RECRUITMENT IN THE AGE OF ARTIFICIAL INTELLIGENCE: HR PROFESSIONALS' PERCEPTION OF SMART RECRUITMENT TOOLS AND THEIR INNOVATIVE READINESS

by

Raghav Johar

Submitted in partial fulfilment of the requirements
for the degree of Master of Science

at

Dalhousie University
Halifax, Nova Scotia
August 2024

Dalhousie University is located in Mi'kma'ki, the
ancestral and unceded territory of the Mi'kmaq.
We are all Treaty people.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Recruitment in the Age of Artificial Intelligence: HR Professionals' Perception of Smart Recruitment Tools and Their Innovative Readiness

Raghav Johar

Artificial Intelligence (AI) is considered the next trend in the field of Information Systems (IS), with the advent of big and digitized data. This research delves into the same realm of AI with its application in the recruitment process focusing on the factors affecting the adoption of these tools. It also seeks to understand the role of personal innovativeness in influencing the tendency to adopt these tools. This Technology Acceptance Model (TAM) based research conducted a survey among Human Resources professionals actively involved in recruitment processes and used the partial least square and structural equation modeling (PLS-SEM) method to test the factors influencing the usage intention of smart recruitment tools. The factors analyzed were 1) Perceived Ease of Use (PEOU), 2) Trust Perception of the Tool (TP), 3) Compatibility (COMP), 4) Attitude (ATT), 5) Personal Innovativeness (PI), 6) Behavioural Intention to Use (BI), and 7) Perceived Usefulness (PU). This study augments TAM literature with a focus on AI-driven smart recruitment tools but also paves the way for future research. It underscores the intricate dynamics between trust, and effectiveness in technology, and user innovativeness.

LIST OF ABBREVIATIONS USED

AI	Artificial Intelligence
ATS	Applicant Tracking System
HRM	Human Resource Management
HR	Human Resource
TAM	Technology Acceptance Model
IS	Information Systems
PEOU	Perceived Ease of Use
TP	Trust Perception of the Tool
COMP	Compatibility with Task
ATT	Attitude
PIN	Personal Innovativeness
e-HRM	Electronic Human Resource Management
HRIS	Human Resource Information Systems

ACKNOWLEDGMENTS

I extend my profound gratitude to Dr. Bo Yu for his invaluable guidance, patience and expert supervision throughout this research. His insights and suggestions have been crucial in shaping this study into its current form. I am equally grateful to the committee members, Dr. Kyung Lee and Dr. Paola Gonzalez, whose tireless efforts and constructive critiques have significantly contributed to the refinement of this study. I would also like to express my gratitude to Dr. Helene Deval, who helped me throughout this journey and showcased immense support for my study.

I would also like to express my heartfelt thanks to my family in India for their unwavering support and understanding in making the most out of any given situation. Thank you for being a part of this educational journey. I would like to express my sincere gratitude to Jenna Green for her meticulous proofreading of my thesis. I would also like to extend my gratitude to Mira Tan for her critical comments on my research and the immense support throughout the whole process of my oral thesis defense.

I would also like to acknowledge the assistance provided by ChatGPT 4.0 in the preparation of this thesis. ChatGPT was used to edit certain sections of the research, ensuring clarity and coherence throughout the document. This tool played a significant role in refining the language, enhancing the fluency of the writing, and aiding in the paraphrasing of complex ideas.

Lastly, I would like to thank Dalhousie University for providing me with the platform to pursue my research ideas.

CHAPTER 1: INTRODUCTION

The birth of Artificial Intelligence (AI) owes much of its context to Alan Turing, who described it as "*the science and engineering of making intelligent machines*" (Turing, 1950, p. 44). There has been an upward trend in AI-related technologies as computing power has increased dramatically, and developers have access to large amounts of data.

AI is considered the next major advancement in Information Systems (IS). With the advent of big data, AI can transform many industries and our society in ways we cannot fathom at this point. Such changes in the field of IS have the potential to diversify human lives by altering the structure and functioning of various domains such as healthcare, education, employment, and business processes. Researchers have considered that AI and innovation are closely intertwined. Still, studies suggest the acceptance and impact of these technologies on innovation development and socio-economic factors that might be affected in the foreseeable future (Shin, 2020b; Lee, 2018).

AI, since its conceptual inception, has been envisioned as a discipline aimed at creating machines that can think and act with intelligence akin to humans. As noted by McCarthy et al. (2006), AI is the "*science and engineering of making intelligent machines, especially intelligent computer programs*" (p. 12). With an understanding of AI in this context, the study focuses on smart recruitment tools, which apply machine learning in recruitment. Through machine learning, the foundational philosophies of AI not only find a pragmatic trajectory but also pave the way for further innovations that continue to redefine the boundaries of what machines can achieve. These advancements in machine learning and AI are not just theoretical breakthroughs, they are fundamentally transforming practical applications across various industries. In Human Resource Management (HRM), these tools are being integrated into the system like Human Resource Information Systems (HRIS). As the markets continue to evolve and new technological advancements emerge, understanding these shifts becomes particularly crucial in developing countries. Particularly, India provides a good environment for investigating these market shifts because the country is at a unique position as a rapidly developing economy with a vast and diverse population and has generated large demand for recruitment in HRM. This shift is a response to the broader technological, cultural, and political changes shaping the Indian market, where the adoption of AI is redefining traditional HR practices.

There have been studies in the past which identified the key applications of HRIS in India. Among HR professionals, recruitment and selection was the most used application (67.2% and 71.9%, respectively) followed by payroll services (67.2%), performance appraisal services (62.5%), and job analysis and design (62.5%) (Saharan & Jafri, 2012). Leong (2017) states, "*Most of the authors are silent about the theoretical lens used to study artificial intelligence in the recruitment process*" (p. 489). The Indian market has been undergoing significant transformations due to rapid technological advancements and evolving cultural and political dynamics. This shift has also been noteworthy with the rise of startup culture, which has introduced new challenges and pathways for HR departments. The emergence of a vibrant startup ecosystem in India, characterized by a surge of new ventures and entrepreneurial activities, has further impacted HR practices. Startups often require agile and adaptable HR strategies to manage a diverse and rapidly changing workforce. This has raised critical questions about HR's preparedness to handle these new challenges effectively. It has been found that HR technologies have an estimated market of $940 million in India alone in 2022, and these numbers are expected to grow over the next few years. Firms have invested highly in certain aspects of the HR management lifecycle, such as people analytics, recruitment, talent acquisition, payroll management, and performance management (Future-Ready HR: A Comprehensive Overview of HRTech in India, 2024). It has been found in a qualitative study that AI in recruitment functions follows three sub-themes as stated by Mehrotra & Khanna (2022), "*current state of adoption, factors to consider while adopting AI, and level of technology integration*" (p. 36). It was also noted that large-scale companies such as TCS, Deloitte, Tech Mahindra, and Infosys have certain processes that are already being handled by AI-empowered recruitment tools. It is important to recognize that the integration of technology in recruitment processes is currently at an intermediate stage. While advancements like AI are becoming more popular, their implementation is not yet fully comprehensive across all organizations. Many companies are still in the early phases of incorporating these tools, with varying degrees of sophistication and coverage. This highlights the ongoing transition within the industry and underscores the potential for further development and optimization of technology-driven recruitment. As noted by Mehrotra & Khanna, (2022)

> "*Concerning the Indian context, the technology adoption level is slower than in countries such as the USA and Japan. Hence, AI is popular in the Indian recruitment industry; however, its adoption is a little slow due to a lack of infrastructure available. Certain factors are responsible for adopting AI, such as the organization's size and scale and the cost-benefit*." (p. 38)

Table 1 below illustrates the specific stages of the recruitment cycle where different organizations in India implement AI technology.

Industry	Organizations	Recruitment Cycle				
		Sourcing	Screening	Interviews-Scheduling	Interviews	Others
Consulting	Deloitte		✔			
	Morgan Stanley	✔	✔	✔	✔	✔
Banking & Finance	Goldman Sachs				✔	
	Std Chartered Bank					
	IBM	✔	✔			✔
Information Technology	Infosys		✔		✔	✔
	MindTree	✔	✔			✔
	Tech Mahindra	✔	✔			✔

Table 1: Adoption of AI tools in the recruitment Adapted from Malaha & Pandey (2023)

An example of AI tools such as TurboHire[1], Manatal[2], and among others are getting deployed in the HR departments of various industries. The integration of AI in the recruitment process has been transformative for HR functions, such as resume screening, which can now be automated to increase efficiency and reduce the possibility of human bias. AI-powered recruitment software can analyze thousands of resumes in a fraction of the time it would take a human recruiter, in addition to helping them identify potential candidates based on predefined criteria. The objective of this study is to investigate the factors influencing the adoption of these tools within the recruitment process framework in a developing nation like India with upcoming start ups and various small and medium enterprises.

[1] TurboHire - Biswas, N., & Khemka, M. (2022). Artificial Intelligence and its Role in Human Resource Management. Indian Business@ 75: Research on Trends and Prospects, 375.

[2] Manatal - Jayakumar, N., Maheshwaran, A. K., Arvind, P. S., & Vijayaragavan, G. (2023, April). On-Demand Job-Based Recruitment For Organisations Using Artificial Intelligence. In 2023 International Conference on Networking and Communications (ICNWC) (pp. 1-6). IEEE.

There is extensive literature surrounding the study of trust perception in AI and various algorithm-driven decision-making tools that imply the trustworthiness of the tools that are used in various organizations (Choung et al., 2023). It is crucial to understand the role of functionality trust, which can be defined as the competence and expertise of the technological features of the tool (Mayer et al., 1995). Furthermore, numerous studies consider the compatibility of the tool with the required task, which explains the congruency of the system with the expectancies of the task as e-learning systems using educational compatibility to understand the behavioural intention. Research shows that improved educational compatibility enhanced the acceptance of the e-learning system (Xu & Wang, 2006, Chen, 2011) which offers an extension to the Technology Acceptance Model (TAM) by analyzing the effects of personal innovativeness on usage intention.

These AI technologies have brought significant changes to the IT landscape as well. They necessitate advanced IT systems capable of handling large volumes of data, processing complex algorithms, and managing the integration of various AI functionalities with existing HR systems. Consequently, the rise of AI in HR has also elevated the importance of robust, secure, and efficient IT infrastructure, fostered innovation, and pushed for improvements in data management, system integration, and security protocols. In essence, the adoption of AI-empowered recruitment (or smart recruitment tools) is reshaping the HR department of different industries and driving technological advancements in the broader IT field. To understand the adoption of AI-empowered recruitment tools, the following research questions are formulated:

1. *What key factors among perceived ease of use, perceived usefulness, trust perception, and compatibility shape HR professionals' intention to adopt smart recruitment tools via forming a positive attitude toward the tools?*

2. *How does HR professionals' innovativeness moderate the relationship between attitude and intention to use smart recruitment tools?*

To answer the research questions, based on the TAM (Davis, 1989; Venkatesh & Davis, 2000) in conjunction with existing literature on the adoption of AI in different contexts, this study intends to investigate the behavioural intention to use smart recruitment tools. Specifically, it examines how trust perception, perceived ease of use, perceived usefulness, and compatibility influence the attitude of HR professionals using the tools in different organizations. Furthermore, the research explores the moderating effect of personal innovativeness on the relationship between attitude and behavioural intention to use smart recruitment tools. Additionally, it analyzes the relationship between perceived ease of use and trust perception regarding smart recruitment tools.

Findings from the survey data collected from HR professionals working in recruitment processes in organizations based in India with at least one year of experience in the process underscore the importance of the trust perception of individuals towards smart recruitment tools. Trust perception plays a crucial role in forming positive attitudes amongst the users directly influencing the behavioural intention to use smart recruitment tools. Moreover, the relationship between attitude and perceived ease of use was found to be crucial and relevant to the context of smart recruitment tools. Perceived usefulness is another important factor in influencing the intention to use these tools. Contrary to prior studies, compatibility did not significantly influence the attitude of professionals toward using smart recruitment tools. Personal innovativeness, contrary to expectation, also did not have any significant moderating effect on the relationship between attitude and behavioural intention to use.

The findings of this study offer various theoretical contributions. It contributes to the theory of the TAM. This study applied the following theoretical framework to investigate the factors affecting the adoption of smart recruitment tools used by HR professionals. This study also adds trust perception as an important construct when studying applications of artificial intelligence. The results underscore the significance of perceived ease of use and perceived usefulness in fostering positive attitudes toward smart recruitment tools. Data collected brings forth certain practical insights that provide executives and employers with a deeper understanding of the factors that drive behavioural intentions to adopt smart recruitment tools. By focusing on enhancing perceived usefulness, ease of use, compatibility, and trust, executives can develop effective strategies to promote adoption. Managers should focus on strategies that enhance employees' attitudes towards smart recruitment tools such as: communicating benefits like increased efficiency and better candidate matching, and addressing any concerns related to job displacement or changes in job roles.

The upcoming sections of this study will explore the role of AI in recruitment processes. The study will examine how AI is used in decision-making, electronic human resource management, and smart recruitment tools. This study will also outline the research model and hypotheses. Furthermore, the methodology for the survey and data collection will be discussed in detail. Finally, the findings of the study will be presented, along with its limitations, and concluding statements will be provided.

CHAPTER 2: RESEARCH BACKGROUND

To competently develop insights about the influence of AI, it is essential to understand the confluence of technology, philosophy, and practical utility. Thorough comprehension of the core of AI requires a thought process beyond the binaries of codes and algorithms and into the realms of rationality, cognition, and philosophical thinking, cognition and rationality. Russell & Norvig (2010) explains "*A system is rational if it does the 'right' thing, given what it knows,*" (p. 1) which delves into the decision-making processes involved in various AI systems in multiple fields such as healthcare, management, public relations, marketing, and human resources. The 'right' thing may not entail moral or ethical values. Every decision-making entity, whether human or machine, functions within the range of its knowledge. In the case of AI systems, the raw knowledge is the data that has been trained on using software or algorithms and any real-time information the system may gather. The decisions made by the system are only as good as the data that is provided to it during the training.

Ongoing issues of constant knowledge expansion and algorithm refinement can be categorized into a 2×2 matrix form, where each position explains the understanding of AI systems in a world, which is multifaceted but is also constantly changing due to the unprecedented amount of data production.

The Ever-Expanding Knowledge Base AI systems depend on data. Data fuels their decision-making processes, empowers them to recognize patterns, and grants them the ability to predict, recommend, or decide.	**Refining Knowledge Base** As better accuracy is achieved, the complexity of the system increases, which creates a black box effect, where it's hard to interpret how they derive specific decisions. Bias in algorithms is an issue, so it is crucial to understand the importance of ethical, unbiased, and fair algorithms.
Aligning Decisions with Desired Outcomes Human-AI collaboration ensures that the decisions are aligned with the desired outcomes. Systems where humans and AI systems work together can combine computational efficiency with human ethics.	**Beyond the Binary** AI systems should be capable of navigating through ambiguity. As AI is integrated into almost all critical systems, ensuring there are fail-safes is crucial to operating safely and without causing harm.

