A STUDY OF FACTORS INFLUENCING EMPLOYEES' ACCEPTANCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN RECRUITMENT

BY

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AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF MASTER OF BUSINESS
ADMINISTRATION PROGRAM IN
BUSINESS INNOVATION
TUXSA ONLINE MASTER'S DEGREE PROGRAM THAMMASAT UNIVERSITY
ACADEMIC YEAR 2023

THAMMASAT UNIVERSITY

TUXSA ONLINE MASTER'S DEGREE PROGRAM

INDEPENDENT STUDY

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ENTITLED

A STUDY OF FACTORS INFLUENCING EMPLOYEES' ACCEPTANCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN RECRUITMENT

was approved as partial fulfillment of the requirements for the degree of Master of Business Administration (Business Innovation)

on December 29, 2023

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Independent Study Title	A STUDY OF FACTORS INFLUENCING EMPLOYEES' ACCEPTANCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN RECRUITMENT
Author	Piriyapong Wongras
Degree	Master of Business Administration (Business Innovation)
Major Field/Faculty/University	TUXSA Online Master's Degree Program Thammasat University
Independent Study Advisor	Associate Professor Tanatorn Tanantong, Ph.D.
Academic Year	2023

ABSTRACT

Recruitment plays a vital role in enhancing organizational performance within the realm of Human Resource (HR) Management. Traditional recruitment approaches, which involve manual stages, are not only time-consuming but also inefficient. The emergence of AI, which proves its effectiveness in various sectors, is currently transforming recruitment by automating tasks to boost efficiency. Despite the growing demand for talent in Thailand, the utilization of AI in recruitment within the country is relatively limited.

This independent study emphasizes on gaining insights from HR and recruitment experts in Thailand to understand their perspectives on integrating AI into recruitment processes. The study adapts the Unified Theory for Acceptance and Use of Technology (UTAUT) model to align with the specific requirements of Thai recruitment practices. It explores the factors influencing user's intention to accept AI in recruitment. Survey questionnaire was developed based on existing literature and refined through interviews to ensure relevance within the Thai recruitment context. The survey involved 364 HR and recruitment experts in the Bangkok metropolitan area, achieving insightful responses.

The findings reveal that a number of factors, including Perceived value, Perceived autonomy, Effort expectancy, and Facilitating conditions, significantly influence the intention to use AI in recruitment. While social influence and trust in AI technology do not directly impact intention, social influence impacts perceived value. Additionally, trust in AI technology positively affects effort expectancy. This study provides insights for HR and recruitment experts, corporates, and AI provider by deepening the understanding of AI adoption. It also contributes to enhancing recruitment processes and promoting the use of AI in this area.

Keywords: Recruitment, Artifical Intelligence, UTAUT, Technology Adoption, Talent Acquisition, AI in Recruitment, Human Resource

ACKNOWLEDGEMENTS

This independent study was successfully conducted with significant support from various individuals who played a crucial role in facilitating my study. Firstly, I would like to express my heartfelt gratitude to my advisor, Associate Professor Dr. Tanatorn Tanantong, for providing precious advice and assistance throughout the course of this independent study.

I also want to acknowledge and thank Associate Professor Dr. Surat Teerakapibal, who served as the chairperson during the qualifying examination for this research. I extend my heartfelt gratitude to all the professors and lecturers at Thammasat University for sharing their knowledge across diverse fields, thereby contributing to the applicability and success of this study. Special recognition is due to the university staff whose efforts were crucial in ensuring the triumph of this study.

I am profoundly grateful to the participants who generously responded to my inquiries. Most importantly, I express my gratitude to my family members for their constant love, understanding, and unwavering support throughout this endeavor.

Piriyapong Wongras

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LIST OF ABBREVIATIONS

Symbols/Abbreviations	Terms
AL	Artificial Intelligence
HR	Human Resources
HRM	Human Resource Management
UTAUT	Unified Theory of Acceptance and Use of Technology
TAM	Technology Acceptance Model
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Conditions
PS	Privacy and Security
TA	Technology Trust in AI
PV	Perceived Value
PA	Perceived Autonomy
IU	User's Intention to Use AI in Recruitment
AVE	the Average Variance Extracted

CHAPTER 1
INTRODUCTION

This section provides an overview of the study, beginning with an exploration of the background and importance of problem statement, followed by the independent study goals and expected results.

1.1 Background

In the midst of the 4th Industrial Revolution, marked by the rapid integration of cutting-edge technologies across various industries, the demand for highly skilled and specialized employees has reached unprecedented heights. The advent of Industry 4.0 is transforming jobs and organizations, highlighting the significance of talent acquisition and management. To remain competitive, companies are actively pursuing highly skilled professionals and investing in technology to streamline recruitment processes. The ability to attract new talent is crucial for seizing opportunities in this industrial revolution. The standard recruitment process includes stages such as job analysis, candidate profile creation, scheduling, interviews, psychological testing, shortlisting, contract signing, and onboarding (Rezzani, Caputo, & Cortese, 2020).

The trend of digital disruption has come beforehand causing over 50% of Fortune 500 companies to encounter bankruptcy, acquisition, or even closure since 2000. This digital transformation acceleration necessitates an urgent revamp of HR practices. Organizations need to integrate digital labor into their strategic planning, whether they are in the process of adopting cloud solutions, establishing shared services, or undergoing other transformations. Noteworthily, 41% of CEOs have already put chatbots and cognitive AI technologies into operation or are in the process of planning their implementation (Zeoli & Billeter, 2019).

As companies strive to remain competitive in this digitally-driven landscape, the role of AI in recruitment has emerged as a game-changer. AI-driven recruiting has become crucial due to several key factors. Job candidates are increasingly active in digital spaces, necessitating digital recruitment strategies. The digitization of job information has led to a surge in applicants, requiring AI tools for screening. These AI tools now surpass human efficiency and effectiveness in early-stage recruitment. However, despite recognizing the importance of AI in recruiting, many executives have been slow to adopt these systems, with only 31% feeling their companies are ready to leverage AI's potential, even though 72% see it as critical according to Deloitte Insights 2018 (van Esch & Black, 2019).

While AI is still in its early stages of development and deployment, industry experts foresee a significant surge in its utilization in the coming decade. This increased use of AI is anticipated to result in a 14% global GDP growth by 2030, with the most significant impacts expected in China, where a projected 26% GDP increase is foreseen. AI has demonstrated its potential to revolutionize HRM, exemplified by IBM's successful reduction of HR costs by $107 million in 2017 through AI implementation. Companies like IBM believe that AI will be a cornerstone of future HRM practices (Pan, Froese, Liu, Hu, & Ye, 2022). Amid the COVID-19 pandemic, HR leaders conducted by Gartner showed that swiftly integrated new virtual technologies into their hiring processes, a move observed in 86% of organizations according to a Gartner survey with over 300 HR leaders in mid-April 2020. As lockdown measures persisted and AI adoption surged across various sectors, coupled with dissatisfaction with conventional recruitment methods, HireVue reported a striking 614% surge in AI-driven hiring activities among organizations in Japan (Drage & Mackereth, 2022).

In the view of recruitment, even though the technology like automation, internet of things (IoT), robotics or even AI is coming to replace non-skilled labors or routine jobs, anyway, there will be more jobs created especially highly skilled workforces. Thus, a demand of highly skilled employees with specific functions of engineering and digital technology will be increasing. The concept of Industry 4.0 was introduced as part of the 20-year strategy of the nation spanning from 2017 to 2036. Thailand, situated in Southeast Asia, is transitioning to a developed nation. As part of this transformation, the country aims to raise its GDP per capita significantly, from $4,121 to $15,000 over the next two decades. In response to economic challenges and an aging population, Thai government has introduced a new development policy known as Thailand 4.0, aligning closely with the principles of Industry 4.0, focusing on innovation, a digital economy, and advanced technology industries as drivers for the country's future growth (Puriwat & Tripopsakul, 2020).

Figure 1.1

Thailand 4.0 Infographic

Source: Sullivan, 2018.

This can lead to intense competition among companies in the recruitment of talented employees. Since traditional recruitment procedures, such as manually posting job ads, sourcing, and screening, demand significant time and effort from HR experts, the possibility of promptly acquiring highly qualified candidates becomes exceedingly challenging. Traditional recruitment faces challenges like identifying suitable candidates and reducing costs during the hiring process. However, in the digital age, leveraging information technology and AI can enhance recruitment effectiveness. Globally, companies such as L'Oreal, Unilever, Amazon, and IKEA have already embraced AI in their recruitment processes (Lisa & Talla Simo, 2021). As talent recruitment is one of the key factors in organization’s success, adopting AI technology in recruitment can make companies in Thailand to be more competitive in the region.

1.2 Problem Statement

Currently, the recruitment process has been a time-consuming, primarily relying on human involvement for tasks including reviewing resumes, assessing candidates' online profiles, initiating initial contact, conducting pre-screening interviews, and providing feedback to applicants (O’Donovan, 2019). In recruitment, applicant tracking systems handle a significant portion of resume sorting, yet human involvement remains essential in carrying out the subsequent stages of the hiring process. Thus, with AI implementation, recruitment processes can be significantly automated, reducing the need for human involvement. AI now can handle tasks like CV screening, automated messaging, interview scheduling, and reference checks. This automation not only facilitates the swift resolution of employee inquiries but also ensures timely responses (Dutta & Gankar, 2021).

Thailand has recently emerged as an industrialized nation within Southeast Asia. The government has launched a nation initiative namely Thailand 4.0. The purpose is to leverage economy towards digital technology like AI, digitalization, and automation, aiming to achieve a 5-6% economic growth rate, reaching full capacity within the next 5 years and raising the per capita national income from to $15,000 by 2032. In the view of recruitment, talent acquisition becomes more competitive.

