential candidates to conducting interviews and making hiring decisions.
10		R10		R10 was employed by a multinational corporation that has a century-long history and is part of the Fortune 100 list. The corporation specializes in developing AI technologies that function as platforms for global companies. R10 worked for a division of this corporation, which functioned as a recruitment agency for other Fortune 100 companies on a global scale. Although based in the United Kingdom, R10's clients were primarily located in the United States of America. R10 held the official title of Talent Acquisition and Offering Lead and was responsible for designing and implementing talent acquisition strategies for other global corporations.
11	HR Executive	HRE1	8	HRE1 served as an HR Executive and held the position of Human Resource Manager for an Indian financial institute in the banking and financial sector. In addition to his role as an HR Executive, he acted as an internal recruiter, being responsible for hiring approximately 150 candidates monthly, resulting in 1800 candidates annually. HRE1 was involved in the recruitment of credit analysts, risk analysts, credit monitoring professionals, sales, and marketing managers, among others. His total experience in the industry amounts to eight years.

Continued

12	HR Executive	HRE2	7	HRE2 served as an HR manager and as a recruitment specialist. He also has his own recruitment agency which has been involved in hiring for various companies in India. He has been using LinkedIn as the main sourcing platform and had exposure to many AI technologies which have been requested by the companies he worked for.
13	Recruiter	R11	13	R11 was employed in an Australian professional services company and served as an internal recruiter. With the official title of Talent Acquisition and HR Business Partner, she was responsible for recruiting candidates for middle to senior positions, including director-level positions, in the accounting and auditing profession. In addition to being involved in all phases of the recruitment process, she also collaborated with external recruitment agencies to source suitable candidates.
14	Hiring Manager	HM1	14	HM1 was employed as a Business Development Manager and acted as a hiring manager for a natural resources company. His primary responsibility was to recruit sales and marketing professionals, with an average hiring volume of 2 - 4 hires per year. HM1 relied on the internal recruitment function of the HR division to aid in making hiring decisions, and although external recruitment agencies were available to him, he opted to utilize the internal recruitment team due to the low volume of hiring in his business division. HM1's career history includes working for retail companies in Russia before relocating to Australia.
15	Recruiter	R12	3	R12 was an employee of an Australian recruitment agency and had a tenure of three years. Her primary responsibility was to serve accounting clients by recruiting professionals holding a CPA certification. The official title she held was Recruitment Consultant, and her average monthly hiring rate was 15 candidates or 180 candidates per year. The roles she hired for ranged from junior to senior positions.
16	Recruiter	R13	2	R13 was employed by a legal firm located in the Netherlands, where she functioned as an internal recruiter. Her official title was that of a recruitment consultant, and she was entrusted with the task of employing legal professionals such as lawyers and partners within the said profession.
17	Recruiter	R14	15	R14 was employed as an internal recruiter by an IT enterprise situated in the Netherlands. Furthermore, he rendered recruitment services to client companies, primarily for executive-level hires. On an average basis, his recruitment activities resulted in hiring 3 individuals per month or 36 annually, which included C-level executives.

Interviewee profile (Source: Author).

conversion of a candidate into an employee thus is outside the scope of the study in RSP. The inclination to employ AI in the recruitment phases varied amongst the participants, and the underlying reasons for such variations are delineated in the following sub-sections.