Table 2: AI and Its Challenges Adapted from Russell & Norvig, (2010)

Four streams of thought have provided foundations for the birth of AI, "*thinking humanly*", "*thinking rationally*", "*acting humanly*", and "*acting rationally*" (Russell & Norvig, 2010). This study aligns with one of the thoughts, i.e. "*acting rationally*". As the world has started advancing in developing AI systems, the challenge remains in expanding their knowledge bases and refining their algorithms.

2.1 Usage of AI in Decision-making

AI, especially Machine learning algorithms, has changed the structure of various industrial sectors by introducing unmatched levels of efficiency, predictive power, and automation. As Zhang et al. (2020) explained, "*Machine learning models can perform impressively, in many situations full delegation of machine learning models is not desired because their probabilistic nature means that there is never a guarantee of correctness for a particular decision*". (p. 295). Autonomous systems are favoured instead of users performing certain tasks utilizing control systems, instead of the social norms, regulations, and institutions that govern human agents when performing tasks. Such systems can perform tasks without the intervention of these laws and regulations (Yu et al., 2021). There have been a significant number of issues when the user-artifact relationship is considered in IS research. The shifting of technological preferences poses questions such as neglecting the features of IT artifacts or the weak conceptualization of user-artifact combinations.

This model in Figure 1 from Yu et al., (2021) serves as a helpful tool to categorize and comprehend the artifacts based on two primary dimensions: how the systems participate in decision-making processes and how they affect the broader world. The proposed 2 x 2 matrix, as seen in Figure 1, will provide a comprehensive framework to understand the multifaceted realm of autonomous artifacts. By categorizing these artifacts based on their role in decision-making and the impact of their actions. The potential benefits and pitfalls can be understood. It can be noted from such interference that a hybrid model that builds upon a collaboration of human experts and AI models is crucial for decision-making. This transformation of hybrid models is extremely evident in the domain of HRM, a field that has benefited immensely from the integration of AI.

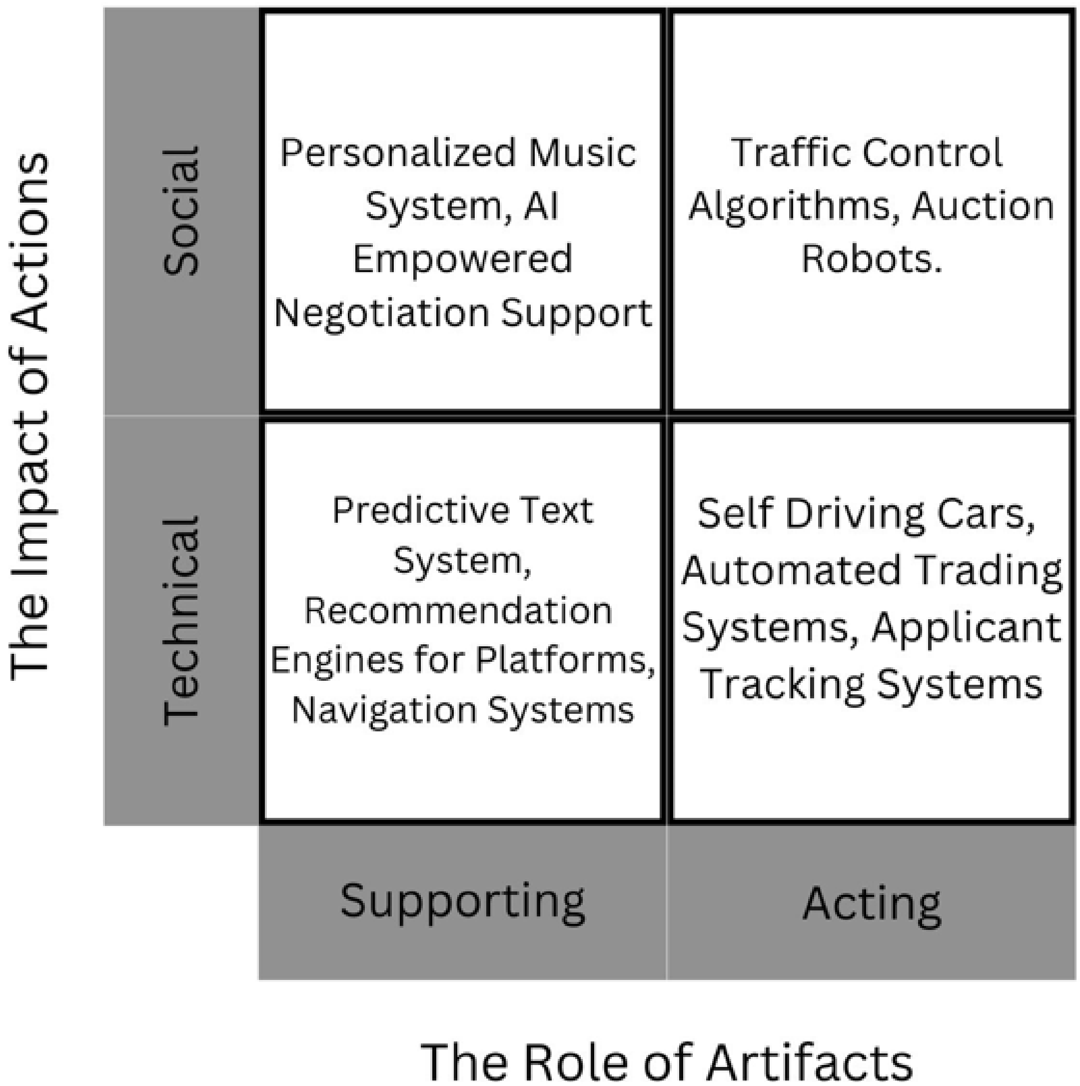


Figure 1: Example of AI Artifacts Application Adapted from Yu et al., (2021)

HRM is understandably seen as a human-centric department, which now relies on AI to streamline processes, reduce biases, and make more informed decisions about potential and current employees. The swift adoption of AI highlights numerous quantifiable advantages stemming from its learning and predictive capabilities. Effective utilization of AI in organizational decision-making necessitates a comprehensive understanding of both its strengths and limitations. Despite the continuous development of AI, the use of AI in a decision-making process would still require that the manager using the technology be held responsible for any outcomes (Shrestha et al., 2019). One of the most prominent recruitment tools used in HRM is the Application Tracking System (ATS), which assists companies in managing recruitment processes efficiently. ATS is responsible for sifting through an abundance of applications and scanning numerous resumes for keywords and qualifications that align with the job's requirements stated in the job description. Introducing automation will reduce delays in the initial stages of the hiring process of new employees, while also providing a prediction of future performance, cultural fit, and potential tenure. These predictions are developed based on assessing data from previous candidates and ensure that decision-making processes are forward-thinking and consider not just individual, but future organizational needs as well.

The power of trust perception in the field of human-computer and human-machine interactions, and whether users decide to trust or accept the decision provided by the system, has been extensively researched. Recently, understanding trust and usage intention towards machine learning models and AI has been an area of interest in the field of management information systems, rapidly increasing the research in the field of adoption of AI and machine learning (Zhang et al., 2020). Human decisions, especially in HR, are nuanced and multifaceted, while AI offers objectivity. Due to contradictions in perspectives and understandings, there can be underlying skepticism about AI's ability to completely hone the skills of an applicant despite the help of an algorithm based on extensive datasets.

As a result, this leads to another paramount consideration, the compatibility of the task. While the initial screening and filtering of candidates via smart recruitment tools is well suited for the automation of other tasks, in-depth interviews or conflict resolution still require human intervention. It is essential to delineate which tasks can be efficiently automated and which ones benefit from the human touch. Therefore, expecting AI to completely replace a department as old as HRM can lead to suboptimal outcomes. Furthermore, the usage of AI in decision-making can be linked to the ease of use of the technology, which is essential for its implementation.

2.2 Artificial Intelligence and Human Resource Management

The literature on HRM, HRIS and AI adoption in HR presents a broad spectrum of research, highlighting various aspects of technology integration and its impact on HRM. In the current study, a total of 25 published papers were identified to evaluate the present state of research in these areas. The review identified that substantial attention has been given to the general adoption of HRIS and HRM technologies. The acceptance of smart recruitment tools remains underexplored. This gap underscores the need for further investigation into how these tools are embraced within recruitment processes. Table 3 offers a summary of the research context, findings, and methods employed from previous studies.

HRM is a comprehensive and strategic approach to managing people within an organization (Boselie, 2014). It encompasses activities designed to optimize employee performance, align workforce capabilities with organizational goals, and foster a productive and engaging work environment. HRM involves key functions such as recruitment and selection, performance management, employee relations, and compliance. One defining characteristic of HRM is its holistic and integrated perspective (Kaur et al., 2021). For instance, in HRM, recruitment is not just about filling positions but is closely linked to the organization’s broader talent management strategy (Panda et al., 2023). It can also be noted that with the advent of the Fourth Industrial Revolution, AI played a critical role in HRM. It has been deployed in almost all processes in HR practices. HRM conducts a substantial amount of data through various tasks such as performance management and organizational operations, which can be handled efficiently and sustainably with the help of AI integration (Nawaz et al., 2024).

Access to highly skilled individuals is easier with the acceptance of AI in HRM (Meshram, 2023). There is a new approach to tackling HR processes such as performance management and talent management while providing vast opportunities for HR professionals to utilize AI (Khaled et al., 2023; Hemalatha et al., 2021). AI-powered tools and technologies have enabled HR professionals to efficiently identify, evaluate, and engage top talent. This has been possible by overcoming different traditional barriers associated with recruitment and talent acquisition, which explains that the shift is not merely about enhancing operational efficiency. It also incorporates strategically placing organizations to compete in an increasingly globalized and competitive talent market. The increasing adoption of AI in HRM is propelled by its capacity to create significant value for employees, and organizations (Chowdhury et al., 2023). Research has shown that AI offers valuable solutions for HR professionals, streamlining processes from applicant screening to employee retention. By automating tedious and repetitive tasks, AI not only frees up the HR team to focus on more strategic initiatives. Additionally, AI's ability to minimize biases in decision-making contributes to more objective and equitable outcomes (Hmoud & Varallayi, 2020). As stated by Kalia & Mishra (2023), "*The application of AI in HRM is perceived as an optimistic opportunity since it ought to bring maximum value at minimum cost*" (p. 221). It is critical to understand the current condition of AI capabilities in HR procedures while it continues to expand and progress (Nawaz et al., 2024). Managers should be prepared to evaluate their IT infrastructure to implement AI functionalities into existing workflows and procedures (Nawaz et al., 2024). Studies have shown that AI plays a vital role in HRM. Companies and organizations have been utilizing new technologies and tools to attract and select new candidates from a globalized market (Van Esch & Mente, 2018).

The provided context explains the need for research in the field of AI capabilities within HRM. This also underscores AI's capacity to create value for organizations by enhancing the quality of hires, reducing the time to fill positions, and ensuring better candidate-organization fit. The need for organizations to adapt their IT infrastructure to integrate AI technologies is becoming increasingly crucial. Studying AI-powered recruitment tools is essential for understanding how these tools contribute to strategic HR goals, maximize efficiency, and promote fair hiring practices, making them a vital area of research in the evolving landscape of HRM.

Study	Context	AI Application	Theory	Independent Variables	Moderating Variables	Dependent Variables	Data Collection	Analysis	Key Findings
Hmoud & Varallyai, (2020)	HRIS	AI-HRIS	UTAUT	Facilitating Conditions, Technological Readiness, Performance Expectancy, Trust	Age and Experience	Behavioural Intention	Survey	PLS-SEM	Trust and a favorable attitude are crucial factors influencing the incorporation of emerging technologies. The importance of technology readiness and supportive conditions is declining.
Sivathanu & Pillai, (2018)	Smart Human Resources 4.0	Talent Management	SHR Framework	Emerging Technologies, Talent Onboarding and Offboarding		SHR Adoption	Case Study		An organization needs an effective SHR framework to navigate transformational challenges successfully.
Bhatt & Shah, (2023)	AI in HR practices	HR activities	Technology Readiness Index, Technology Acceptance Model, and TOE model			Change Readiness	Survey	EFA	Employees are knowledgeable about AI and its application in HR practices but remain cautious about certain aspects of it.
Handra & Sundram, (2023)	HRIS	HRIS in the defence industry		HRIS and Job Satisfaction		Employee Performance	Survey	PLS-SEM	HRIS has a strong connection to job performance, while AI is closely linked to employee performance.

Study	Context	AI Application	Theory	Independent Variables	Moderating Variables	Dependent Variables	Data Collection	Analysis	Key Findings
Panda et al., (2023)	HRM applications	Digitalisation, Machine Learning	UTAUT	Competitive pressure, performance expectancy, management support		AI adoption	Survey	CFA	Increased performance expectations and strong management support are both key predictors of AI adoption.
Masum et al., (2018)	HRIS	i-HRIS		Input & Decision Processing Subsystems,		Knowledge Extraction			A proposed intelligent HRIS equipped with essential systems.
Sivathanu & Pillai, (2020)	IT firms	Talent acquisition	TOE and Task Technology Fit	Relative advantage, HR readiness, competitive pressure	Stickiness to traditional methods	Actual usage of AI	Survey	PLS-SEM	Economic efficiency, competitive edge, executive endorsement, HR readiness, and backing from AI vendors all favorably impact the adoption of AI technology.
Yadav & Kapoor, (2024)	Business firms	Employee recruitment	TOE model, transaction cost theory	Relative advantage, firm size, industry, regulatory	Asset specificity, uncertainty	AI usage	Survey	CFA	Businesses' views on the complexities of AI serve as a barrier to its implementation, while technological competence and regulatory support are factors that encourage its adoption.
Kaur et al.,	HRM domain	Artificial Intelligence	TOE, Technology	Relative advantage,	Adoption of AIT in				The study notably aligns with current

Study	Context	AI Application	Theory	Independent Variables	Moderating Variables	Dependent Variables	Data Collection	Analysis	Key Findings
(2021)		Technologies (AIT)	Adoption Model	compatibility, HR readiness, perceived ease of use, perceived usefulness	HRM				theoretical models, enriching the research on AI technology adoption.
Tuffaha et al., (2022)	HRM domain	AI-powered chatbots	Development of chatbots in different contexts			Usefulness and limitations of chatbots	Interview		The necessity for advanced chatbots in recruitment arises due to the substantial positive impact of effective hiring on employee performance.
Kumar et al., (2022)	Micro, small, and medium enterprises	AI-powered workforce management	AI-based WFM drivers	Intelligent risk management, information sharing, workforce management, business and marketing		Effective revenue growth	Survey	SEM	AI-powered workforce management can support revenue growth, streamline the workforce, enable intelligent business and marketing strategies, and facilitate information exchange.
Pan et al., (2023)	HRM in Chinese companies	AI in HRM	TOE model and transactional cost theory	Relative advantage, complexity, firm size, industry, regulatory	Asset specificity, uncertainty	AI usage	Survey	SEM	Perceived complexity hinders AI adoption, whereas technological competence and regulatory support promote it.
Islam et al.,	HR departm	AI in human	UTAUT	Effort expectancy,		Actual behaviour	Survey	PLS-SEM	Performance expectancy, effort

Study	Context	AI Application	Theory	Independent Variables	Moderating Variables	Dependent Variables	Data Collection	Analysis	Key Findings
(2022)	ent in Bangladesh	resource analytics		social influence, facilitating conditions, perceived credibility					expectancy, social influence, and facilitating conditions significantly influence the intention to use.
Huang & Martin-Taylor, (2013)	e-HRM		Technology acceptance model					Action research approach	HR can take a more active role in influencing users' perceptions of technology acceptance by gaining a deeper understanding of how to develop, implement, and evaluate systematic interventions.
Panos & Bellou (2016)	e-HRM in Greece		Extension of technology acceptance model, Ulrich's HRM goals	e-HRM goals, HRM role,		e-HRM outcomes	Survey	SEM	In the interaction between HRM functions and results, administrative experts typically attain primary results, while change strategists are more likely to accomplish transformational outcomes.
Kolatshi, (2017)	HRIS in Libya		Information systems success model, technology	Organisational factors, social factors, perceived usefulness,		Turnover intention	Survey	Regression analysis	Perceived usefulness, ease of use, and risk influence a positive attitude toward the tool. Additionally, perceived

Study	Context	AI Application	Theory	Independent Variables	Moderating Variables	Dependent Variables	Data Collection	Analysis	Key Findings
			acceptance model	satisfaction, ease of use					usefulness, social risk, and influence, company support, communication, and attitude predict the intention to use it.
Votto et al., (2021)	Tactical HRM	AI in HRIS	Strategic and Tactical Perspective					Systematic literature review	This paper examines the tactical HRIS (T-HRIS) components discussed in the literature and analyzes how each component is represented.
Nawaz et al., (2024)	HRM	AI in HRM	Conceptual HRM Framework	Accuracy, automation, capacity, real time experience, and personalization		Time saving and cost reduction	Survey	SEM	Accuracy, computing power, capacity, and personalization have a significant impact on saving time and reducing costs.
Horodyski, (2023)	Recruiting talent	AI-powered tools	UTAUT	Performance expectancy, effort expectancy, social influence, facilitating conditions	Voluntariness of use	Behavioural intention	Survey	Hierarchical regression analysis	Behavioural intention was significantly and positively affected by performance expectancy, with the frequency of AI use acting as a moderating factor.