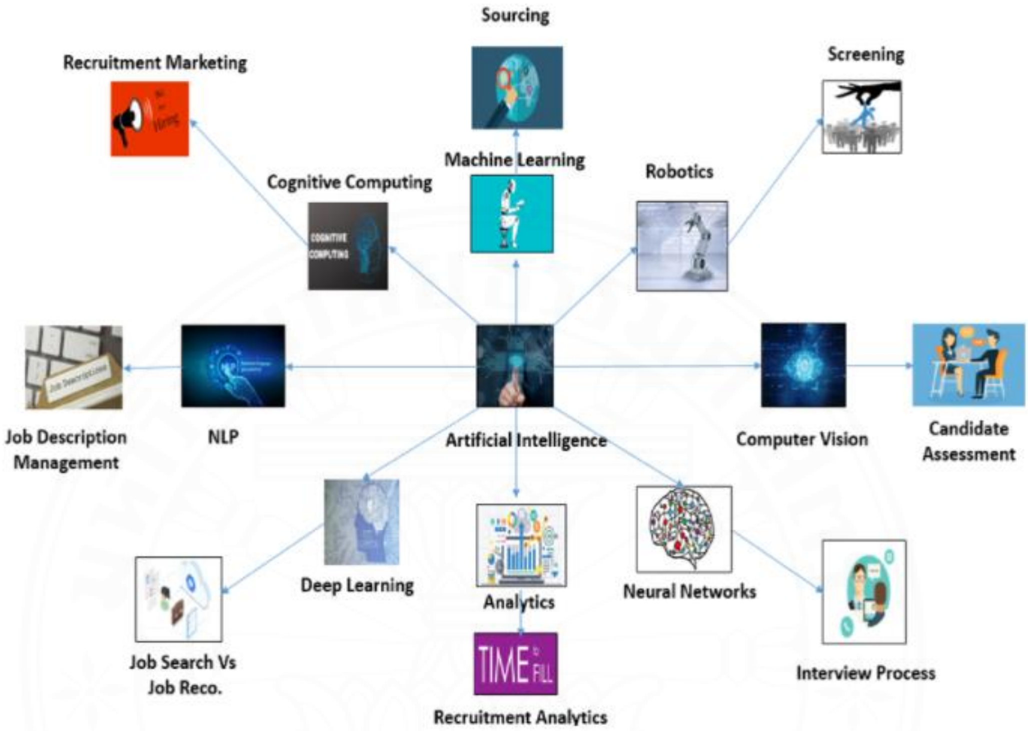
In Thailand, there is a high demand for talents with specialized skills, but the talent supply is insufficient. Recruiters are primarily struggling to find candidates who fit their company culture, which is the most pressing challenge. These difficulties are further reducing the already limited pool of potential hires (Talent Trends 2022 Michael Page The Great X Report Thailand 2022).

In the Job Market Projection post-crisis session by JobsDB, it was reported that Thailand's job demand started recovering from February 2021. Notably, there was a significant 24.65% surge in the demand for skilled labor following the second wave of the pandemic. What's even more striking is the job market's competitiveness, with a ratio of one job opening for every 100 job applications (JobsDB, 2021). The high job application-to-opening ratio poses challenges for talent recruiters, demanding more time and effort. Hiring additional recruiters may not be cost-effective. HR professionals are facing challenges due to technology and innovation in their quest to find skilled individuals for their companies. To address this, HR practices must become more efficient, ensuring quick and precise recruitment while remaining cost-effective.

AI-driven recruitment goes beyond simply expanding a company's reach. it also enables a more in-depth assessment of the compatibility between potential employees and job positions. For instance, Nvidia employs AI chips in smartphones to analyze behavior and speech patterns of users, enabling the matching of candidates with roles aligning with their characteristics. Additionally, companies such as eBay, IBM, Intel, and Verizon utilize AI-powered tools, such as Hiretual, to evaluate job applicants' availability, experience, skills, and market value by comparing them against a vast database from 30 online platforms with over 700 million career profiles (van Esch & Black, 2019).

Figure 1.2

Recruiting life cycle and AI use cases



Source: Vishwanadh, 2021.

Nonetheless, the adoption of AI in recruitment in Thailand is currently not widespread, mainly due to a range of concerns. AI in recruitment faces limitations, including dependence on human-created data and algorithms, leading to potential decision uncertainty. Concerns exist about AI replicating human biases and its ability to replicate the nuanced human touch in assessing intangible qualities not visible in resumes judgment (Wan Ibrahim & Hassan, 2019). Challenges also arise in trustworthiness, data privacy, and the replacement of human recruiters persist (Hemalatha, Kumari, Nawaz, & Gajenderan, 2021; Ore & Sposato, 2021). It is essential to consider the readiness of the Personal Data Protection Act of Thailand (PDPA) and make necessary preparations for the integration of AI. This includes incorporating AI regulations within the PDPA framework and bolstering security and privacy infrastructure (LEESA-NGUANSUK, 2019).

Therefore, this study is aimed to explore perspectives of HR and recruitment professionals in Thailand regarding the integration of AI in the recruitment domain, acknowledging its crucial contribution to achieving sustainable success within an organization. Given the widespread applications of The Unified Theory for Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) model in numerous studies examining the acceptance of new information technology and AI-driven innovations in areas such as mobile applications, educational, and public services. It is well-regarded for its substantial capacity to explain behaviors related to new technology adoption (Byoung-Chol & Bo-Young, 2021). Thus, this study is specially tailored to construct a fresh structural model by integrating UTAUT components with additional factors that are in the context of recruitment practices in Thai companies.

1.3 Research Objectives

The research objectives can be outlined as follows:

1) To gain insights and analyzing the perspectives of HR and recruitment professionals in Thailand regarding the integration of AI technology in recruitment processes.

2) To Examine professionals' viewpoints on AI in recruitment with the identification of influential factors related to AI use in recruitment.

3) To assess the structural model through quantitative evaluation.

4) To assess the feasibility of AI adoption in the recruitment domain.

1.4 Expected Results

1) Acceptance factors influencing user’s intention to use Artificial Intelligence in recruitment.

2) Guidance for HR and recruitment experts, corporate entities requiring their employees to utilize Artificial Intelligence in recruitment, and software developers specializing in AI for recruitment applications.

CHAPTER 2
REVIEW OF LITERATURE

This chapter aims to familiarize readers with key terms in recruitment, encompassing conventional approaches, digital-age recruitment, and the incorporation of artificial intelligence. It explores theories on technology adoption, with a focus on the Unified Theory of Acceptance and Use of Technology (UTAUT). Additionally, it details the methodology for constructing the conceptual framework, extending the UTAUT model by incorporating additional factors identified in pertinent research studies.

2.1 Recruitment Introduction

In this section, the definition of recruitment is outlined based on insights from numerous research studies. An explanation of recruitment types is provided, and both traditional recruitment practices and contemporary recruitment processes in the digital age are explored as follows:

2.1.1 Recruitment Definition

Recruitment is a fundamental aspect of HRM (Human Resource Management), encompassing the steps of identifying, evaluating, narrowing down, and hiring potential individuals to occupy available positions within an organization. The primary goal is to select the right candidates for specific roles, ensuring they join the organization when needed. This involves the processes of attracting, selecting, and appointing suitable candidates to meet the organization's staffing requirements (Saroj Bandi & Kumar, 2017). In organizations, recruitment serves as a crucial procedure that identifies the staffing requirements and assembles a pool of potential employees for particular roles. It is an essential element of HRM, alongside selection. Well-executed recruitment and selection processes can lead to enhanced performance in areas like employee development and decreased employee turnover for the organization (Nanor, Owusu, Senyah, Owusu, & Agyei, 2022).

Similarly, from the employee's viewpoint, recruitment involves their efforts to align their knowledge, skills, and capabilities with the opportunities provided by the employer. A job hunt involves with evaluating how well an individual matches the opportunities and resources provided by the organization. It's evident that the employee places significant importance on this alignment when participating in the recruitment process (Muslim, Dean, & Cohen, 2016). A business organization needs to employ employees for skills that are newly demanded. Therefore, to ensure successful recruitment, organizations must monitor market conditions for any changes and assess how these changes impact their resources. This proactive approach helps adapt recruitment strategies to align with evolving labor market dynamics (Saroj Bandi & Kumar, 2017).

2.1.2 Recruitment Types

Recruitment can be classified into two methods: internal and external recruitment.

1) Internal Recruitment: This is related to people or talent development in the organization. This type of recruitment is a cost-effective approach and increases the chances of finding suitable candidates since the company has a clear understanding of the candidate profile. is a cost-effective approach and increases the chances of finding suitable candidates since the company has a clear understanding of the candidate profile. (DeCenzo, Robbins, & Verhulst, 2013).

2) External Recruitment: Numerous job openings are applied by individuals from outside the organization. Additionally, when an organization's internal candidates are transferred or promoted to other roles within the company, it creates a new vacant position that needs to be filled externally (Yaseen, 2016). This hiring process aims to identify suitable candidates externally because the company may not possess the particular skills required or because new skills are necessary (Lisa & Talla Simo, 2021). As the demand for new skills remains consistently high, organizations must actively seek external candidates who possess the requisite skills that align with the

organization's needs. Additionally, it is crucial to ensure that incoming employees are a good fit for the company's culture in order to maintain a low attrition rate.

2.1.3 Traditional Recruitment

According to (Holm, 2012), A traditional recruitment model comprises four primary tasks, each with its associated activities, outlined as follows:

1) Identifying applicants: This is the fundamental step like a job analysis for understanding the requirements as well as creating the job description containing responsibilities, tasks, and skills required. The job responsibility is to analyze knowledge and skills for the position where specific job description is required from the human resources.

2) Attracting applicants: This phase can be carried by job announcement traditionally through paper-based media, television or radio, depending on organization and the candidates' target. The advertisement needs to be attractive and engaging with job seekers to let them understand more about the job.

3) Processing incoming applicants: This step includes sorting, early screening job applicants. The recruiter plays a key role to communicate with a hiring team. As well, the hiring team can assist the recruiter to start the next recruitment step.

4) Communicating with applicants: This is to inform the applicants towards official letter or a phone whether for going to a next step or rejection. Those who are selected will be planned for face-to-face interviews to get the right candidate for the position.

Traditional recruiting has basic steps to ensure that candidate selection match the specific role. These include recruitment planning, strategic development, searching and attraction, screening, evaluation and finally tracking (Kerrin & Kettley, 2003). The fundamental steps in traditional recruitment encompass: 1) Identifying job vacancies 2) Crafting job descriptions and preparing the necessary soft skill criteria 3) Sourcing and screening qualified candidates 4) Compiling a shortlist for interviews 5) Making the selection to hire the most suitable candidate (Oswal, Ateeq, & Mathew, 2021).

Traditional recruitment mostly means face-to-face together with paper-based process using newspaper and job boards as media. Also specific places were selected for meeting and attracting job seekers. Therefore, human judgment was mainly used to obtain people with potentials (Chapman & Webster, 2003). In essence, traditional recruitment may be ineffective since it was a long process for hiring, expensive, limitation in location, and poor relationship management with job applicants.