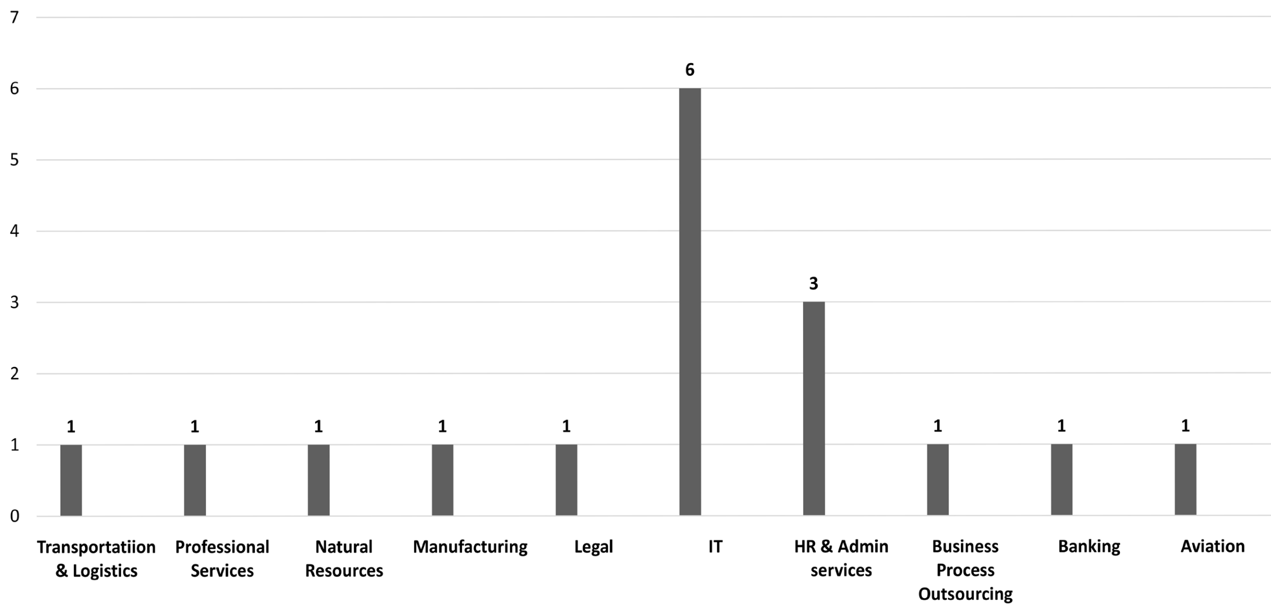

Figure 3. Industry representation of the research participants (Source: Author)

4.3.1. Recruitment Pre-Planning

The study revealed that most interviewees intended to use AI for recruitment pre-planning, except for a few participants (R1, R2) HR managers (HRM1/2) expressed a stronger inclination towards using AI in this phase of the recruitment process than recruiters. This finding suggests that the role of professionals in RSP may influence their adoption of AI in recruitment pre-planning. HR managers, who are more involved in recruitment planning (Cascio, 2018), may find AI to be more beneficial in this phase than recruiters who are primarily responsible for executing the hiring process.

The study also found that the intention of not using AI in recruitment pre-planning was associated with various factors such as the volume of hiring, job category, industry, and interpretation of AI capabilities. Some recruiters (R1) did not intend to use AI in recruitment pre-planning due to the perceived limitations in AI capabilities, particularly in handling a large volume of business data required for planning the future workforce. They explained (R1) that planning recruitment demands requires historical data as well as future strategic data, which their organization does not have. Thus, he suggested that many organizations in such situations may not be able to use AI since data is a main requirement for analyzing and detecting patterns, and thus predicting future patterns.

The challenges related to the limitations of data required in AI have also been reported in other industries, such as healthcare (Ahmed & Kang, 2019), where workforce pre-planning has been hindered by the lack of timely and usable data on the healthcare workforce. The study suggests that the current use of AI in recruitment pre-planning may be limited due to the lack of technology provisioning. Thus, this study provides insights that recruitment pre-planning may not be best in some industries due to the restrictions from data unavailability.

4.3.2. Candidate Sourcing

In the sourcing phase, 15 out of 17 interviewees expressed their intention to use AI, with LinkedIn being the primary platform. However, one recruiter, R7, who works in the transportation industry, did not express an inclination to use AI in sourcing, revealing a connection to industry and role type. R7 noted that the recruitment process for roles such as "vendor developers" and "marketing and sales managers" in the transportation industry is different from those in other industries like Finance or IT.