Study	Context	AI Application	Theory	Independent Variables	Moderating Variables	Dependent Variables	Data Collection	Analysis	Key Findings
Laurim et al., (2021)	Recruitment	AI-based recruiting	Technology acceptance model	Ease of use, perceived usefulness, technological readiness		Intention to use	Interview	Coding	Recruiters, managers, and applicants consider transparency, the supplementary features of AI tools, and a feeling of control as key elements influencing the acceptance of AI-based technology.
Troshani et al., (2011)	Public sector organizations	HRIS	TOE model	Environment context, organizational context, technology context		HRIS adoption	Interview	Coding	In public sector organizations, showcasing the benefits of HRIS is essential for successful adoption.

Table 3: Literature Review on AI applications in HR

2.3 Adoption of AI in HRIS and Recruitment

HRIS has been evolving rapidly with numerous technological advancements, which has gained much attention from HR leaders and researchers alike. It has been confirmed that these systems contribute to saving costs and gaining competitive advantage (Hmoud & Varallayi, 2020). Chatbots, search engines, and automation tools are being utilized to source, interact, and shortlist candidates, boosting the selection process's efficiency (Hmoud & Varallayi, 2019). Chowdhury et al., (2023) noted "*Organisations are investing in AI-enabled HR software packages to collate and make sense of the employee data available for achieving strategic organizational goals*" (p. 33). Originally, AI's role in HR was primarily associated with developing expert systems for job evaluation (Margherita, 2022). However, its application has since expanded to encompass activities throughout the entire HR life cycle. It was found in a Hong Kong organization that HRIS facilitated faster responses and improved access to information (Ngai & Wat, 2006). Krishnan and Singh (2007) noted that the HR department's limited understanding of HRIS hinders its ability to clearly articulate system requirements, leading to inadequate needs assessment. Additionally, the HR department is often not prioritized within the organization, further exacerbating the issue. It was concluded that HR professionals foster a positive attitude and show trust toward new emerging technologies, which includes the integration of AI to support HRM processes.

Recruitment is one of the key processes in the HR department, it has been enhanced with the help of HRIS. As noted by Horodyski (2023) "*Recruitment encompasses the entire process of attracting, screening, and appointing available qualified candidates for available positions in an organization*" (p. 2). AI is now enhancing the selection process by utilizing algorithmic assessment platforms designed to minimize bias and enhance objectivity. Using predictive analysis and neuroscience, HR professionals can effectively eliminate both conscious and unconscious biases. These technologies also enable the identification of emotional traits, soft skills, and cognitive characteristics, ensuring the selection of the most suitable candidates (Horodyski, 2023). AI plays a crucial role in fine tuning recruitment strategies, AI-powered tools transform the traditional recruitment processes by automating routine tasks, such as resume screening and candidate shortlisting. Laurim et al., (2021) carried out a qualitative study utilizing Davis's (1989) TAM model to explore AI acceptance criteria among recruiters, managers, and job seekers in the recruitment process. The study conducted by Laurim et al., (2021) indicates recruiters' motivation to integrate AI into their daily tasks is largely driven by the technology's capacity to enhance individual job performance.

Given the emerging nature of AI in recruitment and HRM, coupled with the fast-paced technological advancements and their profound impact on the recruitment industry, exploring this area presents a compelling opportunity for further research (Horodyski, 2023). As AI-driven tools increasingly redefine recruitment processes, understanding their influence, effectiveness, and adoption becomes crucial. This is particularly important for the study of smart recruitment tools, which not only streamline operations but also offer the potential for more strategic, data-driven hiring decisions (Meshram, 2023).

2.4 Smart Recruitment Tools and Electronic-Human Resource Management

Smart recruitment tools, developed by software providers, are integrated into a company's recruitment process. These tools transform the traditional candidate selection process (Votto et al., 2021). Instead of simply submitting a CV and motivation letter, candidates now undergo various digital assessments, such as culture fit evaluations, personality tests, language proficiency assessments, and video interviews. These tools aim to automate repetitive tasks that would typically fall to recruiters. AI-powered tools share certain similarities, but their level of technological sophistication can differ (Pan et al., 2023). As noted by Turkeli (2020), "*AI-powered tools are part of the increasing trend of new computing platforms. Technological advancements have enabled vendors to open their infrastructure technologies to other companies*" (p. 16)

A comprehensive understanding of recent developments in the HRM field is essential, as the evolution supports the increasing involvement of IT in the recruitment process, as well as other HR functions. The introduction of Electronic-Human Resource Management (e-HRM) in workforce management, employee portals, and recruitment through HRIS has transformed traditional HR into a more efficient and cost-effective framework. e-HRM plays a vital role in the generation of employment opportunities for both developed and developing economies. In recent times, small and medium-sized enterprises have also incorporated the technologies and tools to integrate HRIS into the organizational structure. This integration helps in the optimization of process management, cost-savings, and efficient undertakings in the organization

(Mukherjee et al., 2014). The main motivation for adopting electronic recruitment is to make the process of recruitment more efficient and cost-effective. Such tools leverage technology to streamline various stages of hiring, from posting job vacancies and screening resumes to communicating with candidates using chatbots. A global survey supports the usage of digital transformation as 32% of the respondents are developing their firms to become more adaptable to the changes in technological systems (Mehrotra & Khanna, 2022). Manual resume screening is often inefficient, as about 75% to 80% of the resumes submitted for a position are unqualified. On average, a recruiter typically spends approximately 23 hours screening and shortlisting candidates for a single position (Albert, 2019). AI-powered recruitment tools have the potential to revolutionize this process by automating the alignment of candidate data such as knowledge, skills, and experience with specific job requirements (Kumar & Nagrani, 2020). While AI's role in recruitment and selection has primarily focused on screening and sourcing candidates, its application can be utilized in various other domains within the recruitment process such as predicting vacancies, administering psychometric tests, and performing background checks. This broader application can significantly enhance the overall efficiency and effectiveness of the recruitment process (Mehrotra & Khanna, 2022).

An important application in the e-HRM system is the usage of information extraction, which is commonly referred to as "*CV parsing*". The following function is achieved with the support of ATS, which is described by Mukherjee et al., (2014) as, "*a software application that enables the electronic handling of recruitment needs. At an enterprise level, it functions as a module or functional addition to the HRIS. Most of the reputed business organizations use some form of applicant tracking system to handle job applications and to manage resume data*." (p. 5). There have been recent improvements in ATS, which include the introduction of AI and natural language processing to support the usage of semantic search abilities through cloud-based servers, which makes it easier for organizations to sort and filter candidates according to the job role and descriptions (Mukherjee et al., 2014). Companies like IKEA, L'Oreal, Unilever, and Amazon have started employing AI-powered recruiting tools to filter top talent in the most unique and individualized way possible. Certain examples of these tools include Robot Vera, Mya the chatbot, and HireVue Assessments (Meshram, 2023).

2.5 Trust Perception and Attitude Towards AI

Within the last decade technologies used by managers and their employees granted organizations full authority over its functionalities and responses, prompting a level of risk and variability depending on the individual user. As previously discussed, the AI used in recruitment processes is highly dependent upon machine learning models, often considered as a black box, where the foundations of the functionality can be laid but the working of the algorithm cannot be easily manipulated (Choung et al., 2023). This builds on the factor of trust perception of the users when using and implementing such tools in areas of recruitment and hiring for organizations. Kim et al., (2019) have noted the factors of fairness, accountability, and transparency, which provide a bottom line for the users' satisfaction with different machine learning models and algorithms.

Literature suggests that trust perception towards any technology, and in this case of AI, plays an important role and affects the attitude of the users in the acceptance of AI technologies or AI tools for recruitment processes. There have been multiple studies in the field of healthcare

AI (Lee & Rich, 2021), algorithmic journalism (Shin, 2020b), and AI used for work evaluations (Lee, 2018). Still, none of the studies take a quantitative approach toward understanding the behavioural intention of the usage of AI in the domain of HRM. There are various combinations of AI in the field of HRM, but the focus of this study remains on the AI technologies used for hiring processes such as ATS and TurboHire. In recent times, such smart recruitment tools have emerged as indispensable tools in HRM. It is known for revolutionizing the recruitment process in the digital age.

2.6 Technology Acceptance Model

The IS field has adopted various theories over time to understand the user acceptance of IT, which is synonymous with IS. This includes the TAM based on the Theory of Planned Behaviour. The focus of this study remains on the usage of TAM to understand the behavioural intention to accept the advancement of smart recruitment tools in collaboration with AI for HRM processes such as hiring and recruitment.

TAM posits that individual acceptance and use of technology are determined by two major factors, perceived ease of use and perceived usefulness (Davis, 1986). This model has been extended, criticized, validated, employed, and revised in different contexts (McLean & Osei-Frimpong, 2019). Numerous studies within the HRIS domain have observed that TAM effectively reinforces the predictive validity of perceived usefulness and perceived ease of use (Huang and Martin-Taylor, 2013; Kolatshi, 2017; Panos and Bellou, 2016; Barnel et al., 2014). Menant et al., (2021) believe that as technology is adopted by individuals, other variables such as satisfaction, and experience in technology can influence the acceptance of HRIS. Menant et al.,

(2021) mention, "*These individual variables have often only been tested sporadically and in a restricted national and cultural context, whereas acceptance of a technology is very likely dependent on the economic, cultural, and legal context*" (p. 9). In the financial sector, the early adoption of online banking systems was studied, which provided findings that cemented the importance of PU and PEOU in user acceptance, while it was also found that trust played a crucial role in driving the acceptance parameter (Alalwan et al., 2018). There have been more detailed designs for TAM to address some of the shortcomings such as the ignorance of factors such as system design, individual differences, or social influences. The more elaborated versions of TAM (TAM2, TAM3) consider these certain factors (Venkatesh & Bala, 2008; Venkatesh & Davis 2000; Choung et al., 2023). With the help of the elaborated models, attitude can be considered a factor in predicting behaviour (Choung et al., 2023).

Another important factor to consider is the tool's compatibility with the task sought to perform. It has been noted, in terms of educational compatibility, it seemed to affect the student's acceptance of an e-learning platform (Chen, 2011; Xu & Wang, 2006). Personal beliefs and experiences also play a major role in understanding and accepting new technologies and systems, which translates into the idea of "*personal innovativeness*". Researchers like Rogers (1995), Midgley and Dowling (1978), and Flynn and Goldsmith (1993) have defined "*innovative*", "*individuals as those who are early adopters of innovations*", according to Agarwal and Prasad (1998, p. 206). It has been argued in literature by Agarwal & Prasad (1998) that "*personal innovativeness*" acts as a key moderator for the antecedents along with the consequence of perception, which can include attitude or perceived ease of use.

CHAPTER 3: RESEARCH MODEL AND HYPOTHESES

In the fast-paced world of technological innovation, understanding the factors that influence the adoption and continued usage of AI is paramount to researchers and practitioners alike. The current study developed a research model that delves into the nuanced dynamics of user acceptance and continuance usage by putting forward two comprehensive models that integrate critical variables. It draws inspiration from well-established theories like the TAM (Davis, 1989). At the core of our investigation are seven variables excluding the control variables, each playing a distinct role in shaping users' attitudes and intentions toward AI adoption in the field of HRM.

In the forthcoming sub-sections, each of these variables will be defined and explored for a deeper understanding, which will help unravel the intricacies in action that influence users' decisions to adopt new technologies. Through reasoned analysis, this research aims to provide a better understanding of how these factors come together to shape the adoption of smart recruitment tools. This research seeks to contribute valuable insight to the ongoing discourse on AI in different fields and pave the way for more informed strategies in the design, implementation, and promotion of AI as the new big thing.