2.1.4 Digital Era in Recruitment

The advent of the digital era has brought about significant transformations in the field of recruitment. Technology now plays a pivotal role as both a facilitator for improving management practices and a catalyst for enhancing decision-making processes. This, in turn, promotes the reconfiguration of organizational operations. (Jatoba, Gutierriz, Fernandes, Teixeira, & Moscon, 2019). The electronic human resource management is considered as a new way in HR management and realized as the use of information technology to facilitate the process of human resource management which consists of recruiting, selecting, training, evaluating, and compensation. Digital recruitment, also known as e-recruitment, involves leveraging communication technologies such as websites and social media platforms to identify and engage with skilled job candidates. Its aim is to pique their interest in the organization and influence their decision-making when it comes to selecting a job (R. D. Johnson, Stone, & Lukaszewski, 2021). In addition, e-recruitment offers a valuable strategy for all types of organizations due to its cost-effectiveness, speed, and efficiency in searching for potential candidates. (Dhamija, 2012).

Since talent acquisition is a labor-intensive procedure demanding significant dedication from HR experts, organizations have the option to delegate the recruitment process to specialized talent recruitment agencies. (Kerrin & Kettley, 2003). Screening and testing are crucial steps in evaluating job applicants' suitability. In modern times, online testing has gained extensive popularity. Candidates undergo various assessments, and those who achieve top scores are invited for interviews. Screening plays a pivotal role in recruitment, as it ensures the selection of the most suitable candidates based not only on their hard skills and job-related knowledge but also on their soft skills. (van Esch, Black, & Ferolie, 2019).

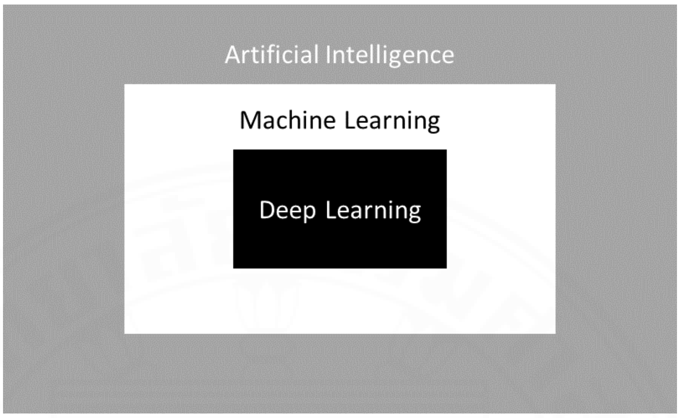
The advantages of e-recruitment include: 1) Wider exposure for job advertisements across local, national, and global markets. 2) Reduced advertising expenses through online platforms. 3) 24/7 availability of job postings. 4) No limitations on the length of advertising content, unlike costly newspaper classifieds and 5) Facilitated online communication between employers and candidates (Plessis & Frederick, 2012). As the competition for highly skilled employees intensifies, there is a growing need for new technology to expedite processes. Simultaneously, candidate recruitment, which is typically a repetitive and time-consuming procedure, necessitates the incorporation of automation across various stages of the recruitment process by organizations (Savola & Troqe, 2019).

2.2 Artificial Intelligence Application in Recruitment

Artificial Intelligence, often referred to as AI is primarily dedicated to understanding and executing intelligent tasks, such as thinking, acquiring new skills, and adapting to different contexts and challenges. It is a branch of science and engineering focused on simulating a broad range of human intellectual issues and functions (Sarker, 2022). AI encompasses a collection of technological advancements designed to mimic human intelligence (Harwood, Maltby, & Mukaetova-Ladinska, 2019). AI encompasses technologies like machine learning and deep learning. Machine learning involves systems learning from data to solve specific problems, playing a central role in data science and AI across various industries. Deep learning, a subset of machine learning, enables computers to understand tasks directly from examples, achieving high accuracy and contributing to technologies. Deep learning has been seen in various applications like computer vision, autonomous vehicles, fraud prevention, natural language processing or NLP and recognition of human activities (Raj & Kos, 2023).

Figure 2.1

Overview of the association between artificial intelligence, machine learning, and deep learning



Source: Raj and Kos, 2023.

AI found its way into numerous applications, including voice assistants, robotics, loan and credit card processing, online banking services (Pujari et al., 2021), stock market price forecast (Srijiranon, Lertratanakham, & Tanantong, 2022), social medial data analysis (Tanatorn & Ramjan, 2021) or even classification of unsuitable video content on the internet (Tanatorn & Yongwattana, 2023). Additionally, the impact of AI extends to education through ChatGPT (Kamalov, Santandreu Calonge, & Gurrib, 2023), healthcare domain such as resource management in a hospital (Tanatorn, Pannakkong, & Chemkomnerd, 2022), image diagnostics and virtual patient care using wearables (Al Kuwaiti et al., 2023; Tanantong, Nantajeewarawat, & Thiemjarus, 2015) and even the area of recruitment. Therefore, integrating AI into the recruitment process will be advantageous for organizations, helping them attain their ultimate objectives and financial goals.

In recent years, the global economy has experienced significant growth, leading many companies to actively seek the most suitable candidates for their needs. As talent recruitment has become increasingly competitive, professionals in various industries have extensively embraced the use of AI. Consequently, AI has emerged as the latest trend in the field of recruitment services (Upadhyay & Khandelwal, 2018).

To cope with issues and increase efficiency of recruitment process, recruitment industries need to implement AI to lead to high level of success. Several international companies like L'Oreal, IKEA, Amazon and Unilever have deployed AI in their recruitment process. The AI recruitment-based systems include Chatbot named Mya, and HireVue to better their talent recruitment processes as well as to reduce unqualified job applicants (Lisa & Talla Simo, 2021). Therefore, AI has been increasingly integrated into the recruitment process, resulting in a notable enhancement of candidate selection from a vast pool of potential candidates (Sekhri & Cheema, 2019).

AI has the capability to initially review resumes and identify promising candidates, matching them to suitable job positions. Subsequently, virtual assistants will engage with these candidates persistently via text messages, emails, and various communication platforms. (Upadhyay & Khandelwal, 2018). Furthermore, AI proves valuable in ensuring that job descriptions employ accurate terminology without making assumptions about a candidate's gender, while also precisely targeting the job requirements. What's advantageous in the recruitment process is that it now operates with full automation, eliminating the need for human intervention at every stage, including job description creation, resume screening, interview scheduling, hiring, and onboarding, among others (Rąb-Kettler & Lehnervp, 2019).

L'Oreal harnessed AI to achieve gender balance among job applicants and streamline their recruitment process. They deployed machine learning to eliminate non-value-added tasks and prioritize high-value ones. The company also employed a chatbot called Mya, which used natural language processing to handle candidate inquiries about company policies, culture, and benefits. Following this, AI conducted candidate interviews and pre-screening, ultimately identifying the best-fit and least-fit candidates for the job openings. (Anushree, 2018). Consequently, this AI enhances efficiency, reducing the time required for tasks.

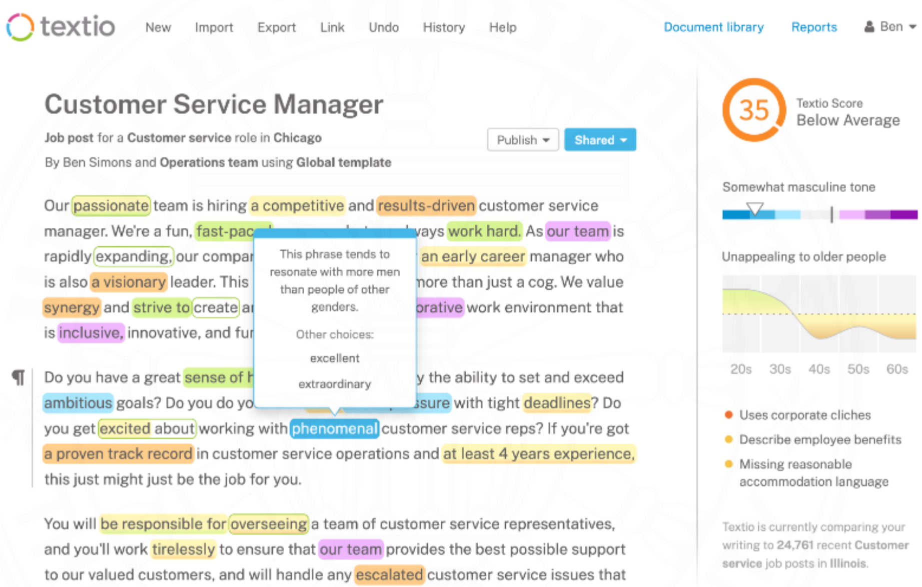
The most popular AI recruitment platforms by several companies are as follows:

1. Job Postings

Textio: A tool enhances job postings by using Natural Language Processing (NLP) to make subtle wording adjustments that can significantly impact candidate response rates and the quality of applicants. This AI writing platform is free from bias related to gender, age, and language performance, offering valuable data insights. Organizations such as Atos, McDonald's, Nestle, Zillow Group, Micron, and Atlas Sian are known users of this software. (Oswal et al., 2021).

Figure 2.2

Example of How NLP is Utilized to Adjust Job Postings with Textio



Source: Texito, 2022.

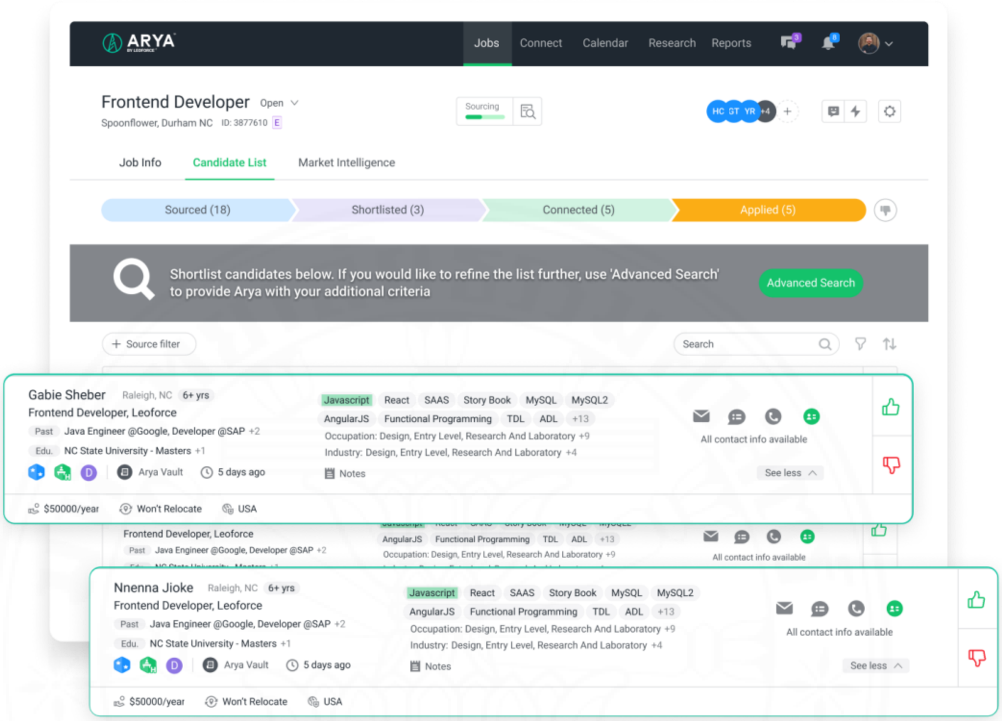
2. Sourcing

Hiretual: Companies like eBay, IBM, Intel, and Verizon utilized AI-driven technology, such as Hiretual, to evaluate job applicants' accessibility, expertise, competencies, and market valuation. (van Esch & Black, 2019).