According to R7, these rural drivers deliver goods to rural areas in India where international transportation companies do not operate. Recruitment of these drivers occurs through word of mouth and referrals from rural areas, and most of them do not have resumes or use social media platforms like LinkedIn. Therefore, they must be sourced through local references. Thus, this informs implications from different industries and types of job groups in which AI can be used in the recruitment process.

4.3.3. Pre-Screening or Shortlisting

The willingness to use AI in pre-selection varies among recruiters, except for R5, R7, and HRE2 who do not plan to use AI in this stage. R4, on the other hand, reports a higher success rate in pre-selection by utilizing AI technology that assesses candidates against predetermined criteria. She took the candidates recommended by AI to the next level in the recruitment process. She also reported that every 7 to 8 candidates out of 10 recommended by AI ended up hiring. R4 praised the success of this AI tool and attributed the tool to the success of her organization being competitive and hiring the best candidates faster than her competitors. However, it should be noted that she was hired in a large volume in the competitive IT sector. However, not all interviewees shared the same view.

R5 preferred to evaluate candidates' behavioural traits, such as politeness, communication skills, and empathy, through direct interaction and thus was not inclined to use AI in the pre-selection. R7 cites the unavailability of data for certain job groups, such as truck or lorry drivers, as a reason for not using AI in pre-selection. The lack of AI capabilities to assess criteria such as empathy and mannerism, as well as the difficulty of evaluating certain job groups like blue-collar workers, may limit the use of AI in pre-selection, as reported by some RSP professionals. However, some RSP professionals intend to use AI in pre-selection to manage high-volume recruitment.

Overall, the preference for using AI in pre-selection varies among RSP professionals and depends on factors such as the nature of the job role and the volume of hiring managed and the industry. While some professionals report high success rates with AI assistance, others prefer direct interaction with candidates or cite the limitations of AI in assessing certain criteria or job groups.

4.3.4. Selection or Interviewing

The interview phase of the hiring process is often the most time-consuming and expensive aspect of recruitment, leading to increased hiring costs and longer time-to-hire (Cook, Cripps, & Tuckey, 2019). However, except for one participant, HRE2, most participants in a study on the use of artificial intelligence (AI) in recruitment did not consider AI suitable for the interview phase. HRE2, a vice president of a technology company in India, suggested that AI could be used as a cost-saving measure to replace downsized hiring managers.

However, R2 found AI assessment in interviews to be unreliable, and R10 stressed the importance of face-to-face interviews in addressing the variability of human behaviour during the selection process. And he feared that candidates may be hesitant to participate in interviews conducted entirely by AI and perceived it as an indication of that organization's lack of commitment to invest in selecting the right workforce for the company. Similarly, R11 emphasized the need to meet and get to know the candidate before making a hiring decision. R5, R6, and R8 in the hospitality industry agreed that face-to-face interviews are necessary to gain a "sense" of the candidate's suitability.

R12 assists big firms in hiring professionals such as auditors, Certified Practicing Accountants (CPAs), and financial advisors. However, R12 opposes the use of AI in candidate selection due to the skills shortage in this area and the limited candidate pool. On the other hand, R4 suggests using a combination of AI and human evaluators to enhance the selection process. According to R4, AI can be used in the initial stage to collect data on potential candidates, and the insights gathered can be verified through human evaluators during interviews to identify the top candidates.

R9 provided insights on industry-specific complexities in the selection process from her industry of aviation. R9, who is involved in the recruitment of pilots, stated that AI would not be able to evaluate personality traits crucial to the job. According to her, these personality and behavioural traits are unique to these positions like pilots or cabin crew and AI would not be able to assess such complex and situational leadership personality traits. Similarly, HM1, responsible for recruiting sales and marketing managers, highlighted the complexities associated with the interview phase and the limitations of AI in assessing candidates for such positions.