3.1 Pre-adoption Model

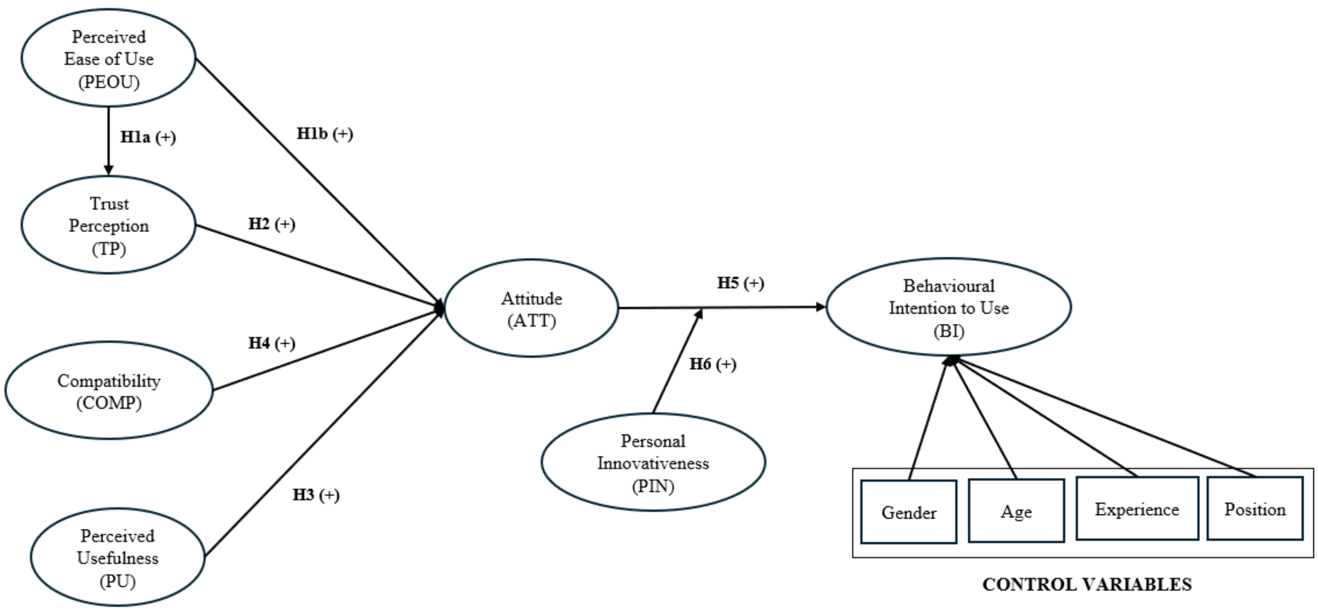


Figure 2: Pre-adoption Research Model

3.1.1 Perceived Ease of Use

Perceived ease of use is defined by Davis et al., (1989) as "*the degree to which a person believes that using a particular system would be free of effort. This follows the definition of 'ease' and 'freedom from difficulty or great effort'*." (p. 320). Perceived ease of use is undeniably a critical predictor of new technology adoption. This factor is not just a peripheral factor but a central one in shaping how users perceive the technology. Wu et al., (2011) in a meta-analysis, provided further evidence of perceived ease of use's substantial impact on core components of TAM such as attitude.

Furthermore, Shin (2020b) demonstrates real-life implications of ease of use in technology adoption, depicting how perceived ease of use and trust can impact the frequency with which a news recommendation or personalized AI system is used. The levels of trust and ease of use concerning the user affect their behaviour and attitude. This demonstrates the symbolic relationship between ease of use and trust, as one reinforces the other factor. Therefore, perceived ease of use influences the attitude of the user toward a new technology or tool (Choung et al., 2023), which provides the basic foundations for the following hypotheses:

H1a: The perceived ease of using smart recruitment tools in HRM positively influences users' trust perception.

H1b: The perceived ease of using smart recruitment tools in HRM positively influences users' attitudes towards the technology.

3.1.2 Trust Perception

Sollener et al., (2016) highlighted the importance of trust as a predictor of new technology adoption. It is highly intertwined with the user's perception of technology, which affects their willingness to use it. AI systems used in the field of HRM, and recruitment raise the question of fairness, reliability, and data security, which makes trust an important concept to be studied when understanding the TAM model (Davis et al., 1989). It has been noted by Tung et al., (2008), "*Trust is defined as the measure of the belief and goodwill that policymakers feel in and for, trusted people. In other words, we can divide the trust into two dimensions and discuss the objective component of 'belief' and the psychological component of 'goodwill'*." (p. 326). In commerce, trust is a key factor with the antecedents of perceived usefulness and perceived ease of use (Tung et al., 2008). The connections and relationships between trust and TAM constructs have been studied comprehensively (Gefen, 2004; Gefen et al., 2003; Pavlou, 2003; Saeed et al., 2003). It is also noted above that perceived ease of use has a significant effect on the trust perception of the users when focusing on new applications related to AI (Mohr & Kuhl, 2021). Wu et al., (2011) in a meta-analysis, provided further evidence of trust and perceived ease of use's substantial impact on core components of TAM such as attitude. Furthermore, Shin (2020b) demonstrates the real-life implications of trust in technology adoption, trust can impact the frequency with which a news recommendation or personalized AI system is used.

H2: Users' trust in smart recruitment tools positively influences their attitude toward the technology.

3.1.3 Perceived Usefulness

Chatterjee et al., (2021) provide an interpretation of "*perceived usefulness*" as, "*the potential users' subjective possibility that using a system or an application of the system will enhance the job performance of the users within the context of the firm*" (p. 5). Perceived usefulness was the initial basis for determining the technology adoption process (Davis et al., 1989). Thadatritharntip et al., (2020) suggested a strong impact of perceived usefulness on users' attitudes, significantly affecting the intention to use. It has been noted in various studies around the technology acceptance model (TAM) that perceived usefulness serves to have stronger connections to the different mechanisms that influence technology adoption in diverse contexts (Davis et al., 1989; Kim et al., 2021). Normalini (2019) states the strong relationship that exists between perceived usefulness and attitude toward internet banking. The study explains the continued intention to use internet banking has significant links with perceived ease of use and perceived usefulness (Normalini, 2019). The following studies regarding the use of perceived usefulness as a construct would depict the judgments formed by individuals due to the comparison between what the tool can do with what needs to be accomplished in a task (Chatterjee et al., 2021).

Hence, it can be stated that the usefulness of a tool would lead an individual to use the new tool in an organizational setup. Therefore, the following hypothesis is proposed:

H3: The perceived usefulness of smart recruitment tools positively influences users' attitudes toward technology.

3.1.4 Compatibility

The construct of compatibility provides the foundation for the study of an information system to which it is deemed '*compatible*' with the system and the task to be performed in the context of AI and recruitment processes. As mentioned above, the "*compatibility*" of an IS is defined by Chen (2011) as "*It is the extent to which accepting a new system is congruous with the characteristics of the potential user and the conditions of utilizing the technology*." (p. 1504). Chen (2011) used the term 'compatibility' to explain the context of educational learning systems and hypothesized that educational compatibility positively influences technological expectancy. Multiple studies have focused on the sociocultural, control-based, and systemic factors, extensively studied using the TAM model (Chen, 2011). It has been noted by Chatterjee et al., (2021), "*The sense of compatibility of employees attempting to use a new technology is perceived to influence their attitude to use that technology*" (p. 1302). This notion provides an insight into how compatibility plays a pivotal role in the successful adoption of new technology in any organization. Compatibility can be isolated using two distinct roles: compatible with values and compatible with prior experience. The former explains the interaction between an individual's or an organization's core values and beliefs in alignment with the new technology. Compatibility refers to the harmonious alignment of various systems, and components interacting together with existing technologies without conflict or disruption. It ensures that diverse elements can function collectively, minimizing conflicts and initiating smooth operations. It is like the concept of "*alignment*" which connects to the strategic coordination of technologies with broader technological goals, which enhances the overall objectives and workflows of an organization. Another term, "*fit*" can be defined as the suitability or appropriateness of a particular technology for a given task or purpose. It reflects on the choice of solution and its alignment with the specific requirements and objectives of the use cases.

There are various dimensions surrounding the construct, such as alignment with mission and vision, ethical and moral alignment, and cultural fitness. The latter revolves around an individual's or an organization's knowledge base, and practices. It balances the importance of user experience, skill transferability, and most importantly, interoperability, which means a seamless integration with existing mechanisms, structures, and tools. Attitude and compatibility have been studied in the context of mobile banking in China, which provided more reference to the usage of such a structure in the existing TAM model (Laforet & Li, 2005). It was also found by Wang et al., (2017) that alignment with prior e-banking experiences and personalization create an interactive effect on both performance expectancy and effort expectancy. It has also been researched that compatibility affects a user's behaviour through the attitude of the user

(Chatterjee et al., 2021; Rana et al., 2017; Kim et al., 2009). Hence, with the following foundations, we hypothesize:

H4: Compatibility will positively influence the attitude towards using smart recruitment tools in HRM.

3.1.5 Attitude and Behavioural Intention to Use

Fishbein & Ajzen (2011) state that "*According to reasoned action framework, attitudinal, normative, and control considerations determine a person's intention*." (p. 179). Attitude plays an important role in the decision-making of an individual's favourable and unfavourable feelings about a new technology or object (Chai et al., 2021). There has been research in the field of computer science education (Goldweber et al., 2011) that investigates the influence of intention to learn AI from different attitudinal perspectives. In the ever-evolving realm of technology adoption, technology readiness is a pivotal determinant in explaining the acceptance of new technologies and their application. This sense of readiness is determined by the users based on their knowledge, preparedness, and confidence (Chai et al., 2021). This can be characterized by a self-oriented positive attitude, which is a key factor in explaining one's intention to use and apply new technologies (Chiu, 2017; Teo & Tan, 2012; Chai et al., 2021). In this study, personal attitude towards a specific tool is considered as the attitude towards the intention of using AI systems in the recruitment process and HRM. According to Mohr & Kuhl (2021), "*This factor captures the degree to which the behaviour in the question is assessed positively or negatively.*" (p. 1822).

It is also important to note the role of TAM in the construction of the research model. TAM (Davis, 1986) offers a valuable framework for understanding users' acceptance at an individual level. By focusing on the pivotal role of attitude and intention to use, TAM offers insights into how individuals make decisions regarding the acceptance and utilization of technology. This connection between personal attitude and the TAM framework is important for understanding the technology adoption in HRM and recruitment. Therefore, considering the traditional TAM theory, this study aims to hypothesize:

H5: The more positive the attitude towards smart recruitment tools, the stronger the intention to use the smart recruitment tools.

3.1.6 Personal Innovativeness

Personal innovativeness has been found to explain a person's interest or willingness to try out new tools and technologies (Rogers, 2014), it has been included in various studies that study the behavioural intention and usage of new technologies (e.g., Wijesundara & Xixiang, 2018; Chen, 2022; Fagan et al., 2012). Personal innovativeness plays a crucial role in technology adoption. Studies have shown that personal innovativeness moderates the relationship between attitude and intention to use new systems, with higher innovativeness strengthening this relationship (Tsou, 2012; Hwang, 2014). It can be perceived that adopting an innovative and unique tool is likely to create positive feelings in its user base, which may enhance motivation and support the adoption process (Flynn & Goldsmith, 1993). Fu & Elliot, (2013) noted "*Consumers are more willing to process the new product information cognitively, and their attitude toward the product will have a greater impact on the intention to purchase*" (p. 261). Fu and Elliot (2013) extended this concept to product innovativeness, showing that perceived product innovativeness strengthens the relationship between attitude and purchase intention. Chen and Chen (2011) found that personal innovativeness moderates the relationship between attitude and behavioural intention to use GPS devices. Another study noted that manager's intention to innovate is influenced by their attitude towards specific innovation, ideation, and perceived organizational support for creativity (Massu et al., 2018). Similarly, Shin (2010) demonstrated that personal innovativeness moderates the influence of subjective norms on the intention to use mobile internet. In the context of this study, it is anticipated that for HR professionals with high levels of personal innovativeness, the influence of a positive attitude on the intention to use smart recruitment tools will be significantly stronger compared to those with lower levels of innovativeness. It can be attributed to the fact that individuals with higher personal innovativeness tend to be more open to new experiences, so their tendency to explore and experiment with novel systems will make their intention to try the smart recruitment tools more responsive to the degree to which they have a positive attitude toward the system.

H6: The effect of HR professionals' attitude on their intention to use smart recruitment tools will be greater when HR professionals' innovativeness is high than when it is low.

CHAPTER 4: RESEARCH METHODOLOGY

This chapter presents the methodology employed for data collection and analysis. Data was gathered through an online survey created on the Qualtrics platform. Partial least squares and structural equation modeling (PLS-SEM) techniques were utilized for data analysis.

4.1 Survey and Data Collection

To achieve the research objectives, an online survey was created using the Qualtrics platform. The platform employs an array of data security measures, which include high-end firewalls, vulnerability scans, restricted access, and encryption.

The demographic targeted in this study was HR professionals who had a minimum of 1 year of experience specifically in the roles directly related to recruitment processes within an organization based in India. The eligible participants needed to have a comprehensive understanding of the recruitment process. This criterion was noted with the help of the screening question, "*Do you have experience in the recruitment process in your organization?*". Only those who responded affirmatively were permitted to proceed with the survey. Additional criterion was related to the familiarity and knowledge of smart recruitment tools, the online survey also contained a short informative video on AI and smart recruitment tools to help respondents understand the concept of the tools in the recruitment process. This criterion was analyzed with the help of two screening questions, "*What describes your familiarity with the concept of artificial intelligence?*" and "*Have you ever utilized smart recruitment tools to streamline the* *recruitment process?*". As an expression of gratitude for participating in the study, respondents were given the opportunity to enter a draw for a $50 gift card by providing their email address following the completion of the survey. The email addresses were stored separately from the research data and not linked with the data collected in the survey.

To recruit participants, the snowballing sampling method was used. Also referred to as networking sampling, it is a non-probability sampling method used in various social science studies. The method is most advantageous when the ideal sample group is difficult to identify or access, as the demographic needed for the study requires a particular skill set. The efficacy of the snowball sampling method was assessed for this study by using various pieces of evidence, exploring various advantages (Cohen & Arieli, 2011; Dusek et al., 2015; Wohl et al., 2017) and addressing concerns about such a sampling method (Marcus et al., 2017; Naderifar et al., 2017; Regan et al., 2019). The snowball sampling method usually begins with the selection of a small number of participants who meet the study's criteria. These participants are selected based on their knowledge, experience, demographics, and relevance to the research topic. Once the first round of the selection procedure is initiated, everyone is asked to refer other individuals, who also meet the study's eligibility criteria. This creates a "*snowball effect*," exponentially increasing the sample size of the target population. This method also leverages existing social networks and professional circles, enabling participants' access to peers who have the required knowledge and skill set relevant to the research topic. Evidence shows there has been a decline in the response rates from the "*hard-to-reach*" population as it becomes increasingly classified and difficult to contact such a target sample (Baruch & Holtom, 2008). In the current study, the process began by identifying the initial pool of participants, HR professionals who fit the study criteria. These initial participants were identified through professional networks, primarily on LinkedIn. Personalized invitation messages were sent to this first pool via LinkedIn, the message explained the purpose of the research, outlined the criteria for participation, and invited them to complete the survey. It also included a request for all participants to forward the invitation to other professionals in their network who also met the study's criteria. As the first pool of participants shared the invitation with their connections, the poll of respondents expanded, creating a chain of referrals. This technique helps in leveraging the professional networks of initial participants to identify and engage others who were similarly qualified but might not have been accessible through traditional sampling methods.

Sample size was carefully considered prior to conducting the study, with reference to Barclay et al.'s "*ten-times rule*" (1995), which states that the sample size should be ten times higher than the number of paths aiming at any variable in the model. This rule was further endorsed by Hair et al., (2012), stating that the minimum sample size can be calculated by multiplying the number of relationships in the model by 10. In this study, excluding controlled variables, the research model examines 7 relationships between the latent variables and moderating variables. Accordingly, the requisite minimum sample size would be 70 (calculated as 7 relationships multiplied by 10). To ensure greater statistical robustness, the study aimed to obtain 120 valid responses.