Arya: The system enables organizations to enhance their talent search by efficiently sourcing candidates from more than 50 veteran social platforms, while also facilitating interaction between candidates and corporate recruitment teams (Vishwanadh, 2021)

Figure 2.3

Example of AI-Driven Candidate Evaluation with Arya



Source: Arya, 2023.

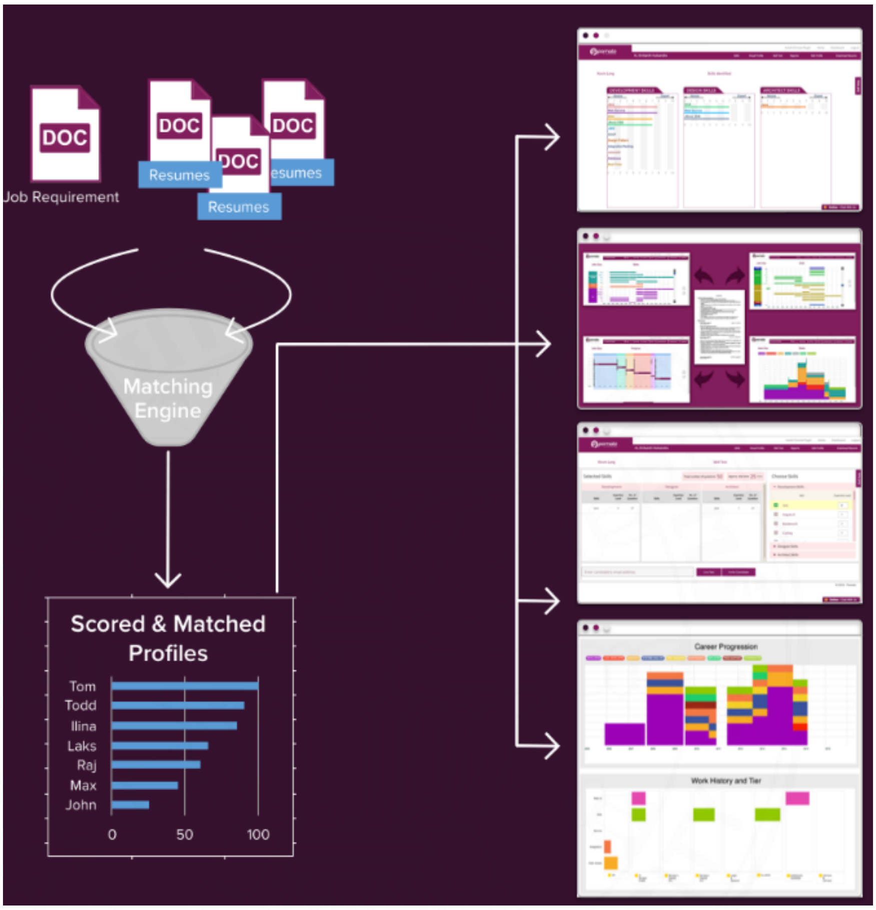
3. Screening

Pomato: This employs both machine learning and pattern recognition to align skills and qualifications, subsequently creating a shortlist of candidates. Following this step, all candidates will undergo assessment and be assigned rankings (Vishwanadh, 2021).

Textkernel and SAP's Resume Matcher: Textkernel efficiently processes numerous candidates, while the Resume Matcher assesses candidate against the job requirements and employment opportunities, enabling the ranking of applicants based on their alignment with the job requirements (Fraij & Várallyai, 2021).

Figure 2.4

Example of AI-Enabled Candidate Screening Using Pomato



Source: Pomato, 2018.

4. Candidate Pre-assessment

GoBe: GoBe is a recruitment chatbot capable of importing your company's job listings, conducting initial candidate assessments using tailored prescreening queries, and directing candidates to either job-specific recruiters, your company's career portal, or your applicant tracking system. (Wan Ibrahim & Hassan, 2019).

Mya: Mya Systems harnesses conversational AI to streamline the hiring process for prominent organizations such as L'Oréal, Adecco, Hays, and Deloitte. The software assists candidates throughout their entire job-seeking experience, from searching for positions to securing employment, delivering a smooth and intuitive interaction using advanced natural language processing and dynamic conversation management (Trziszka, 2023).

2.2.1 Benefits of AI in Recruitment

Obviously, AI implementation in recruitment can helps human recruiters to work more efficiently as the system automate such time-consuming activities. Then HR people can pay better attention on strategy and policy (Dutta & Gankar, 2021). HireVue stands as the most renowned AI-driven recruitment platform, utilized by over 700 firms including Unilever, Vodafone, PwC, and Oracle, significantly reduces recruitment time by 90% and boosts employment diversity by 16%. This innovative tool employs voice and facial recognition, along with its proprietary algorithm, which assesses candidates' suitability based on vocabulary, speech patterns, body language, tone, and facial expressions (Trziszka, 2023).

AI in recruitment considers all candidate traits and performance equally, avoiding bias and prioritizing job fit over performance comparisons. It is programmed to exclude demographic information to further prevent bias (Raveendra, Satish, & Singh, 2020). AI can overcome the inconsistency in data processing that is often a human limitation. Additionally, it excels at handling vast datasets and employs predictive algorithms for decision-making (Jarrahi, 2018). AI can address complex issues by employing predictive models to analyze cause-and-effect relationships. It can streamline various aspects of the hiring process, such as screening applicants, scheduling interviews, and answering candidate questions. This not only saves a significant amount of time but also enhances the candidate experience. With AI's help, HR professionals can allocate more attention to higher-value tasks (Graham, 2021). Utilizing AI in HR systems allows for the automatic updating of extensive candidate data. For instance, tools like AllyO can expedite the screening process by using AI to search for candidates on social media who match job requirements. Similarly, applications like Seekout can swiftly identify potential job applicants by matching their profiles with job descriptions, drawing from both online sources and an organization's internal database. Chatbots can also be employed to enhance communication with candidates, fostering a positive perception and experience with the hiring organization (Nidhi, Majdi, & Ayman, 2020).

2.2.2 Limitation of AI in Recruitment

AI in recruitment offers numerous benefits but relies heavily on data and algorithms programmed by humans. The effectiveness of AI tools for job matching, screening, and pattern analysis depends on the availability of vast data. Decision uncertainty arises as AI primarily relies on data rather than human judgment (Wan Ibrahim & Hassan, 2019). Concerns also exist about AI potentially replicating human biases through machine learning. Additionally, there is skepticism about the ability of AI to replicate the human touch, as experienced interviewers can pick up on intangible qualities not visible in resumes and appearances, which AI currently cannot replicate (Wan Ibrahim & Hassan, 2019). The human touch is crucial in recruitment for candidate engagement and a positive experience, which AI cannot replace. Qualities like intuition, empathy, and emotion are unique to humans. AI relies on data input by humans, introducing the possibility of bias. AI also faces challenges in assessing candidates' gestures and emotions during interviews (Hemalatha et al., 2021). The participants in the study of (Ore & Sposato, 2021) mainly voiced apprehensions about the trustworthiness and precision of AI, along with worries about safeguarding data privacy. Recruiters also voiced unease about the diminishing human element, and the possibility of AI completely replacing human recruiters.

2.3 Technology Adoption Theories and Relevant Literatures

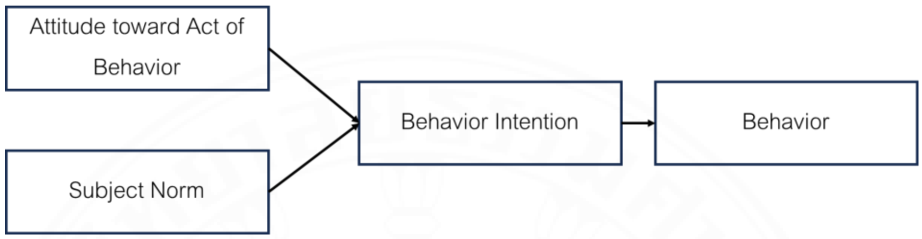
The theories related to technology adoption, particularly emphasizing the Unified Theory of Acceptance and Use of Technology (UTAUT) are outlined with time sequence as follows

2.3.1 The Theory of Reasoned Action (TRA)

In 1975, (Fishbein & Ajzen, 1975) presented The Theory of Reasoned Action (TRA), a foundational concept in the examination of human behavior. According to this theory, the driving force behind human actions is the intention to participate in a particular behavior, and this intention is influenced by a person's attitude and subjective norms.

Figure 2.5

The Theory of Reasoned Action (TRA)



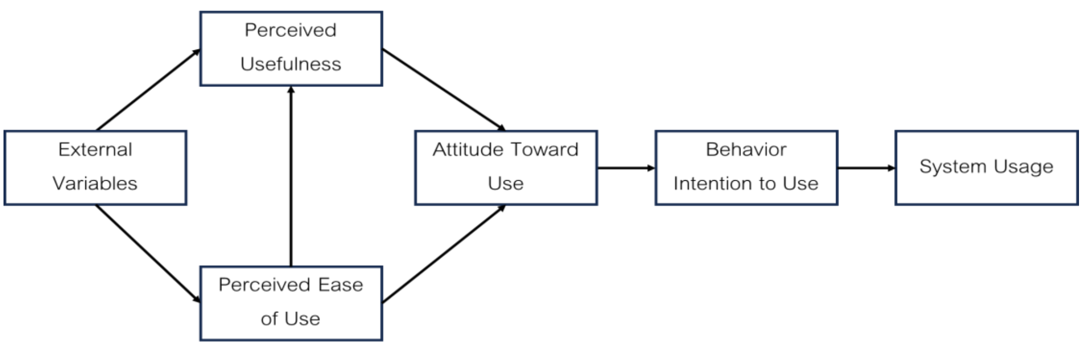
Source: Fishbein and Ajzen, 1975.