Thus, this insight provides unique perspectives on whether AI can be used in the interview phase. Most of the RSP professionals were not included in using AI in the interview phase, and the rationales were based on the different types of assessments required in certain industries and job groups.

4.3.5. Candidate Engagement and Communication

Candidate experience is a critical aspect of the recruitment process for many enterprises, as highlighted by Keaney (2021). However, as recruitment volume increases, it becomes challenging to maintain the same level of engagement based on human interaction (Fuchs, Schreurs, & Van der Velden, 2017). Thus, a significant proportion of interviewees, including R2, R6, R8, R9, R10, HRE1, and

HRE2, expressed their intention to use AI in candidate engagement. They believed that AI could automate certain recruitment activities, such as answering candidate questions, providing updates, and scheduling interviews.

Despite the anticipated benefits of using AI in candidate engagement, R13 raised concerns about the potential negative impact on candidate experience. According to R13, using a tool for the first interaction with the company might signal a lack of commitment from the organization thus may resulting in a decline in candidate experience.

R14, who was responsible for hiring executive-level candidates, opposed using AI in candidate engagement. He argued that candidate engagement at this level must be customized and involve human interaction. R14 stated that using AI might imply a lack of commitment on the organization's part and not provide the desired level of engagement with the candidate. In his view, executive-level candidates are passive candidates already employed in senior executive roles and require engagement through personal connections rather than a mechanical approach using AI.

R14 elaborated by stating that connecting with candidates on a personal level is a means of demonstrating the organization's appreciation for them. This connection justifies the investment of time and effort to establish a personal connection with executive-level candidates. However, it is worth noting that R4 and R9, who had experience in managing high volumes of recruitment, did not express similar concerns.

This observation suggests that the decision to use AI in candidate engagement is influenced by several factors, including the type of positions being recruited for and hiring volume.

Important comments made by research participants are listed in **Table 6** below.

5. Discussion

The present study investigated the impact of recruitment phases on the intention to adopt AI in the recruitment process. The recruitment phases that were examined include pre-planning, sourcing, pre-screening, interviews, and candidate engagement & communication. The findings revealed that RSP professionals are more inclined to use and adopt AI in sourcing and pre-selection, as opposed to pre-planning and candidate engagement & communication. Although pre-planning and candidate engagement showed mixed enthusiasm, most participants were not eager to use AI in the interview phase. The rationale behind their decisions is primarily related to providing a better candidate experience through human-based interactions, lack of trust in AI concerning the necessary capabilities required to perform the function in specific recruitment phases like interviews, limitations of infrastructure such as data availability used by AI technologies, and simply the nature of business or industry, such as manufacturing or transportation.

Table 6. Comments made by interviews (Source: Author).

Recruitment phase	Research participant	Comments
Sourcing	HM1	companies with a larger volume of hiring may benefit from AI for recruitment planning
	R2	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
Pre-selection	R7	most of these people don't have resumes. And they are not on social media or on LinkedIn. They must be sourced through local references
Pre-selection	R4	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
Interviews	R5	I prefer to talk to the candidates to get a feeling about the candidate
	R8	You would not marry a person whom you did date online. Would you? You want to meet the person and know the person better before you select the person to get married to. The analogy is the same when it comes to hiring a person
	R12	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.
	HM1	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 give the answer. I don't assume AI is going to help with such situational-based complex assessments.
	R11	even if AI can handle all these complexities, I still prefer to select candidates through human interaction
Candidate engagement and communication	R13	Candidate engagement is the first interaction a candidate has with the company. So that first interaction should not be with a tool.
	R14	"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."

Comments made by interviews (Source: Author).

5.1. Positive Rationales

Positive reasons for using or considering using AI in sourcing, pre-selection, and candidate engagement were related to managing a large volume of hiring in certain job groups, such as non-blue-collar or non-critical jobs.