The sample size was assessed by considering the reliability and validity of the findings and providing a more comprehensive understanding of the data. Overall, 225 responses were collected. To increase the reliability of the results and reduce participant bias, the responses were also screened. All incomplete responses or surveys completed in less than three minutes were removed from the final sample. Furthermore, participants who responded "*Yes*" in response to: "*Have you ever utilized smart recruitment tools to streamline the recruitment process?*" were omitted from the final dataset. This exclusion was necessary due to their responses not providing sufficient details to ensure confidence in the study. By omitting these responses, integrity could be maintained, and the focus of the research could instead focus on individuals who had not yet adopted the technology. This approach ensures that the analysis accurately reflects the factors influencing the intention to adopt smart recruitment tools. This led to the final 107 usable responses, well over the minimum required sample size.

Of all the participants, males (including transgender men) were 83.18%, females (including transgender women) were 14.02%, and a minority group chose not to disclose was 2.80%. The gender distribution indicates a significant male predominance in the sample set. The age distribution of respondents shows a high concentration in the 30-59 age range. The largest segments were 40-49, representing 33.64%. The evidence emphasizes that nearly half the respondents have 3-5 years of experience, indicating a relatively solid workforce with significant exposure to recruitment processes. The majority experience group was 3-5 years comprising 45.80%. Respondents holding mid-level positions comprised 46.73% of the data collected, followed by mid-senior level positions at 36.45%. Table 4 provides the descriptive results of the participants' demographic data.

Variable	Category	Frequency	Ratio (%)
Gender	Male (Including Transgender Men)	89	83.18%
	Female (Including Transgender Female)	15	14.02%
	Prefer Not to Say	3	2.80%
Age	18 – 29	11	10.28%
	30 – 39	24	22.43%
	40 – 49	36	33.64%
	50 – 59	35	32.72%
	Over 60	1	0.93%
Experience	1 – 2 years	26	24.30%
	3 – 5 years	49	45.80%
	5 years or more	32	29.20%
Position	Entry Level Position	8	7.48%
	Mid-Level Position	50	46.73%
	Mid-Senior Level Position	39	36.45%
	Senior Level Position	10	9.34%
Total		107	100%

Table 4: Descriptive Statistics of Participants Characteristics

4.2 Measurement

The scale items of the variables were adopted from various existing studies and literature. The variables have been adapted to the specific context of this study. The "*perceived usefulness*" construct was measured with four measurements adapted from the TAM scale (Davis, 1989). The "*perceived ease of use*" construct was measured using four measurements adapted from the primary TAM scale. (Choung et al., 2023; Davis et al., 1989). "*Compatibility*" was measured using the four items developed from the Diffusion of Innovations (Chen, 2011; Rogers, 1983). "*Trust perception*" and "*attitude*" were measured with the help of four items developed in the study of AI usage in voice assistance (Choung et al., 2023). The construct "*personal innovativeness*" used in the study using four measurements (Mohr & Kuhl, 2021). Lastly, "*behavioural intention to use*" for recruitment services is measured by using the extended TAM scale (Chai et al., 2021; Venkatesh & Davis, 2000). A survey was created predominantly utilizing a seven-point Likert scale, ranging from "*strongly disagree (1)*" to "*strongly agree (7)*". Other demographics and screening questions employed different scales, such as multiple-choice questions.

Construct	**Definition**	**Reference**
Perceived Ease of Use (PEOU)	Users' belief that using smart recruitment tools would require minimal effort.	(Choung et al., 2023; Davis, 1989).
Perceived Usefulness (PU)	Users' subjective understanding that using smart recruitment tools will enhance job performance in the organization.	(Normalini., 2019; Chatterjee et al., 2021)
Trust Perception (TP)	Users' perspective of the degree of confidence and reliability placed on the organization's use of smart recruitment tools.	(Choung et al., 2023)
Compatibility	The extent to which smart recruitment tools are	(Chen, 2011; Rogers,

Construct	Definition	Reference
(COMP)	congruous with the characteristics of the task of hiring and screening new candidates.	1983)
Attitude (ATT)	The feelings, beliefs, and intentions of a user towards smart recruitment tools.	(Choung et al., 2023)
Behavioural Intention to Use (BI)	A user's propensity or probability to use smart recruitment tools through the organization.	(Chai et al., 2021; Venkatesh & Davis, 2000)
Personal Innovativeness (PIN)	Users' interest or willingness to try out new smart recruitment tools and technologies.	(Mohr & Kuhl, 2021)

Table 5: Conceptual Definitions of Constructs

4.3 Data Analysis

4.3.1 Measurement Validation

Partial least squares and structural equation modelling (PLS-SEM) was applied for the analysis of this study. This technique has gained prominence in various research fields due to its versatility and robustness, especially in the context of smaller sample sizes with multiple-item variables (Hair et al., 2021). This method is adept at handling complex models with various indicators, providing reliable estimates even when the sample sizes are small. This validation of constructs follows the methodology outlined by Hair et al., (2017).

The measurement model was evaluated to confirm internal reliability, as well as construct and discriminant validity. Also, an assessment for the common method bias was conducted to ensure the collinearity of the variables did not appear to be a concern. After validation of the measurement, a structural model was fitted aligning with the research model and tested to verify the proposed hypotheses and connections in Figure 2 including the demographic variables regarding the respondents, such as age, gender, experience in recruitment processes, and position in the organization as control variables. SmartPLS 4.0 was chosen to run the above analysis for the study. SmartPLS 4.0 also incorporates a bootstrapping procedure to assess the significance of path coefficients, which is highly effective with smaller sample sizes. In this study, all the constructs (PEOU, PU, TP, PIN, BI, COMP, ATT) were treated as reflective measures.

Table 6 presents the internal reliability of the constructs. The Cronbach's α values for these constructs exceed the threshold value of 0.70, thereby affirming their reliability with the standards set by Henseler et al., (2016) and Hair et al., (2012). To examine the convergent validity, the composite reliability, factor loadings, and Average Variance Extracted (AVE) were measured for each variable. As demonstrated in Table 6, all item factor loadings exceed the threshold of 0.60, meeting Hulland's (1999) criterion. Furthermore, the composite reliability values for all variables surpass the 0.70 mark (Aguirre-Urreta et al., 2013), and the average variance extracted values are all above 0.50, thereby confirming an acceptable level of convergent validity as recommended by Fornell and Larcker (1981).

Construct	Item	Factor Loadings	Cronbach's α	Composite Reliability (rho_c)	AVE*
Perceived Ease of Use (PEOU)	PEOU1	0.611	0.734	0.834	0.560
	PEOU2	0.762			
	PEOU3	0.772			
	PEOU4	0.831			
Trust Perception (TP)	TP1	0.767	0.811	0.874	0.636
	TP2	0.711			
	TP3	0.833			
	TP4	0.870			
Compatibility (COMP)	COMP1	0.914	0.880	0.917	0.735
	COMP2	0.835			
	COMP3	0.828			
	COMP4	0.849			
Perceived Usefulness (PU)	PU1	0.757	0.777	0.855	0.596
	PU2	0.824			
	PU3	0.754			
	PU4	0.750			
Attitude (ATT)	ATT1	0.857	0.854	0.902	0.699
	ATT2	0.873			
	ATT3	0.883			
	ATT4	0.721			
Behavioural Intention to Use (BI)	BI1	0.864	0.836	0.890	0.669
	BI2	0.847			
	BI3	0.771			
	BI4	0.786			
Personal Innovativeness (PIN)	PIN1	0.786	0.774	0.854	0.595
	PIN2	0.834			
	PIN3	0.726			
	PIN4	0.735			

Table 6: Internal Reliability and Convergent Validity (Multiple Item Variables)

Discriminant validity ensures that each variable is measured differently by its own set of scale items. It was assessed using two criteria. Firstly, the Fornell-Larcker (1981) criterion was applied, whereby the square roots of the AVE value for each variable (bold in Table 7) were found to be greater than the covariance among the variables, as depicted in Table 7. This indicates that each variable is uniquely associated with its respective construct (Fornell & Larcker, 1981). Secondly, the Heterotrait-Monotrait (HTMT) ratios as shown in Table 8. The values of these constructs were all below 0.90, reinforcing that the constructs are distinct and measure different concepts (Hamid et al., 2017). Collectively, these results from CR, AVEs, HTMT ratio and Fornell & Larcker (1981) matrix substantiate that our measurement model possesses adequate reliability and validity.

Construct	ATT	BI	COMP	PEOU	PU	PIN	TP
ATT	**0.836**						
BI	0.592	**0.818**					
COMP	0.497	0.351	**0.857**				
PEOU	0.529	0.357	0.620	**0.748**			
PU	0.670	0.660	0.378	0.431	**0.772**		
PIN	0.483	0.632	0.255	0.311	0.446	**0.771**	
TP	0.673	0.571	0.640	0.565	0.538	0.386	**0.798**

Table 7: Fornell and Larcker Criteria, Intercorrelation Matrix with AVE

Construct	ATT	BI	COMP	PEOU	PU	PIN	TP
ATT							
BI	0.685						
COMP	0.563	0.392					
PEOU	0.651	0.439	0.754				
PU	0.803	0.860	0.437	0.545			
PIN	0.574	0.747	0.293	0.407	0.571		
TP	0.766	0.682	0.737	0.694	0.669	0.445	

Table 8: Heterotrait Monotrait (HTMT) Matrix

The collinearity test is instrumental in identifying the potential common method bias by analyzing the variance inflation factors (VIFs), which assess the strength of correlations among predictor variables (Kock, 2015). According to Diamantopoulos and Siguaw (2006) and Venkatesh et al., (2012), values below the conservative threshold of 5.0 suggest an absence of severe multicollinearity issues among the latent variables.

Table 9 presents the VIFs obtained by treating all variables except the dependent variable (BI), as independent variables for BI. The results in Table 7 indicate that all the VIFs are below the threshold of 3.3 (Kock, 2015). This demonstrates that the study does not suffer from an issue with common method bias and there are no serious correlations amongst the latent variables.

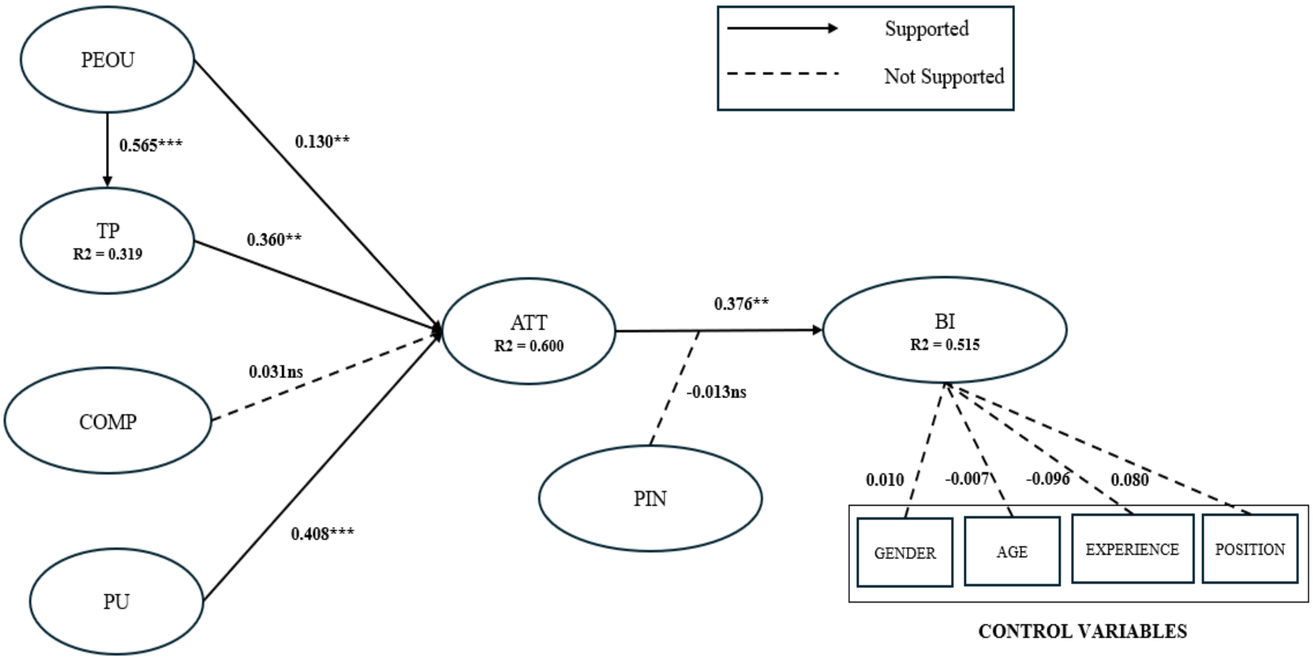
	VIF
Attitude → Behavioural Intention to Use	2.331
Compatibility → Behavioural Intention to Use	2.029
Perceived Ease of Use → Behavioural Intention to Use	1.857
Perceived Usefulness → Behavioural Intention to Use	1.748
Personal Innovativeness → Behavioural Intention to Use	1.360
Trust Perception → Behavioural Intention to Use	2.373

Table 9: Multicollinearity (VIF) of Reflective Measures

4.3.2 Structural Model Testing

After the successful completion of the reliability and validity tests, the structural model was tested to assess the explained variance (R^2) of the dependent variables, the path coefficients (β), and their significance level (t-values). SmartPLS 4.0 employs a robust statistical technique using the bootstrapping method to analyze variance, significance levels, and path coefficients. This non-parametric resampling procedure generates empirical sampling distributions to test the stability and reliability of the estimated model parameters. The path coefficients highlight the strength and direction of the model's relationship between predictor and outcome variables. Specifically, it can assess the extent to which a change in a predictor variable is associated with a change in the outcome variable. A higher path coefficient indicates a stronger relationship between the predictor on the outcome, while a lower path coefficient indicates a weaker relationship. The R^2 value represents the proportion of variance in the dependent variable that is explained by the research model. This metric is a crucial indicator of the model's predictive efficacy (Gefen et al., 2000).

As shown in Figure 3, the model explains 31.9% of the variance in trust perception, 60% in attitude towards smart recruitment tools, and 51.5% in BI. PEOU accounts for the 31.9% variability in trust perception towards these tools. PEOU, TP, COMP, and PU account for the 60% variance in the attitude towards these tools. ATT and the control variables are responsible for the 51.5% variability in the BI. Furthermore, it was noted through Figure 2 using path coefficients showing that the hypotheses H1a, H1b, H2, H3, and H5 were significant, whereas H4 and H6 were not significant. It can also be noted from Figure 2 that none of the control variables displayed any statistical significance to the use of smart recruitment tools.



Note(s): +=p<0.1, *=p<0.05, **=p<0.01, ***=p<0.001, n.s=not supported

Figure 3: Structural Test Results

CHAPTER 5: DISCUSSION

The following section delves into the findings of the study, examining their significance and implications to the real world. It addresses the crucial relationships between the latent variables. It explores both the theoretical and practical contributions of the research, highlighting how the results advance the body of knowledge and practice in the field. Additionally, this chapter addresses the limitations and suggests avenues for future research, providing a comprehensive understanding of the current study's impact and potential for further investigation.