2.3.2 Technology Acceptance Model (TAM)

In 1989, (Davis, 1989) developed the Technology Acceptance Model (TAM), establishing it as a widely acknowledged framework for depicting user behavior toward technology acceptance. Rooted in the Theory of Reasoned Action (TRA), which suggests that beliefs impact attitudes, subsequently shaping intentions and behaviors, TAM is represented in Figure 2.6. The model incorporates variables: perceived usefulness (PU), perceived ease of use (PEOU), attitude, and the intention to use.

Figure 2.6

Technology Acceptance Model (TAM)



Source: Davis, 1989.

External Variables: “These encompass external elements like experience, beliefs, knowledge, and social influence, which can impact an individual's intention to use technology. These external factors can differ among individuals due to factors like age and gender” (Davis, 1989).

Perceived Usefulness: “This refers to the degree to which an individual perceives the advantages of using a particular technology or system. This factor gauges whether the technology can enhance efficiency, which in turn influences attitudes and intentions to use it” (Davis, 1989).

Perceived Ease-of-Use: “This signifies the level at which an individual recognizes that using a specific system or technology demands little effort or is user-friendly” (Davis, 1989).

Attitude toward Use: “This represents an individual's attitude and inclination toward utilizing a particular technology or system, which is shaped by both perceived usefulness and perceived ease of use” (Davis, 1989).

Behavior Intention to Use: “This is the intention or likelihood that an individual will attempt to use or accept and continue using that technology over the long term” (Davis, 1989).

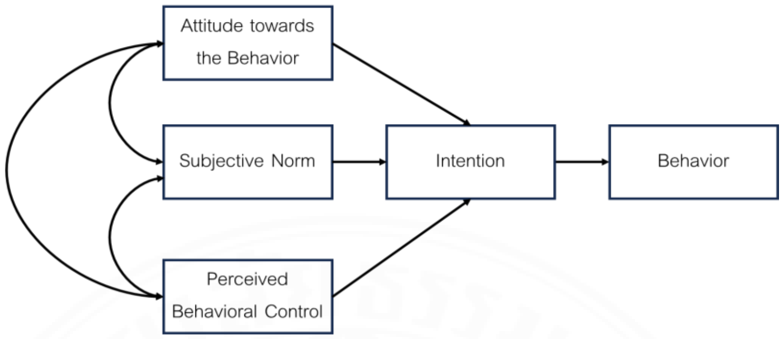
Actual System Use: “This pertains to the observable actions or behaviors, which represent the final actions that an individual undertakes” (Davis, 1989).

2.3.3 Theory of Planned Behavior (TPB)

In 1991, (Ajzen, 1991) extended the Theory of Reasoned Action (TRA) with the introduction of the Theory of Planned Behavior (TPB). This expanded theory proposed that an individual's conduct is influenced by their behavioral intention, which is formed by factors including attitude, subjective norms, and perceived behavioral control. Ajzen (1991) defined perceived behavioral control as an individual's perception of the feasibility or difficulty associated with a specific behavior.

Figure 2.7

Theory of Planned Behavior (TPB)



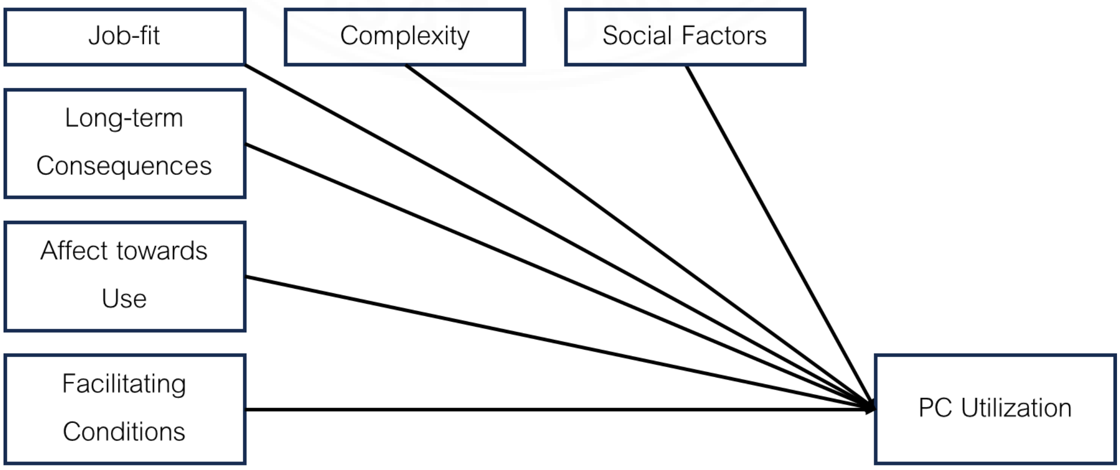
Source: Ajzen, 1991.

2.3.4 The Model of PC Utilization (MPCU)

Thompson, Higgins and Howell (1991) introduced the Model of Personal Computer Utilization (MPCU) in 1991 as an alternative viewpoint to the TRA and TPB. They took an existing human behavior model, modified and improved it, and applied it to forecast personal computer usage. According to this model, behavior is shaped by a combination of attitudes, social norms, habits, and anticipated outcomes.

Figure 2.8

Model of Personal Computer Utilization (MPCU)



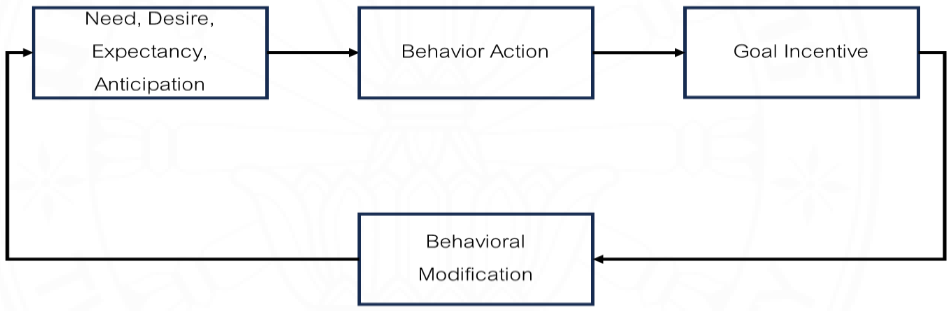
Source: Thompson, Higgins and Howell, 1991.

2.3.5 Motivational Model (MM)

Davis, Bagozzi, and Warshaw (1992) presented the Motivational Model (MM) in the context of technology utilization. According to the MM, both extrinsic and intrinsic motivations significantly impact an individual's propensity to participate in a specific behavior. Individuals' intentions to use computers at work are predominantly shaped by their perception of the benefits computers offer in improving job performance, with a secondary influence from the enjoyment derived from using computers (Davis, Bagozzi & Warshaw, 1992).

Figure 2.9

Motivational Model (MM)



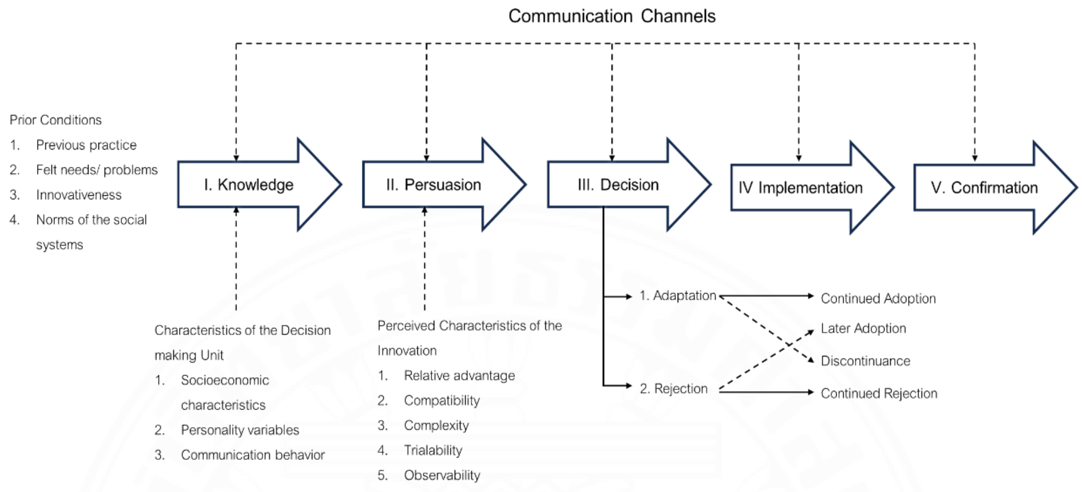
Source: Davis, Bagozzi and Warshaw, 1992.

2.3.6 The Theory of Innovative Diffusion (IDT)

Innovation Diffusion Theory (IDT), introduced by (Rogers, 1995) in 1995, stands as one of the primary models employed for examining how innovations are communicated within a group of individuals. This theory concentrates on the progression of an innovation as it spreads through a social system over time. The theory focuses on key factors impacting the adoption and diffusion of technologies. These factors encompass the innovation-decision process, the characteristics of the innovation, and the characteristics of adopters. This theory outlines five crucial stages in the innovation-decision process, as depicted in Figure 2.10 (Rogers, 1995).