5.1.1. Managing High Volume Hiring

The use of artificial intelligence (AI) has great potential in reaching a vast candidate pool by utilizing big data capabilities and advanced algorithms that require less involvement from human recruiters. Elia and Rodríguez (2019) state that AI can help identify potential candidates and engage them with personalized messaging, using large volumes of data to analyze and target underrepresented groups. They also noted that AI can assist in diversity and inclusion efforts by developing targeted recruitment strategies based on data analysis. Similarly, Ognjanović, Pamučar, and Stankić (2020) found that AI can analyze data from various sources, including social media, online job boards, and internal databases to help reach a broad candidate pool. Moreover, they suggest that AI can predict job performance and identify talent gaps in the recruitment process.

These findings support the rationale explained by the RSP professionals in this research to justify the usefulness of AI in the sourcing stage for high-volume hiring. Therefore, integrating AI into the recruitment process can be a promising way to reach a more extensive candidate pool.

5.1.2. Managing Non-Specific Job Group Hiring

The research findings indicate that RSP professionals are in favor of using AI for non-specific job groups, such as white-collar jobs like software engineers, sales and marketing professionals, and accountants. While specialized job categories such as pilots, mechanics, and C-level executives may not be suitable for AI-based recruitment, generic job groups are ideal for this approach.

These findings are supported by previous studies. For example, Black and van Esch (2021) demonstrated the potential of AI in recruiting employees across different industries, showing that it can automate the process, reduce bias, and enhance efficiency. Similarly, Collings and Mellahi (2019) found that AI can be used to recruit white-collar professionals such as managers, economists, and lawyers. They suggested that AI can assist in candidate selection, screening, and communication.

Overall, these studies along with the findings of this research provide evidence that AI can be a valuable tool for recruiting non-specific job groups.

5.1.3. Increasing Work-Life Balance

The research findings suggest that AI can improve work-life balance for recruitment professionals, which is a newly emerging theme. Research participants believed that AI could streamline and automate tasks like sourcing, pre-screening, and candidate engagement, thus reducing the workload and freeing their time.

This concept is supported by a study conducted by Collings and Mellahi (2019), who found that AI can help HR professionals work more efficiently and focus on higher-value tasks, leading to better work-life balance. Similarly, Haider and Anwar (2021) found that AI can reduce the workload of recruitment professionals, leading to lower stress levels and improved work-life balance. They suggest that AI can help recruitment professionals achieve a better work-life balance by enabling them to spend more time on important tasks like strategic planning, building relationships with candidates, and developing their skills.

5.2. Negative Rationales

5.2.1. Managing Low-Volume Hiring

The findings of this study have highlighted the effectiveness of AI in high-volume hiring. However, they pointed out that AI may not be suitable for low-volume hiring, which involves recruiting for specialized or niche positions that require a more targeted approach. This is because AI algorithms rely on vast amounts of data and may not have access to the specific data required for these positions, such as those for C-level executives (Galanaki & Papalexandris, 2019).

In addition, low-volume hiring requires a more personalized approach that may not be possible with AI. Galanaki and Papalexandris (2019) support this view, suggesting that recruitment for specialized positions requires a more human-centred approach, where recruiters are more involved in the sourcing, screening, and selection process. Similarly, Black and van Esch (2021) found that the use of AI in recruitment can have limitations in low-volume hiring, as it may not be able to capture the specific requirements and nuances of specialized positions.

Therefore, while AI can be effective in high-volume hiring, it may not be suitable for low-volume hiring, where a more personalized and human-centred approach is required.

5.2.2. Managing Specific Job Groups Hiring

The research participants in this study suggested that AI-based sourcing may not be effective in finding certain job groups, such as drivers and mechanics. These jobs are classified as occupational jobs by the Standard Occupational Classification (Bureau of Labor Statistics, 2022) and as blue-collar jobs by other scholars (Kalleberg, 2018). The reason why these jobs may not be feasible to source through AI is due to the unavailability of data in the required format or location for AI algorithms to access. For instance, drivers may not have resumes in the format that AI algorithms can use, making them difficult to reach through AI sourcing. However, Liu, Li, and Liu (2019) suggest that AI can be used to select blue-collar workers like drivers if data is available in the format that AI can use.