5.1 Findings

Perceived ease of use shows a positive significant association with the smart recruitment tools' trust perception ($\beta=0.565$, $p\text{-value}<0.001$). Therefore, H1a is supported, consistent with previous studies (Zhang et al., 2020; Choung et al., 2023; Voermans and Veldhoven, 2007). This indicates that when users find recruitment tools easy to use, they can experience less frustration and cognitive load, which fosters a sense of confidence and comfort in interacting with the system, leading to higher levels of trust. A system that is easy to understand and operate can minimize the perceived risks associated with using it, making it more likely for users to trust said system. The simplicity of use reassures users that they are less likely to make errors or encounter unforeseen issues. Systems that are easy to use can also provide clear instructions and transparent processes. This approach ensures users clearly understand the system's operation, strengthening their trust in its fairness.

Similarly, perceived ease of use demonstrated a positive and significant effect on the attitude toward using smart recruitment tools ($\beta=0.130$, p-value<0.01) supporting H2a. This result is consistent with studies on the AI-enabled e-learning systems (Kashive et al., 2021) in addition to several studies applying the TAM (Mohr & Kuhl, 2021; Park, 2009). Through deductive reasoning, it can be concluded that user-friendly systems tend to engage users more effectively, as when users find smart recruitment tools easier to use, they are more likely to explore and utilize their features fully. This increased engagement leads to a positive attitude toward the technology being used. Moreover, new technology is typically met with initial resistance but if the tools are easy to navigate, this resistance would diminish, making users more willing to embrace the new technology (Bhattacherjee & Hikmet, 2007). The current study is consistent with previous research based on the acceptance of e-HRM systems, which suggest that tools that are easy to use will have less cognitive load making the adoption process smoother and less daunting (Yusoff & Ramayah, 2012; Omar et al., 2015; Shahreki, 2020).

The smart recruitment tools' trust perception is found to have a positive and significant effect on the attitude toward using smart recruitment tools ($\beta=0.360$, p-value<0.01). This clearly demonstrates that H2 is supported, further proving trust perception's significant role in shaping people's attitudes towards new AI technologies (Choung et al., 2023). This finding is consistent with previous studies (Mohr & Kuhl, 2021). It can be confidently stated that trust in smart recruitment tools can often be linked to perceived fairness and transparency of the processes and algorithms used. When users believe that the tools operate transparently and provide fair outcomes, their trust in the technology itself will increase, which results in a positive influence on their attitude. Increased trust in the tools encourages users to engage more positively, leading to higher satisfaction and more favorable results; thus, proving that trust can be linked with overall user experience. Employees who trust the technology are more likely to perceive it as dependable and beneficial from the organization's perspective, which will enhance their overall attitude toward its use.

For hypothesis H3, perceived usefulness is found to positively influence attitude toward smart recruitment tools ($\beta=0.408$, p-value<0.001), supporting H3. It was found that perceived usefulness plays a significant role in the study as it impacts attitudes towards the usage of smart recruitment tools with the highest significance level. This finding is in line with previous research in the context of the usage of AI in online shopping (Hajdú & Nagy, 2021). It is said that as a result the more useful the smart recruitment tools are to get the job done, the more likely users will consider the implementation of recruitment tools as judicious and will be enthusiastic to work with them. Perceived usefulness is considered to have a direct impact on job performance, as smart recruitment tools can assist in screening potential candidates and analyzing candidate data, which can positively affect efficiency and accuracy in recruitment tasks. Users who experience the implementation of new technologies first-hand are more likely to view the tools favourably, forming a positive attitude towards the tools themselves as well as an enthusiasm to work with them. When tools deliver benefits, such as cost and time savings, their user will consider their organization's decision as astute. These decisions align with organizational goals, providing users with a visual of these goals, resulting in an inclination to view the tools positively, further contributing to the success of the organization.

In contrast to several previous studies (e.g., Chen, 2011; Poonpanich & Buranasiri, 2022), compatibility with a task does not have a significant association with users' attitude towards smart recruitment tools (β=0.031, p-value>0.1). Therefore, the analysis of the current study did not provide significant evidence supporting H4. Various studies found that compatibility insignificantly influences attitude towards the adoption of new IT technologies (Soon et al., 2020; Yang et al., 2012). Participants were observed to have a high level of familiarity with the recruitment tools. If users are comfortable and proficient with these tools, the compatibility of the task with the new tools may not significantly alter their attitudes; for example, individuals might value other factors such as trust, ease of use, and usefulness of the technology. Organizational culture, policies, and support for adopting new technologies can play a more critical role than task compatibility. It is important to note that implementation of these tools is typically guided by the organization's broader goals. This centralized decision-making process can significantly affect how a recruiter perceives the tools and their level of control over the decision to use them (Kishore & McLean, 2007). When the use of smart recruitment tools is non-negotiable, recruiters may adopt a more passive stance towards the tools. Their attitude towards the tools is shaped more by the organizational mandate and the necessity to comply with it, rather than by a genuine assessment of how compatible the tools are with their existing methods.

For H5, it was found that attitude toward smart recruitment tools has a significant and positive effect on the user's behavioural intention to use the tools (β=0.376, p-value<0.01). This finding aligns with previous studies in the context of studying AI technologies in various domains such as e-commerce, and agriculture (Wang et al., 2023; Mohr & Kuhl, 2021). This can confirm that users' positive attitude towards smart recruitment tools can be a strong indicator of users' behavioural intention to use the tools for recruitment tasks. This finding is also consistent with research focused on the theory of reasoned action and cognitive approach to predict and explain human social behaviour (Fishbein & Azjen, 2011).

Finally, it was discovered that the moderating effect of personal innovativeness on the relationship between the attitude toward smart recruitment tools and the user's behavioural intention to use the tools is insignificant (β=-0.013, p-value>0.1). It was also found during discriminant validity testing (Fornell Larcker criterion) that the relation between personal innovativeness was measured to be 0.632, which is lower than the relationship between attitude and behavioural intention to use the tools. Subsequently, H6 is not supported, meaning that the interaction effect of personal innovativeness and users' attitudes did not significantly influence the behavioural intention to use smart recruitment tools. In the current study, the users' attitudes toward smart recruitment tools alone were observed as sufficient to determine their intention to use them, regardless of their level of innovativeness. In an organizational context, the influence of personal traits like innovativeness may be overshadowed by other factors such as organizational culture, peer influences, or management directives. HR professionals, regardless of their level of innovativeness, might prioritize organizational norms and expectations over their personal inclinations when deciding to adopt new tools. Parzefall et al., (2008) suggests that "*Organizational level factors that play role in individual innovativeness are most complex to analyze and may range from organizational culture to the size of the firm*" (p. 174). Within technology adoption, the role of personal innovativeness within a structured organizational setting may be less pronounced, implying that other factors may play a more critical role in shaping HR professionals' intention to use smart recruitment tools.

No control variables, such as age, gender, experience, position in the organization significantly affected the intention to use smart recruitment tools. This indicates that factors such as age, gender, position in the organization, or experience in the field do not significantly change an employee's perception or intention to use smart recruitment tools in the hiring process. The control variables do not affect the users' perception of the tools used in an organization.

The results of the hypothesis testing are summarized in Table 10 along with the corresponding t-values and p-values.

Hypotheses	**Path**	**Path Coefficients**	**t-Values**	**p-Values**	**Supported or Not Supported**
H1a	PEOU → TRT	0.565	5.149	0.000	Supported***
H1b	PEOU → ATT	0.130	2.603	0.009	Supported**
H2	TP → ATT	0.360	3.244	0.001	Supported**
H3	PU → ATT	0.408	4.062	0.000	Supported***
H4	COMP → ATT	*0.031*	*0.239*	*0.811*	*Not Supported*
H5	ATT → BI	0.376	3.234	0.001	Supported**
H6	PIN × ATT → BI	*-0.013*	*0.243*	*0.808*	*Not Supported*

Note(s): +=p<0.1, *=p<0.05, **=p<0.01, ***=p<0.001

Table 10: Hypothesis Testing

5.2 Theoretical Contributions

This study contributes to the existing body of knowledge and literature by applying TAM and other factors such as trust and compatibility to explore the acceptance of smart recruitment tools by HR professionals for organizations. It investigates the direct and indirect effects of users' perception of the tools and how they shape the user's attitude while using the smart recruitment tools.

Firstly, this study contributes to the cluster studying technology acceptance (Davis et al., 1989; Venkatesh & Davis, 2000) by adapting and extending TAM to the specific context of smart recruitment tools in HRM. The original TAM, which focuses on perceived usefulness and perceived ease of use as primary determinants of technology acceptance, has been instrumental in understanding technology adoption across various domains. However, the model does not inherently include the concept of capturing individual use for organizations such as compatibility and trust perception. To address this gap, the current study integrates compatibility and trust perception as two critical constructs in the framework. By incorporating these constructs, the study enhances the robustness and applicability of the TAM to smart recruitment tools. This modification acknowledges that beyond usefulness and ease of use, the perceived fit of technology with existing practices like compatibility and the confidence of users in the technology, such as trust perception are vital for predicting technology acceptance. By reflecting the complexity and specificity of the HRM environment, offering deeper insights into factors influencing technology adoption. The current study contributes to enriching the TAM by integrating compatibility and trust perception, which makes the model more tailored to the HRM context.

Secondly, the integration of smart recruitment tools into decision-making processes within HRM represents a significant theoretical contribution to the existing studies on the use of AI. The importance of trust perception in human-computer and human-machine interactions has been highlighted, especially the acceptance of decisions made by an AI system. Human decisions are inherently nuanced and multifaceted. AI, on the other hand, offers a level of objectivity by analyzing large datasets to identify patterns and make predictions. Incorporating smart recruitment tools into the study of AI decision-making in HRM enriches the broader field of Management Information Systems. It provides empirical evidence on how AI can be harnessed to make more informed and objective decisions in a traditionally human-centric domain. This contribution not only advances theoretical frameworks but also offers practical insights for organizations seeking to leverage AI for strategic decision-making. The integration of smart recruitment tools into AI decision-making research offers a multifaceted contribution to the literature. It underscores the importance of trust, highlights the balance between objectivity and human nuance, and demonstrates the measurable benefits of AI in HRM.

Furthermore, the significant and positive association of trust perception on attitude toward smart recruitment tools underline an important construct in the acceptance model. The current study helps in conceptualizing the perception of HR professionals' trust in AI-powered smart recruitment tools. The use of trust perception as a crucial variable can help guide future research in the field of AI and HRIS. Traditionally, the TAM has focused on perceived ease of use and perceived usefulness as primary determinants. However, this study contributes to the growing body of knowledge by factoring the psychological factor of trust perception as a fundamental element in the acceptance of smart recruitment tools among HR professionals. This integration into TAM is not merely an enhancement but an important evolution of the model, reflecting the complexities and nuances of modern technological adoption. By incorporating trust as a core variable, this research addresses the psychological and relational dimensions that influence the acceptance of AI tools, thereby providing a more comprehensive understanding of how HR professionals interact with these technologies (Choung et al., 2023). The current study urges researchers to examine various dimensions of trust along with other critical psychological factors that can influence the adoption of AI in organizations.

Ultimately, the current study provides a valuable addition to the existing body of knowledge on the integration of AI into HRIS. It addresses a gap in the literature regarding the factors influencing this adoption. While much of the existing research has focused on the functional aspects of HRIS and AI (Masum et al., 2018; Handra & Sundram, 2023; Sivathanu & Pillai, 2018). This study brings a focus on the human and psychological factors that significantly influence the adoption of AI-powered tools. The Unified Theory of Acceptance and Use of Technology model has been extensively studied in the context of HRM and HRIS (Horodyski, 2023; Islam et al., 2022; Chen, 2011). It has provided insights into how factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions affect the adoption of new technologies in HR. It is important to study AI adoption in HRIS through the lens of TAM through the full spectrum of factors that influence technology acceptance in this rapidly evolving field. However, the integration of AI into HRIS represents a more complex challenge, as it introduces autonomous decision-making processes that require a higher level of trust and confidence from HR professionals. By examining HR professionals' perceptions of smart recruitment tools through the lens of trust, this study contributes to the evolving understanding of AI adoption in HRIS.

5.3 Practical Contributions

This study provides several practical implications for employees, managers, and organizations to adopt the upcoming AI-enabled smart recruitment tools. Firstly, this study offers valuable insight for executives and employers, providing important factors that influence the behavioural intention to adopt smart recruitment tools in the HR department for various industries. Managers are encouraged to focus on strategies that enhance employees' attitudes toward smart recruitment tools. This can include communicating the benefits, such as increased efficiency and better candidate matching, and addressing any concerns related to job displacements or changes in job roles. It is also crucial for managers to build trust in the AI-enabled tools by ensuring transparency in their functioning and decision-making processes. Managers should be willing to address data privacy and security concerns that might be paramount in gaining employee trust and acceptance. It is also important for managers to ensure that the new tools are compatible with existing human resource practices and workflows. This involves selecting tools that integrate seamlessly with existing systems.

Secondly, organizations can benefit from understanding and implementing a strategic approach to the implementation of AI-enabled recruitment tools. This can include, but is not limited to, phased rollouts, pilot testing, and gathering feedback from users to understand the environment of the organization towards the changes. Higher significance to trust perception towards the tools and their acceptance should allow organizations to check beforehand that the use of such tools complies with relevant laws and regulations, particularly concerning data privacy and non-discrimination. Establishing clear policies and guidelines will help mitigate risk and build trust among users. Executives from the organization should tailor their communication strategies to address the specific needs and concerns of various stakeholders.

Thirdly, employees should be provided with comprehensive training to familiarize them with the functionalities and benefits of AI-enabled recruitment tools. This training will help employees build confidence and ensure smooth integration into their daily tasks. Understanding that establishing robust support systems, including user manuals, can assist employees in overcoming initial hurdles and technical challenges, thereby fostering a positive attitude towards the technology.

Lastly, the study's findings revealed the significance of perceived ease of use and perceived usefulness in providing a positive attitude toward smart recruitment tools. Developers of smart recruitment tools should prioritize user-centric design principles. Tools need to be intuitive, with user-friendly interfaces that require minimal training. By focusing on ease of use, developers can lower the barrier to entry and increase the number of early adopters engaging with the technology. The perceived usefulness of smart recruitment tools is pivotal in shaping positive attitudes. Establishing a robust feedback mechanism that helps employees share their experiences and challenges with the tools, promoting a positive mindset. This feedback is invaluable for developers to refine and improve the tools, ensuring they meet user needs more effectively. HR managers and professionals should be able to communicate the practical benefits of these tools. By demonstrating real-world applications and success stories, users will understand the tangible advantages and foster positive perceptions.

5.4 Limitations and Future Research

While this study contributes valuable insights into the adoption of smart recruitment tools in HRM, several limitations should be acknowledged. These limitations not only stress the need for cautious interpretation of findings but also suggest promising avenues for future research.