Figure 2.10

Theory of Innovative Diffusion (IDT)



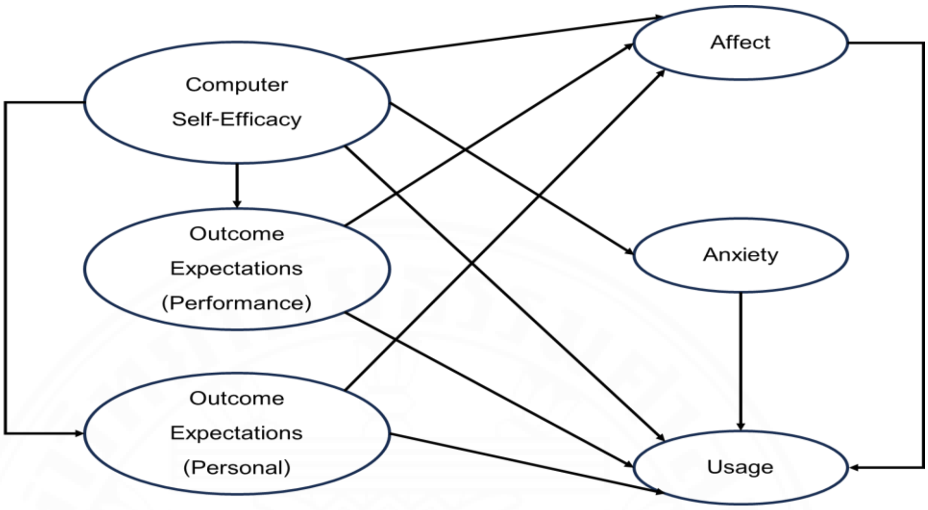
Source: Rogers, 1995.

2.3.7 Social Cognitive Theory (SCT)

The model of Social Cognitive Theory was developed in 1999 by applying Bandura's Social Cognitive Theory (Heffernan, 1988) to investigate how computer self-efficacy, outcome expectations, emotions, and anxiety affect computer use. The model shows significant links between computer self-efficacy and outcome expectations, emotions, anxiety, and computer use. Performance outcomes influenced emotions and usage, and emotions influenced computer use. In essence, the study confirmed that self-efficacy and outcome expectations impact how individuals emotionally and behaviorally respond to technology (Compeau, Higgins, & Huff, 1999).

Figure 2.11

Social Cognitive Theory (SCT)



Source: Compeau, Higgins and Huff, 1999.

2.3.8 Unified Theory of Acceptance and Use of Technology (UTAUT)

The most evident way to illustrate the connections between how corporates embrace information, and their willingness to use these technologies, is through the Unified Theory for Acceptance and Use of Technology (UTAUT) (Tűrkeș et al., 2020; Venkatesh et al., 2003). This model was created by integrating various prior research models in the scope of technology adoption, building upon the foundation of the general technology adoption model. (Venkatesh et al., 2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) model in 2003 by extensively examining research in the technology acceptance field. This model was created to address the limitations of TAM (Technology Acceptance Model).

In an effort to advance the understanding of TAM, UTAUT was developed, which integrated several relevant models, including the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Technology Acceptance Model (TAM) (Davis, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1991), Model of PC Utilization (MPCU) (Thompson et al., 1991), Motivational Model (MM) (Davis et al., 1992), Social Cognitive Theory (SCT) (Compeau et al., 1999; Heffernan, 1988) and Innovation Diffusion Theory (IDT) (Rogers, 1995)" as stated by (Venkatesh et al., 2003).

The UTAUT model provides insights into why users plan to employ an information system and how their usage behavior unfolds. This theory posits the existence of four essential constructs: Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), and Facilitating conditions (FC). According to (Venkatesh et al., 2003), the four constructs are defined as follows:

Performance Expectancy: "This refers to a person's confidence level in the idea that using a specific system will enhance their job performance. It is closely related to the concept of perceived usefulness in TAM."

Effort Expectancy: "Effort expectancy signifies the ease with which an individual can use a particular system or technology. This factor assesses how user-friendly the technology is and is associated with the notion of "perceived ease of use" in TAM."

Social Influence: "Social influence gauges the extent to which a person perceives the importance that others place on their adoption of the new system This factor also corresponds to a concept in TAM."

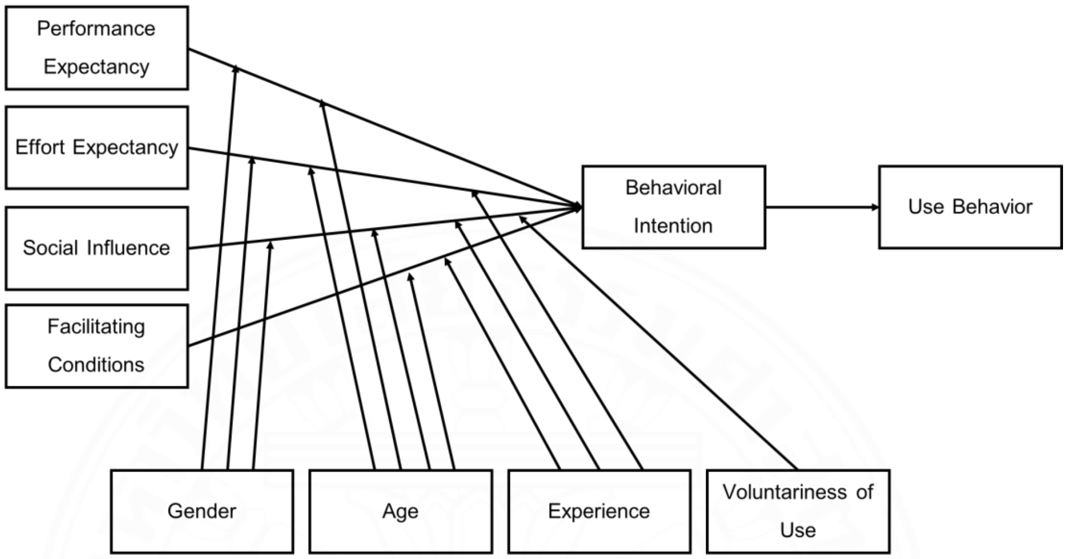
Facilitating Conditions: "Facilitating conditions measure a person's belief in the presence of organizational infrastructure that supports the use of the specific system."

These variables are utilized to forecast user Behavioral intention (BI) and Usage behavior (UB) when it comes to adopting a new information technology system. Behavioral intentions reflects an individual's level of intent to embrace the use of a new system. Performance expectancy (PE), Effort expectancy (EE) and Social influence (SI), all exert an influence on Behavioral Intention, which, in turn, directly affects Usage Behavior, while Facilitating Conditions directly influence Behavioral Intention and Usage Behavior.

Additionally, the UTAUT model takes into consideration the following variables: gender, age, prior experience with IoT or other technologies, the degree of voluntariness, and influencing independent variables along with dependent variables (Behavioral Intentions and Usage Behavior).

Figure 2.12

Unified Theory of Acceptance and Use of Technology Model



Source: Venkatesh et al., 2003.

The UTAUT has found extensive application in various research areas, including the adoption of technologies such as AI, mobile technology, educational technology, and public technology services. Moreover, this model guarantees a 70% accuracy in analyzing behavior when it comes to utilizing information technology. It is also regarded as a dependable model, demonstrating an explanatory capability typically ranging from 40% to 50% on average (Byoung-Chol & Bo-Young, 2021).

2.4 Influencing Factors in Technology Adoption Intention and Relevant Literatures

The UTAUT model has been widely applied in diverse research areas concerning the adoption of emerging technologies. To address the current AI adoption landscape, especially in Thailand's growing tech-driven economy, additional factors are being introduced alongside the ones originally proposed in the UTAUT model.

2.4.1 Performance Expectancy

As stated by (Venkatesh et al., 2003) “Performance expectancy signifies the user's perception of how using the particular system will impact their job performance at a specific level.” In the early studies, the researchers identified a noteworthy impact of performance expectancy on behavioral intention across various areas including a study on Technology Acceptance Model in e-HRM from Fortune Global 500 firms in Malaysia (Shahreki et al., 2020), Adoption of Mobile Health Services in a developing country (M. Z. Alam, Hoque, Hu, & Barua, 2020) and AI based recruitment adoption among HR staffs in Bangladesh (M. Alam, Uz-Zaman Khan, Sutra Dhar, & Munira, 2020).

Hence, individuals’ perception of performance expectancy or how effective new technology, such as AI in talent recruitment, can impact their willingness to use it. The first hypothesis is developed as follows:

H1: Performance expectancy (PE) significantly influences the user’s intention to use AI in recruitment (IU)

2.4.2 Effort Expectancy

When users believe that a new system simplifies tasks and requires less effort to operate, they are more inclined to embrace it (Thompson et al., 1991; Venkatesh et al., 2003). The theory posits that when an information system is perceived as complex and challenging to navigate, it diminishes the user's inclination to use it. Additionally, prior research has indicated that factors such as gender, age, and experience can moderate the impact of effort expectancy on behavioral intention (Ha, Tai, & Chang, 2020; Venkatesh et al., 2003). In a study of the Acceptance and Integration of Enterprise Resource Planning among HR professionals indicated that effort expectancy has a direct and noteworthy impact on the intention to use the ERP (Uddin, Alam, Mamun, Khan, & Akter, 2020). Likewise, research conducted among human resources personnel in the Indian IT industries reveals that a favorable perception of ease of use had a positive impact on employees' willingness to embrace AI (Bhardwaj, Singh, & Kumar, 2020; Singh, Bhardwaj, Singh, & Kumar, 2020). People tend to avoid using technology when they find it difficult to use.

Therefore, the second hypothesis can be formed that effort expectancy has a direct impact on the intention to adopt AI in recruitment as follows:

H2: Effort expectancy (EE) significantly influences the user's intention to use AI in recruitment (IU)

Furthermore, drawing from previous research on mobile payment and mobile self-checkout adoption, it was evident that effort expectancy significantly influences performance expectancy (V. L. Johnson, Woolridge, Wang, & Bell, 2020; Khalilzadeh, Ozturk, & Bilgihan, 2017). Therefore, the third hypothesis regarding this association can be constructed, suggesting that the impact of effort expectancy on performance expectancy is substantial as follows.

H3: Effort expectancy (EE) significantly influences performance expectancy (PE)

2.4.3 Social Influence

The concept of social influence in technology adoption involves how users' perceptions are influenced by their social environment, including peers, superiors, and management. "Social Influence refers to how much people believe that significant individuals in their lives, such as family and friends, think they should utilize a specific technology" stated by (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). It's noted that social influence holds a vital role in technology use across different areas including mobile technology in healthcare (M. Z. Alam et al., 2020), AI based talent acquisition in the view of job applicants (Ochmann & Laumer, 2020) and adopting ERP in the corporates (Uddin et al., 2020).

Drawing from previous studies on social influence, HR and recruitment experts can acquire valuable guidance and information about AI software in recruitment, bolstering their confidence in deciding to implement the system. Consequently, the formulation of the fourth hypothesis arises, proposing that social influence directly impacts the intention of users to adopt AI in the hiring process as follows:

H4: Social influence (SI) significantly influences the user's intention to use AI in recruitment (IU)

In addition to its direct influence on user intention, social influence has been identified as a factor directly affecting security (Khalilzadeh et al., 2017). Thus, the fifth hypothesis suggesting that social influence has a direct impact on privacy and security can be developed as follows.