Several studies have highlighted the limitations of AI in assessing or selecting candidates for specialized job categories, such as pilots, as highlighted by the research participants of this study. The assessment criteria for these job categories are often complex and involve a combination of technical and non-technical skills, which may be challenging to evaluate using AI. Lievens and Chapman (2010) found that the effectiveness of AI in predicting candidate suitability for the job is highly dependent on the nature of the job and the assessment criteria used. They suggest that AI may be more suitable for assessing candidates for jobs that have clearly defined assessment criteria, such as sales or customer service, than for jobs that involve complex cognitive or non-cognitive skills.

Similarly, Ployhart (2006) revealed that although AI can predict the suitability of candidates for some job categories, such as customer service, it may not be suitable for assessing candidates for highly specialized job categories, such as pilots or surgeons, where non-technical skills like decision-making and situational awareness play a crucial role in job performance. The current research also provided insights into the limitations of AI in assessing personality traits, which were identified as critical by the research participants.

Therefore, it is crucial for organizations to carefully evaluate the nature of the job and the assessment criteria used before integrating AI into the recruitment process. While AI may be effective in recruiting for generic or non-specific job groups, it may not be suitable for highly specialized job categories that require a more nuanced evaluation of skills and abilities. Hence, it is recommended that AI be used as a complementary tool to aid human recruiters in the recruitment process rather than a replacement for human judgment.

Overall, this research highlights a critical finding on why AI may not be used to find certain blue-collar candidates and suggests further studies in this area to address gaps in the literature.

5.3. The Aversion to Use AI in the Interview Phase

This study strongly suggests that professionals in the field of human resources and recruitment do not accept the use of AI in the hiring process. Almost all research participants were averse to using AI in interviews, regardless of the volume or job group being hired for. This suggests that there may be a significant level of resistance to integrating AI into the recruitment phase of hiring, even for high-volume hiring jobs. It is worth considering the reasons for this aversion, such as concerns about fairness, bias, and transparency in AI-driven hiring decisions. These factors may be contributing to the reluctance of human resources professionals to embrace AI in recruitment. Other contributing factors to this aversion are the complex assessment criteria and the desire to provide a better candidate experience by "respecting" them and investing time in the interview phase. While these complexities may arise in certain recruitment phases like interviews, this finding highlights the importance of considering the perspectives and attitudes of human resources professionals when designing and implementing AI-based solutions for hiring. Thus, these insights provide some managerial interventions as suggested next.

6. Conclusion

This research interviewed 17 recruitment and selection professionals from various industries and found that the adoption of AI is dependent on the recruitment phases. Some recruitment phases are perceived to be receptive and benefit from AI, while other recruitment phases are not suitable due to the risks introduced by AI. As a result, they will be rejected, resulting in lower adoption.

The professionals are keen to use AI in the sourcing, pre-selection, and candidate engagement stages for high hiring volumes and non-specific job groups. They want to reduce workload, increase work-life balance, and increase the candidate pool. However, they are not keen to use AI in the interview phase regardless of the hiring volume or job group. The professionals are concerned about proving a better candidate experience and fear that using AI as the first interaction with the company indicates a lack of commitment to the candidates. HR leaders should carefully select the recruitment stage for integrating AI and address concerns raised by RSP professionals.

The research utilized a conceptual model that integrated the recruitment phase into the UTAUT theoretical model to uncover these findings, making them contextually relevant to AI adoption in recruitment and selection. By incorporating the recruitment phase into the UTAUT, the research offers a distinctive perspective, highlighting the need for specialized and contextualized theoretical frameworks to comprehend complex phenomena such as AI. The researcher proposes that the same conceptual framework could be applied to explore other emerging technologies, including the metaverse, ChatGPT, robotic process automation, augmented reality, and similar innovations in the recruitment and selection process.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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