First and foremost, the cross-sectional nature of the study means that information was gathered from participants at a single point in time. This limits the ability to establish causality argument, implying that the relationships that are significant in the study cannot be surely generalized. It is challenging to determine whether observed relationships between variables are causal or merely correlational. For example, while we identified a correlation between perceived ease of use and positive attitudes toward smart recruitment tools, we cannot definitively conclude that ease of use causes positive attitudes. Therefore, future research can focus on various factors that affect the acceptance of smart recruitment tools and conduct a longitudinal study to investigate the long-term changes in users' attitudes and behavioural intentions to use different smart recruitment tools. Cross-sectional data can also be susceptible to certain selection and response biases, therefore future researchers can mitigate these risks with more stringent sampling techniques to ensure accurate responses from participants.

Second, the study was established to analyze the moderating effect of personal innovativeness on the relationship between attitudes and behavioural intentions. Other researchers can investigate additional moderating factors such as organizational culture, leadership support, and individual characteristics, such as technology readiness, to provide a more comprehensive understanding of adoption dynamics. Exploring these moderating factors can provide a richer understanding of the dynamics influencing technology adoption in HRM. Researchers can offer more detailed recommendations for HR practitioners and organizational leaders seeking to implement and optimize smart recruitment techniques. This will enhance the theoretical understanding but also provide practical guidelines for promoting successful adoption. Moreover, the insignificant association of compatibility with fostering a positive attitude can be used as a foundation to understand the role of organizational culture and alignment. These findings suggest that the traditional focus on compatibility as a predictor of attitude may need to be reconsidered in contexts where technology adoption is driven by organizational directives. Future studies might explore other factors that could more accurately predict attitude in such scenarios, such as perceived usefulness or perceived organizational support.

Furthermore, this study employs snowball sampling techniques to gather participants for the survey, which introduces several consequential limitations. Since participants are recruited based on existing connections or referrals, the sample may not be representative of the broader population. This can lead to the overrepresentation of certain demographics skewing the study's findings and limiting generalizability. To address these limitations in future research, employing alternative sampling techniques could enhance the study's validity and broaden its applicability. Additionally, researchers can also use online platforms and social media networks to reach a wider audience and recruit participants from varied backgrounds. Using targeted advertisements or outreach campaigns can attract a more diverse pool of respondents. By adopting more rigorous sampling strategies in future studies, researchers can strengthen the reliability and validity of their findings, enhancing the robustness of conclusions drawn about technology adoption, such as smart recruitment tools in HRM.

Moreover, the survey data was collected from HR professionals working in India using an online survey platform. This approach provides the right context and specificity for the study as India is amongst the countries that are emerging as early adopters of AI-enabled technologies, but it limits the generalizability of the findings. The results and responses reflect the perspectives and experiences of HR professionals within a specific geographical and regulatory context. It is important to explore the usage of smart recruitment tools in other countries and cultures.

Finally, this study relied on the TAM (Davis et al., 1989) to examine the acceptance and adoption of smart recruitment tools. While TAM provides a robust framework for understanding initial technology adoption, its age and focus on early-stage acceptance may limit its ability to capture the complexities of continued use and long-term adoption. Future research could explore newer models such as the Unified Theory of Acceptance and Use of Technology, while incorporating additional constructs such as social influence, facilitating conditions, and user experience. Moreover, future studies should consider shifting focus towards investigating factors influencing the continued use of smart recruitment tools. This includes examining variables such as user satisfaction, system quality, system effectiveness, and user confirmation. Comparative studies across different industries or regions with varying regulatory requirements could highlight new variables that interact with the continued use of smart recruitment tools. By expanding beyond TAM and exploring these avenues, future research can provide a more nuanced understanding of technology adoption processes in HRM.

CHAPTER 6: CONCLUSION

As AI becomes increasingly central to organizational setups and frameworks, it is essential to understand the factors that influence the adoption of smart recruitment tools used in HR practices. The integration of AI in HR processes promises to enhance efficiency, accuracy, and fairness in recruitment. The adoption of smart recruitment tools is influenced by multiple factors including perceived ease of use, perceived usefulness, trust perception, and attitude toward the tools. Furthermore, the perception of HR professionals towards AI plays a significant role in its usage and success.

By using the well-established TAM with elements of compatibility and personal innovativeness, this research proposed a research model to include the critical factors that could explain and predict users' behavioural intention to use smart recruitment tools in the HR framework. The key factors analyzed in the study include perceived ease of use, perceived usefulness, trust perception, compatibility, and attitude. The findings of this study emphasize the strong influence of these factors on users' attitudes toward smart recruitment tools, which, in turn, significantly affect their behavioural intention to use these tools. These results suggest that for HR professionals to adopt smart recruitment tools, the tools must be user-friendly, trustworthy, and perceived as beneficial to their recruitment processes. Furthermore, the study highlights the importance of ensuring that the technology aligns well with existing HR practices and values to foster greater acceptance and integration. By incorporating these factors into the TAM, this research provides a more nuanced understanding of the dynamics influencing the adoption of smart recruitment tools.

Contrarily, compatibility did not show any significant association with users’ attitudes toward smart recruitment tools, indicating that the alignment of the technology with users' existing values, needs, and experiences does not necessarily influence their attitudes toward the adoption of the technology. Additionally, personal innovativeness had no moderating effect on the relationship between attitudes and behavioural intentions. This suggests that even individuals who are generally more inclined to embrace new technologies do not show a different pattern in the attitude-intention linkage compared to those who are less innovative. The study found that other demographic factors such as gender, age, experience in recruitment processes, and position within the organization had a negligible effect on behavioral intention to use smart recruitment tools. This lack of clear correlation implies that these demographic variables do not play a crucial role in determining whether HR professionals will adopt smart recruitment technologies. By understanding that factors like compatibility and personal innovativeness do not significantly impact attitudes or intentions, organizations can streamline their implementation strategies to address the more critical determinants.

This study makes a notable contribution to the existing academic literature by applying established theories to investigate a relatively unexplored area: the adoption of smart recruitment tools in HRM. The integration of TAM with elements such as compatibility and personal innovativeness provides a robust framework for understanding the factors influencing the adoption of these advanced technologies. By doing so, the research not only enriches the theoretical discourse but also fills a critical gap in the literature regarding the practical application of AI-driven tools in HR practices. By offering practical recommendations aimed at a diverse range of stakeholders, including employers, organizations, managers, technology developers, and users. Employers and managers gain insights into how to enhance the perceived ease of use and usefulness of these tools, thereby fostering a positive attitude toward their adoption. For technology developers, the findings underscore the importance of building trust and ensuring the reliability and integrity of smart recruitment systems. By addressing these key aspects, developers can create more user-friendly and trustworthy tools that are more likely to be embraced by HR professionals. Moreover, by bridging theory and practice, this study not only advances academic knowledge but also provides actionable strategies for stakeholders to optimize the usage of smart recruitment tools. These strategies include focusing on user training, ensuring robust technical support, and promoting a culture of innovation and trust within the organization. In conclusion, this study serves as a valuable resource for both academics and practitioners. It contributes to the theoretical understanding of technology adoption in HR while offering practical guidance for the successful deployment of smart recruitment tools.

REFERENCES

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technological Forecasting and Social Change, 170, 120880.

Leong, C. (2018). Technology & recruiting 101: how it works and where it's going. Strategic HR Review, 17(1), 50–52.

Troshani, I., Jerram, C., & Rao Hill, S. (2011). Exploring the public sector adoption of HRIS. Industrial Management & Data Systems, 111(3), 470-488.

Voermans, M., & Van Veldhoven, M. J. P. M. (2007). Attitude towards E‐HRM: an empirical study at Philips. Personnel review, 36(6), 887-902.

Türkeli, I. Artificial Intelligence in Recruitment: the ethical implications of AI-powered recruitment tools.

Barnel, N., Kumar Bamel, U., Sahay, V., & Thite, M. (2014). Usage, benefits and barriers of human resource information system in universities. VINE: The journal of information and knowledge management systems, 44(4), 519-536.

Kolatshi, F. H. M. (2017). Factors Affecting the Acceptance and Impact of Human Resource Information Systems (HRIS): Evidence from HR Professionals in Libyan Companies (Doctoral dissertation, University of Huddersfield).

Kaur, M., AG, R., & Vikas, S. (2021). Adoption of artificial intelligence in human resource management: a conceptual model. Indian Journal of Industrial Relations, 57(2), 331-342.

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. International Journal of Information Management Data Insights, 4(1), 100-208.

Van Esch, P., & Mente, M. (2018). Marketing video-enabled social media as part of your e-recruitment strategy: Stop trying to be trendy. Journal of Retailing and Consumer Services, 44, 266-273.

Yang, H. D., Karon, C., & Kang, S. (2012). To Convert or not to Convert to the Upgraded Version of de-facto Standard Software (No. 2012-02). Center for Economic Institutions, Institute of Economic Research, Hitotsubashi University.

Parzefall, M. R., Seeck, H., & Leppänen, A. (2008). Employee innovativeness in organizations: a review of the antecedents. Finnish journal of business economics, 2(08), 165-182.

Massu, J., Caroff, X., Souciet, H., & Lubart, T. I. (2018). Managers' Intention to Innovate in a Change Context: Examining the Role of Attitudes, Control and Support. Creativity Research Journal, 30(4), 329–338.

Soon, A. L., Derashid, C., & Bidin, Z. (2020). The influence of normative beliefs on tax-payers attitude and voluntary tax compliance intention. Indian-Pacific Journal of Accounting and Finance, 4(1), 33-43.

Kishore, R., & McLean, E. R. (2007). Reconceptualizing innovation compatibility as organizational alignment in secondary IT adoption contexts: an investigation of software reuse infusion. IEEE transactions on engineering management, 54(4), 756-775.

Omar, M. K., Zakaria, A., & Mohamed, B. A. (2015). The Determinants of Employee Attitude towards e-HRM "A Study of Engineering Company in Malaysia. Information Management and Business Review, 7(4), 117-121.

Shahreki, J., Jamaluddin, H., Chin, A. L. L., Hashemi, S., & Nakanishi, H. (2020). An examination on the effects of technology acceptance model in electronic human resource management. Journal of Soft Computing and Decision Support Systems, 7(3), 23-31.

Yusoff, Y. M., & Ramayah, T. (2012). Electronic human resource management (e-HRM) and human resource (HR) competencies: some evidence from an emerging market. International Journal of Information and Communication Technology, 4(1), 27-39.

Shin, H. S. (2010). Moderating effects of personal innovativeness on the relationship between perceived usefulness, subjective norm and intention to use mobile internet. The Journal of information systems, 19(3), 209-236.

Fu, F. Q., & Elliott, M. T. (2013). The moderating effect of perceived product innovativeness and product knowledge on new product adoption: An integrated model. Journal of Marketing Theory and Practice, 21(3), 257-272.

Tsou, C. W. (2012). Consumer acceptance of Windows 7 and Office 2010-The moderating effect of personal innovativeness. Journal of Research and Practice in Information Technology, 44(1), 59-80.

Chen, C. F., & Chen, P. C. (2011). Applying the TAM to travelers' usage intentions of GPS devices. Expert Systems with Applications, 38(5), 6217-6221.

Hwang, Y. (2014). User experience and personal innovativeness: An empirical study on the Enterprise Resource Planning systems. Computers in Human Behavior, 34, 227–234.

Menant, L., Gilibert, D., & Sauvezon, C. (2021). The application of acceptance models to human resource information systems: a literature review. Frontiers in Psychology, 12, 659421.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In Handbook of market research (pp. 587-632). Cham: Springer International Publishing.

Malaha, I., & Pandey, S. Unveiling the Potential of Artificial Intelligence (AI) Platforms for Revolutionizing Recruitment Processes in Organizations Operating in India.

Kumar, B. S. P., & Nagrani, K. O. M. A. L. (2020). Artificial intelligence in human resource management. Novateur Publication's JournalNX-A Multidisciplinary Peer Reviewed Journal, 106-118.

Albert, E. T. (2019). AI in talent acquisition: a review of AI-applications used in recruitment and selection. Strategic HR Review, 18(5), 215-221.

Mehrotra, S., & Khanna, A. (2022). Recruitment Through AI in Selected Indian Companies. Metamorphosis, 21(1), 31–39.

Future-Ready HR: A comprehensive overview of HRTech in India. (2024, January 2). https://italics.in/blog/overview-of-hrtech-in-india

Saharan, T., & Jafri, S. (2012). Valuation of HRIS Status an Insight of Indian Companies' Perspectives. Business Management: Key Research Issues, 113-127.

Russell, S. J., & Norvig, P. (2016). Artificial intelligence: A Modern Approach. Pearson.

Bhattacherjee, A., & Hikmet, N. (2007). Physicians' resistance toward healthcare information technology: a theoretical model and empirical test. European Journal of Information Systems, 16(6), 725-737.

Hmoud, B. I., & Várallyai, L. (2020). Artificial Intelligence in Human Resources Information Systems: Investigating its Trust and Adoption Determinants. International Journal of Engineering and Management Sciences, 5(1), 749-765

Sivathanu, B., & Pillai, R. (2018). Smart HR 4.0 – How Industry 4.0 is disrupting HR. Human Resource Management International Digest, 26(4), 7–11.

Bhatt, M., & Shah, P. (2023). Acceptance of Artificial intelligence in human resource practices by employees. In The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B (pp. 13-30). Emerald Publishing Limited.

Panda, A., Pasumarti, S. S., & Hiremath, S. (2023). Adoption of artificial intelligence in HR practices: An empirical analysis. In The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B (pp. 65-80). Emerald Publishing Limited.

Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking: An International Journal, 27(9), 2599-2629.

Handra, T., & Sundram, V. P. K. (2023). The effect of human resource information systems (hris) and artificial intelligence on defense industry performance. IAIC Transactions on Sustainable Digital Innovation (ITSDI), 4(2), 155-163.

Masum, A. K. M., Beh, L. S., Azad, M. A. K., & Hoque, K. (2018). Intelligent human resource information system (i-HRIS): A holistic decision support framework for HR excellence. Int. Arab J. Inf. Technol., 15(1), 121-130.

Yadav, S., & Kapoor, S. (2024). Adopting artificial intelligence (AI) for employee recruitment: the influence of contextual factors. International Journal of System Assurance Engineering and Management, 15(5), 1828–1840.

Tuffaha, M., Pandya, B., & Perello-Marin, M. R. (2022). AI-powered chatbots in recruitment from Indian HR professionals' perspectives: Qualitative study. The journal of contemporary issues in business and government, 28(4), 1971-1989.

Kumar, M., Raut, R. D., Mangla, S. K., Ferraris, A., & Choubey, V. K. (2022). The adoption of artificial intelligence powered workforce management for effective revenue growth of micro, small, and medium scale enterprises (MSMEs). Production Planning & Control, 1-17.

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2023). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. In Artificial Intelligence and International HRM (pp. 60-82). Routledge.

Huang, J., & Martin-Taylor, M. (2013). Turnaround user acceptance in the context of HR self-service technology adoption: an action research approach. International Journal of Human Resource Management, 24(3), 621–642

Islam, M., Mamun, A. A., Afrin, S., Ali Quaosar, G. A., & Uddin, M. A. (2022). Technology adoption and human resource management practices: the use of artificial intelligence for recruitment in Bangladesh. South Asian Journal of Human Resources Management, 9(2), 324-349.