H5: Social influence (SI) significantly influences privacy and security (PS)

Furthermore, social influence was found to have a direct impact on perceived value (Fatima, Kashif, Kamran, & Awan, 2021) in the prior research within the realm of mobile payment adoption. It's essential to consider that social influence significantly affects perceived value. Thus, the sixth hypothesis can be tested as follows:

H6: Social influence (SI) significantly influences perceived value (PV)

2.4.4 Facilitation Conditions

"Facilitating conditions relate to how people perceive the available resources and support for executing a specific behavior" (Venkatesh et al., 2012). To embrace new technology, it is essential to integrate the new technology into both the organizational and technical infrastructure of the technology itself (Uddin et al., 2020). In a research of ERP acceptance in an organization presents that the perception of organizational support in providing necessary infrastructure increases the likelihood of the system adoption and implementation (M. Alam & Uddin, 2019). Additionally, support in facilitating conditions play an important role in adopting new technological systems in various domains, such as chatbot acceptance for public transport (Kuberkar & Singhal, 2020), the implementation of e-commerce platforms by SMEs (Sombultawee, 2020), and IT tool acceptance by medical doctors (Rathinaswamy, Sengottaiyan, & Duraisamy, 2020).

Consequently, it is hypothesized that facilitating conditions can directly influence the intention of HR and recruitment specialists to use AI in talent acquisition, thus developing the seventh hypothesis as follows:

H7: Facilitating conditions (FC) significantly influences the user's intention to use AI in recruitment (IU)

2.4.5 Privacy and Security

This study primarily concentrates on informational privacy. Some people choose to limit "privacy" to specific categories of personal information. When it comes to "private" data, there are undoubtedly worries about ensuring its safety, which are referred to as "security concerns." This essentially recognizes the significance of safeguarding private information and classifies this as a security issue (Elliott & Soifer, 2022). Adopting modern technology in organizations entails security and privacy risks, demanding the formulation of practical policies. Senior management should balance these concerns to avoid hindering technological adoption in the name of security and privacy (Chatterjee, Ghosh, Chaudhuri, & Chaudhuri, 2021). Secure systems with privacy safeguards show a positive impact on technology adoption across various domains, including mobile payment (Khalilzadeh et al., 2017) , mobile self-checkout (V. L. Johnson et al., 2020) and AI adoption in Customer Relationship Management (CRM) application (Chatterjee, Ghosh, et al., 2021). In Thailand, the Personal Data Protection Act of Thailand (PDPA) aims to protect personal information of both individuals and organizations, outlining regulations for "personal data processing" (Trisadikoon, 2022b) and the act becomes fully enforceable in June 2022 (Trisadikoon, 2022a). To prepare for AI integration, Microsoft Thailand recommended integrating AI regulations into the PDPA, enhancing security and privacy infrastructure. The PDPA is poised to transform personal data protection in Thailand, mandating consent from data owners and consumers before data storage, sharing, or utilization (LEESA-NGUANSUK, 2019).

Through the information provided, privacy and security factor can be considered as a positive impact on the intent of HR and hiring professionals to use AI driven hiring tools, therefore assessing the eighth hypothesis as follows:

H8: Privacy and security (PS) significantly influence the user's intention to use AI in recruitment (IU)

2.4.6 Trust in AI Technology

"Trust is recognized as a valuable strategy for navigating the growing intricacies of technology, organizations, and interpersonal relationships that individuals encounter" (J. D. Lee & See, 2004). As trust gains greater importance in shaping the adoption of emerging technologies like AI, there is a growing awareness among corporations, governments, and the general public regarding AI's potential influence (Choung, David, & Ross, 2022; Söllner, Hoffmann, & Leimeister, 2016). This prompts a significant focus on building trustworthy AI systems. In recent years, government organizations, tech giant firms like Google and Microsoft, and professional associations such as the IEEE released guidelines emphasizing the need to design AI systems with trustworthiness as a core principle (Choung et al., 2022). A study on technology acceptance shows that trust is a crucial factor in encouraging the use of information systems. It indicates that the extent of trust that users place in both the information system and the technology provider significantly impacts their willingness to embrace the new system (Söllner et al., 2016). Moreover, trust plays a critical role in shaping user's willingness to embrace emerging technologies including AI-driven CRM (Chatterjee, Ghosh, et al., 2021), AI-integrated HR system (Hmoud & Várallyai, 2020), sustainable mobile banking app acceptance (Cavus, Mohammed, & Yakubu, 2021) or transportation service powered by AI chatbot (Kuberkar & Singhal, 2020).

Therefore, trust in new technology as AI can be a direct impact on user's intention to adopt the new system like AI in recruitment. The ninth hypothesis can be tested as follows:

H9: Trust in AI technology (TA) significantly influences the user's intention to use AI in recruitment (IU)

Furthermore, it is worth noting that trust was observed to directly impact both performance expectancy and effort expectancy, as evidenced by studies on the adoption of emerging technologies in various domains, including mobile payment (Khalilzadeh et al., 2017), information system (Söllner et al., 2016), and e-document authority (j.-h. Lee & Song, 2013). Consequently, it is relevant to assess these relationships, leading to the formulation of the tenth and eleventh hypotheses accordingly as follows:

H10: Trust in AI technology (TA) significantly influences effort expectancy (EE)

H11: Trust in AI technology (TA) significantly influences performance expectancy (PE)

2.4.7 Perceived Value

The term of perceived value, initially introduced by Dodds and Monroe (Dodds, Monroe, & Grewal, 1991), “centers around the balance between how customers perceive quality or benefits and what they are willing to pay or sacrifice.” Perceived value involves assessing the overall usefulness by comparing the benefits gained with the sacrifices incurred (Sun, 2021; Zeithaml, 1988). A study in a journal focused on the adoption of intelligent personal assistants discovered that customers' readiness to use the product is notably affected by their perception of functional, social, and knowledge-related values (Sun, 2021). Furthermore, additional research studies identified that the perception of value has a direct impact on the willingness to embrace various forms of information technology, for instance, the acceptance of mobile payment solutions (Fatima et al., 2021) and adoption of assistance products such as smart speaker, voice assistance, home appliances (Sohn & Kwon, 2020).

Therefore, considering the evidence presented, it is clear that perceived value plays a pivotal role in motivating users to adopt AI-integrated recruitment software. Therefore, the twelfth hypothesis can be assessed as follows:

H12: Perceived value (PV) significantly influences the user’s intention to use AI in recruitment (IU)

2.4.8 Perceived Autonomy

Autonomy is crucial for human well-being and growth, defined as the ability to make self-directed choices and govern oneself. According to self-determination theory, “autonomy means choices initiated by one's conscious self and informed decisions after evaluating options. A broader perspective on autonomy is vital for rebuilding trust in human-machine interactions” (Sankaran, Zhang, Aarts, & Markopoulos, 2021). AI autonomy is defined as the ability of AI technology to perform tasks that originate from human actions without the need for direct human involvement. In the research of intelligent personal assistants, AI autonomy is categorized as sensing, thought and action which have a direct impact on the perception of intelligent personal assistants which also directly influences the use intention (Q. Hu, Lu, Pan, Gong, & Yang, 2021). Similarly from other studies, perceived autonomy has been found to have an influence on IoT adoption (Tűrkeș et al., 2020) and the utilization of online courses (Khalid, Lis, Chaiyasoonthorn, & Chaveesuk, 2021).

Therefore, perceived autonomy positively affects the intention to use AI in the hiring process. The thirteenth hypothesis can be tested as follows:

H13: Perceived autonomy (PA) significantly influences the user's intention to use AI in recruitment (IU)

The table below is a summary of prior research studies focusing on the new technology adoption, exploring factors that directly and indirectly impact user's intentions to use the new technology.

Table 2.1

Summary of Research Related to Influencing Factors to User's Intention to Use a New Technology

No.	Author	Performance Expectancy / Perceived Usefulness	Effort Expectancy / Perceived Ease-of-Use	Social Influence	Facilitating Conditions	Privacy and Security	Trust in AI Technology	Perceived Value	Perceived Autonomy
1	(Shahreki et al., 2020)	✓	✓						
2	(M. Z. Alam et al., 2020)	✓		✓	✓				
3	(M. Alam et al., 2020)	✓	✓	✓	✓				
4	(Uddin et al., 2020)	✓	✓	✓	✓				
5	(Singh et al., 2020)		✓						
6	(Bhardwaj et al., 2020)		✓						
7	(Ochmann & Laumer, 2020)	✓	✓	✓					

Table 2.1

Summary of Research Related to Influencing Factors to User's Intention to Use a New Technology (cont.)

No.	Author	Performance Expectancy / Perceived Usefulness	Effort Expectancy / Perceived Ease-of-Use	Social Influence	Facilitating Conditions	Privacy and Security	Trust in AI Technology	Perceived Value	Perceived Autonomy
8	(Byoung-Chol & Bo-Young, 2021)	✓	✓	✓	✓				
9	(Hmoud & Várallyai, 2020)	✓					✓		
10	(Rathinaswamy et al., 2020)	✓	✓	✓	✓				
11	(Kuberkar & Singhal, 2020)	✓	✓	✓	✓		✓		
12	(M. Alam & Uddin, 2019)	✓		✓	✓				
13	(Sombultawee, 2020)	✓			✓				
14	(Ha et al., 2020)	✓	✓	✓					
15	(Chatterjee, Rana, Khorana, Mikalef, & Sharma, 2021)	✓	✓		✓				
16	(Terblanche & Cilliers, 2020)	✓		✓					
17	(Weiwei, 2020)	✓	✓						
18	(Khalilzadeh et al., 2017)	✓	(✓)	(✓)		(✓)	(✓)		
19	(V. L. Johnson et al., 2020)	✓	(✓)			✓			
20	(Chatterjee, Ghosh, et al., 2021)	(✓)				(✓)	✓		

Table 2.1

Summary of Research Related to Influencing Factors to User's Intention to Use a New Technology (cont.)