Panos, S., & Bellou, V. (2016). Maximizing e-HRM outcomes: a moderated mediation path. Management Decision, 54(5), 1088–1109.

Votto, A. M., Valecha, R., Najafirad, P., & Rao, H. R. (2021). Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review. International Journal of Information Management Data Insights, 1(2), 100047.

Boselie, P. (2014). Strategic human resource management: A balanced approach. McGraw Hill.

Meshram, R. (2023). The role of artificial intelligence (ai) in recruitment and selection of employees in the organisation. Russian Law Journal, 11(9S), 322-333.

Khaled, A. S., Sharma, D. K., Yashwanth, T., Reddy, V. M. K., doewes, R. I., & Naved, M. (2022, June). Evaluating the Role of Robotics, Machine Learning and Artificial Intelligence in the Field of Performance Management. In Proceedings of Second International Conference in Mechanical and Energy Technology: ICMET 2021, India (pp. 285-293).

Hemalatha, A., Kumari, P. B., Nawaz, N., & Gajenderan, V. (2021, March). Impact of artificial intelligence on recruitment and selection of information technology companies. In 2021 international conference on artificial intelligence and smart systems (ICAIS) (pp. 60-66). IEEE.

Horodyski, P. (2023). Recruiter's perception of artificial intelligence (AI)-based tools in recruitment. Computers in Human Behavior Reports, 10, 100-298.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. Human resource management review, 33(1), 100899.

Kalia, P., & Mishra, G. (2023). Role of artificial intelligence in Re-inventing human resource management. In The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B (pp. 221-234). Emerald Publishing Limited.

Hmoud, B. I. F., & Várallyai, L. (2019). Will artificial intelligence take over human resources recruitment and selection?

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. Human Resource Management Review, 32(2), 100-795.

Ngai, E. W. T., & Wat, F. K. T. (2006). Human resource information systems: a review and empirical analysis. Personnel review, 35(3), 297-314.

Krishnan, S. K., & Singh, M. (2007). Issues and Concerns in the Implementation and Maintenance of HRIS. Management and Labour Studies, 32(4), 522–540.

Laurim, V., Arpaci, S., Prommegger, B., & Krcmar, H. (2021). Computer, whom should I hire?–acceptance criteria for artificial intelligence in the recruitment process.

Poonpanich, N., & Buranasiri, J. (2022). Factors Affecting Baby Boomers' Attitudes towards the Acceptance of Mobile Network Providers' AI Chatbot. Jurnal Nasional Pendidikan Teknik Informatika: JANAPATI, 11(3), 176-182.

Hajdú, N., & Nagy, S. (2021). Consumer Acceptance of the Use of Artificial Intelligence in Online Shopping: Evidence From Hungary. Amfiteatru Economic, 23(56), 155–173.

Kashive, N., Powale, L., & Kashive, K. (2021). Understanding user perception toward artificial intelligence (AI) enabled e-learning. Campus-Wide Information Systems, 38(1), 1–19.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research, 18(1), 39-50.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial management & data systems, 117(3), 442-458.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS quarterly, 157-178.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision sciences, 39(2), 273-315.

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. British journal of management, 17(4), 263-282.

Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modelling and regression: Guidelines for research practice. Communications of the association for information systems, 4(1), 7.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.

Aguirre-Urreta, M. I., Marakas, G. M., & Ellis, M. E. (2013). Measurement of composite reliability in research using partial least squares: Some issues and an alternative approach. ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 44(4), 11-43.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. Strategic management journal, 20(2), 195-204.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modelling in new technology research: updated guidelines. Industrial management & data systems, 116(1), 2-20.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2012). Partial least squares: the better approach to structural equation modelling. Long range planning, 45(5-6), 312-319.

Normalini, M. K. (2019). Revisiting the Effects of Quality Dimensions, Perceived Usefulness and Perceived Ease of Use on Internet Banking Usage Intention. Global Business and Management Research, 11(2), 252–261.

Turing, A. M. (1950). Computing Machinery and Intelligence. Mind, 59(236), 433–460.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8), 982-1003.

Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. Human relations, 61(8), 1139-1160.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 51-90.

Cohen, N., & Arieli, T. (2011). Field research in conflict environments: Methodological challenges and snowball sampling. Journal of peace research, 48(4), 423-435.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International journal of electronic commerce, 7(3), 101-134.

Kim, D. W., Jang, H. Y., Kim, K. W., Shin, Y., & Park, S. H. (2019). Design characteristics of studies reporting the performance of artificial intelligence algorithms for diagnostic analysis of medical images: results from recently published papers. Korean journal of radiology, 20(3), 405-410.

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of the moderating influence of subject and context type. International Journal of Information Management, 31(6), 572-581.

Rogers, Everett M., Diffusion of Innovations, (Third Ed.), The Free Press, New York, 1983

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), 186–204.

Davis, F. D. (1989). Perceived Usefulness, Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. International Journal of Human–Computer Interaction, 39(9), 1727-1739.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709-734.

Chiu, T. K. (2017). Introducing electronic textbooks as daily - use technology in schools: A top - down adoption process. British Journal of Educational Technology, 48(2), 524-537.

Teo, T., & Tan, L. (2012). The theory of planned behaviour (TPB) and pre-service teachers' technology acceptance: A validation study using structural equation modelling. Journal of Technology and Teacher Education, 20(1), 89-104.

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California Management Review, 61(4), 66-83.

Xu, D., & Wang, H. (2006). Intelligent agent-supported personalization for virtual learning environments. Decision Support Systems, 42(2), 825-843.

Zhang, Y., Liao, Q. V., & Bellamy, R. K. (2020). Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making. In Proceedings of the 2020 conference on fairness, accountability, and transparency (p.p. 295-305).

Marcus, B., Weigelt, O., Hergert, J., Gurt, J., & Gelléri, P. (2017). The use of snowball sampling for multi-source organizational research: Some cause for concern. Personnel Psychology, 70(3), 635-673.

Naderifar, M., Goli, H., & Ghaljaie, F. (2017). Snowball sampling: A purposeful method of sampling in qualitative research. Strides in development of medical education, 14(3).

Reagan, L., Nowlin, S. Y., Birdsall, S. B., Gabbay, J., Vorderstrasse, A., Johnson, C., & Melkus, G. D. E. (2019). Integrative review of recruitment of research participants through Facebook. Nursing Research, 68(6), 423-432.

Wohl, A. R., Ludwig-Barron, N., Dierst-Davies, R., Kulkarni, S., Bendetson, J., Jordan, & Pérez, M. J. (2017). The project engages snowball sampling and direct recruitment to identify and link hard-to-reach HIV-infected persons who are out of care. JAIDS Journal of Acquired Immune Deficiency Syndromes, 75(2), 190-197.

Chen, J. L. (2011). The effects of education compatibility and technological expectancy on e-learning acceptance. Computers & Education, 57(2), 1501-1511.

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: applying the technology acceptance model and the theory of planned behaviour. Precision Agriculture, 22(6), 1816–1844.

Shin, D. (2020b). User perceptions of algorithmic decisions in the personalized AI system: Perceptual evaluation of fairness, accountability, transparency, and explainability. Journal of Broadcasting & Electronic Media, 64(4), 541-565.

Lee, M. K. (2018). Understanding the perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data & Society, 5(1), 2053951718756684.

Lee, Min Kyung, and Katherine Rich. "Who is included in human perceptions of AI?: Trust and perceived fairness around healthcare AI and cultural mistrust." Proceedings of the 2021 CHI conference on human factors in computing systems. 2021.

Wang, C., Ahmad, S. F., Ayassrah, A. Y. B. A., Awwad, E. M., Irshad, M., Ali, Y. A., ... & Han, H. (2023). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. Heliyon, 9(8).

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. AI magazine, 27(4), 12-12.

Saeed, K. A., Hwang, Y., & Mun, Y. Y. (2003). Toward an integrative framework for online consumer behaviour research: a meta-analysis approach. Journal of Organizational and End User Computing (JOEUC), 15(4), 1-26.

Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems. Cambridge, MA, 17.

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa… examine the variables influencing the use of artificially intelligent in-home voice assistants. Computers in Human Behavior, 99, 28-37.

Flynn, L. R., & Goldsmith, R. E. (1993). A Validation of the Goldsmith and Hofacker Innovativeness Scale. Educational and Psychological Measurement, 53(4), 1105–1116.

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioural intention to use e-learning. Journal of Educational Technology & Society, 12(3), 150-162.

Chai, C. S., Lin, P.-Y., Jong, M. S.-Y., Dai, Y., Chiu, T. K. F., & Qin, J. (2021). Perceptions of and Behavioral Intentions towards Learning Artificial Intelligence in Primary School Students. Educational Technology & Society, 24(3), 89–101.

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. Journal of Retailing and Consumer Services, 40, 125-138.

Goldweber, M., Davoli, R., Little, J. C., Riedesel, C., Walker, H., Cross, G., & Von Konsky, B. R. (2011). Enhancing the social issues components in our computing curriculum: computing for the social good. ACM Inroads, 2(1), 64-82.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in information technology. Information Systems Research, 9(2), 204-215.

Mukherjee, A. N., Bhattacharyya, S., & Bera, R. (2014). Role of information technology in human resource management of SME: A study on the use of applicant tracking system. IBMRD's Journal of Management & Research, 1-22.

Wijesundara, T. R., & Xixiang, S. (2018). Social networking sites acceptance: The role of personal innovativeness in information technology. International Journal of Business and Management, 13(8), 75-85.

Chen, J. (2022). Adoption of M-learning apps: A sequential mediation analysis and the moderating role of personal innovativeness in information technology. Computers in Human Behavior Reports, 8, 100237.

Fagan, M., Kilmon, C., & Pandey, V. (2012). Exploring the adoption of a virtual reality simulation: The role of perceived ease of use, perceived usefulness and personal innovativeness. Campus-Wide Information Systems, 29(2), 117-127.

Rana, N. P., Dwivedi, Y. K., Lal, B., Williams, M. D., & Clement, M. (2017). Citizens' adoption of an electronic government system: towards a unified view. Information Systems Frontiers, 19, 549-568.

VALENTE, T. W., & ROGERS, E. M. (1995). The Origins and Development of the Diffusion of Innovations Paradigm as an Example of Scientific Growth. Science Communication, 16(3), 242–273.

Gefen, D. (2004). What makes an ERP implementation relationship worthwhile: Linking trust mechanisms and ERP usefulness. Journal of Management Information Systems, 21(1), 263-288.

Kim, Y. J., Chun, J. U., & Song, J. (2009). Investigating the role of attitude in technology acceptance from an attitude strength perspective. International Journal of Information Management, 29(1), 67-77.

Tung, F. C., Chang, S. C., & Chou, C. M. (2008). An extension of trust and TAM model with IDT in adopting the electronic logistics information system in HIS in the medical industry. International journal of medical informatics, 77(5), 324-335.

Yu, B., Vahidov, R., & Kersten, G. E. (2021). Acceptance of technological agency: Beyond the perception of practical value. Information & Management, 58(7), 103-503.

Midgley, D. F., & Dowling, G. R. (1978). Innovativeness: The Concept and Its Measurement. The Journal of Consumer Research, 4(4), 229–242.

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In An integrated approach to communication theory and research, 432-448.

Fishbein, M., & Ajzen, I. (2011). Predicting and changing behaviour: The reasoned action approach. Taylor & Francis.

Thadatritharntip, W., & Vongurai, R. (2020). Artificial Intelligence Healthcare: An Empirical Study on Users' Attitude and Intention to Use toward a Personal Home Healthcare Robot to Improve Health and Wellness Conditions in Bangkok, Thailand. UTCC International Journal of Business & Economics, 12(1), 3-25.

Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing organizational users' intentions and behaviour to AI integrated CRM systems: A meta-UTAUT approach. Information Systems Frontiers, 1-15.

Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An expectation-confirmation model of continuance intention to use mobile instant messaging. Telematics and Informatics, 33(1), 34-47.

Söllner, M., Hoffmann, A., & Leimeister, J. M. (2016). Why different trust relationships matter for information systems users. European Journal of Information Systems, 25(3), 274-287.

Laforet, S., & Li, X. (2005). Consumers' attitudes towards online and mobile banking in China. International journal of bank marketing, 23(5), 362-380.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modelling in marketing research. Journal of the academy of marketing science, 40, 414-433.

Tompson, R., Barclay, D., & Higgins, C. (1995). The partial least squares approach to causal modelling: Personal computer adoption and uses as an illustration. Technology Studies: Special Issue on Research Methodology, 2(2), 284-324.

Dusek, G., Yurova, Y., & Ruppel, C. P. (2015). Using social media and targeted snowball sampling to survey a hard-to-reach population: A case study. International Journal of Doctoral Studies, 10, 279.

Wang, M., Cho, S., & Denton, T. (2017). The impact of personalization and compatibility with experience on e-banking usage. International Journal of Bank Marketing, 35(1), 45-55.

Ab Hamid, M. R., Sami, W., & Sidek, M. M. (2017, September). Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion. In Journal of physics: Conference series (Vol. 890, No. 1, p. 012163). IOP Publishing.

APPENDIX A: MEASUREMENT ITEMS

Name of the Variable	Items
Perceived Ease of Use (Davis 1986; Wu et al., 2011)	• It would be easy for me to become skillful at using smart recruitment tools. • I would find it easy to get smart recruitment tools to do what I want it to do. • My interaction with smart recruitment tools is clear and understandable. • I would find smart recruitment tools are easy to use.
Perceived Usefulness (Oghuma et al., 2016; Bhattacherjee., 2001)	• Using smart recruitment tools will improve my performance in managing candidates. • Using smart recruitment tools will enhance my effectiveness in managing recruitment processes. • Using smart recruitment tools will increase my productivity. • I find smart recruitment tools will be useful in my daily life.
Compatibility (Chen, 2011; Chatterjee et al., 2021; Rogers, 1983)	• Using smart recruitment tools is compatible with all aspects of the task. • Using smart recruitment tools is completely compatible with my current work environment. • I think using smart recruitment tools fits well with how I work. • Using smart recruitment tools fits into my job.
Trust Perception (Choung et al., 2023; Sollener et al., 2011)	• I trust that smart recruitment tools can offer information and services best for organizations' interests. • I trust that candidates' data is protected during hiring. • I trust that authorities exert effective control over organizations and companies providing smart recruitment tool services for recruitment. • I trust that authorities exert effective control over organizations

	and companies providing smart recruitment services.
Attitude (Choung et al., 2023)	• I feel positive about smart recruitment tools. • I feel that using smart recruitment tools is pleasant. • Using smart recruitment tools is a good idea. • Using smart recruitment tools is a smart way to get things done.
Behavioral Intention to Use (Venkatesh & Davis, 2000)	• I will continue to acquire AI-related information in the future. • I will keep myself updated with the latest AI applications. • I will continue to use smart recruitment tools to assist with my job. • I will continue to learn about the latest AI technologies in the market.
Personal Innovativeness (Mohr & Kuhl, 2021)	• I am curious about how applications with new technologies work. • I like to explore applications with new technologies. • I enjoy being around people who are exploring new technologies. • I often seek information on new technologies.