No.	Author	Performance Expectancy / Perceived Usefulness	Effort Expectancy / Perceived Ease-of-Use	Social Influence	Facilitating Conditions	Privacy and Security	Trust in AI Technology	Perceived Value	Perceived Autonomy
21	(Casas et al., 2019)	✓	✓			✓	✓		
22	(Söllner et al., 2016)	✓	(✓)				(✓) ✓		
23	(j.-h. Lee & Song, 2013)	✓	(✓)	✓			(✓) ✓		
24	(Sun, 2021)							✓	
25	(Fatima et al., 2021)	✓ (✓)	(✓)	(✓) ✓	(✓) ✓			✓	
26	(Sohn & Kwon, 2020)		✓					✓	
27	(Jain, Garg, & Khera, 2022)	✓	✓	✓	✓				
28	(Q. Hu et al., 2021)								(✓)
29	(Tűrkeş et al., 2020)	(✓)	(✓)	(✓)		(✓)			(✓)
30	(Khalid et al., 2021)			✓	✓				(✓) ✓

Note: ✓ = Factor directly influencing intention to use the new technology

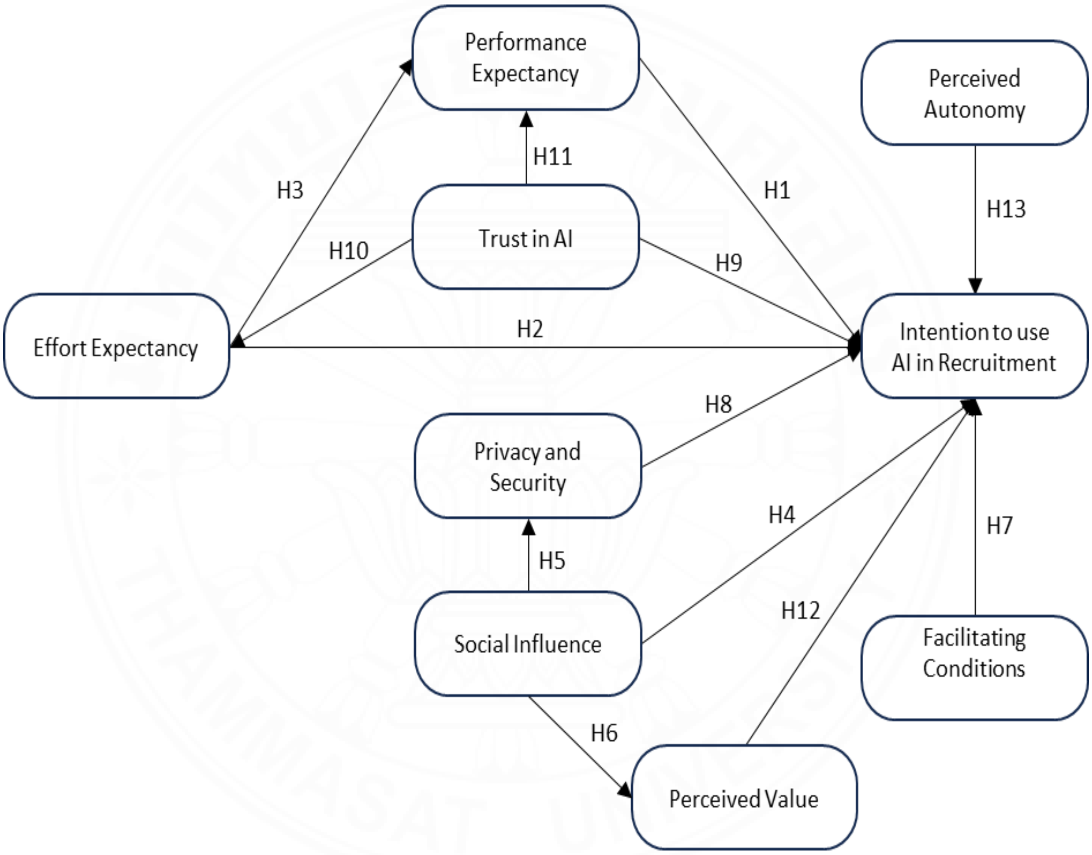
(✓) = Factor indirectly influencing intention to use the new technology (sub element)

2.5 Conceptual Framework

The conceptual model resulted from a comprehensive and evaluative review of current literature. This structure comprises eight distinct factors: Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating condition (FC), Privacy and security (PS), Trust in AI technology (TA), Perceived value (PV), and Perceived autonomy (PA). The dependent variable is the intention to utilize AI integration for recruitment.

Figure 2.13

Research Structural Model



2.6 Research Hypothesis

In the provided structural model, research hypotheses were created for PLS–SEM (Structural Equation Modeling), outlined as follows:

H1: Performance expectancy (PE) significantly influences the user's intention to use AI in recruitment (IU)

H2: Effort expectancy (EE) significantly influences the user’s intention to use AI in recruitment (IU)

H3: Effort expectancy (EE) significantly influences performance expectancy (PE)

H4: Social influence (SI) significantly influences the user’s intention to use AI in recruitment (IU)

H5: Social influence (SI) significantly influences privacy and security (PS)

H6: Social Influence (SI) significantly influences perceived value (PV)

H7: Facilitating conditions (FC) significantly influences the user’s intention to use AI in recruitment (IU)

H8: Privacy and security (PS) significantly influence the user’s intention to use AI in recruitment (IU)

H9: Trust in AI technology (TA) significantly influences the user’s intention to use AI in recruitment (IU)

H10: Trust in AI technology (TA) significantly influences effort expectancy (EE)

H11: Trust in AI technology (TA) significantly influences performance expectancy (PE)

H12: Perceived value (PV) significantly influences the user’s intention to use AI in recruitment (IU)

H13: Perceived autonomy (PA) significantly influences the user’s intention to use AI in recruitment (IU)

CHAPTER 3
RESEARCH METHODOLOGY

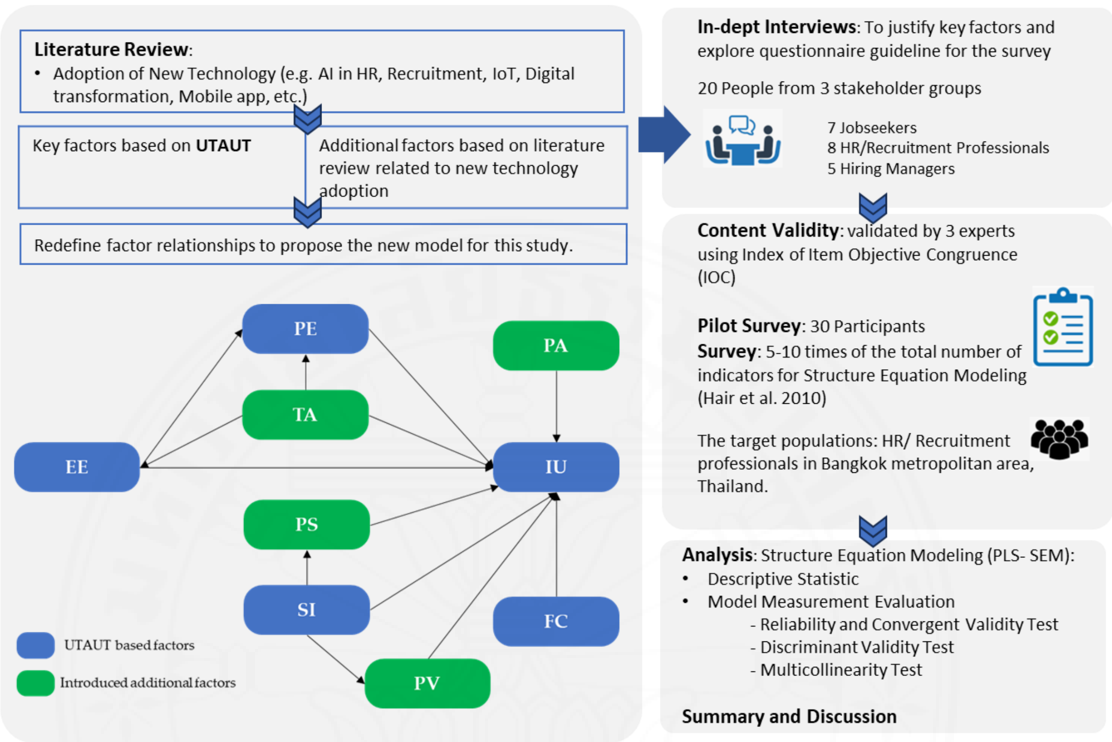
This chapter provides a detailed explanation of the research methodology used to validate the research framework. It covers the specific research procedures, justification for the sample size, data collection methodology, analytical procedures, use of descriptive statistics, and model measurement. The model measurement involves evaluating the model constructs through reliability tests, convergent validity, and discriminant validity. Additionally, it assesses the structural model by examining the relationship between independent and dependent variables. The evaluation includes the coefficient determinant test and hypothesis testing through the analysis of total effects. The aim is to offer a comprehensive account of the systematic approach employed to ensure the robustness and reliability of the research framework.

3.1 Research Design

The study utilized both quantitative and qualitative methodologies, utilizing data sourced from secondary information and in-depth interviews. These inputs were crucial for refining the study framework and crafting a questionnaire tailored for descriptive research. Subsequently, a questionnaire was formulated and created based on these insights. The outline for the research procedure is in figure 3.1.

Figure 3.1

Overview of the Research Framework



3.1.1 Secondary Research

Secondary research was gathered from reputable published sources, which included E-Journals, Business article, research, online news. The data obtained through this study will be the first step that gives the researcher with an understanding of the characteristics of AI technology and application in recruitment, motivating factors and other relevant information.

3.1.2 In-Depth Interview

Although the survey questions primarily target HR and recruitment professionals, a thorough investigation involved conducting comprehensive interviews with diverse groups, including job seekers, hiring managers, and HR recruitment professionals. The primary aim of these interviews was to gather insights and additional perspectives from job seekers and hiring managers initially. Subsequently, these insights were summarized before engaging with HR recruitment professionals. This sequential approach aimed to validate the proposed model incorporating elements from UTAUT, along with additional factors relevant to companies in Thailand. It also aimed to refine the instructions for crafting questions in preparation for the forthcoming questionnaire survey.

In-depth interviews were carried out with a total of 20 participants, comprising individuals with prior exposure to AI-based recruitment software and those without such experience. The group consisted of 7 jobseekers, 5 hiring managers and 8 HR professionals from various business sectors. These participants varied in terms of age, encompassing both Generation Y and Generation Z, as well as gender and levels of technological experience. The interview is conducted align with the research objectives, which are open-ended questions on the following topics:

1) Opinions regarding influential factors proposed in the research structural model

2) Perceived benefits of using AI in recruitment

3) Concerns or challenges of using AI in recruitment

4) Other suggestions for AI approach in recruitment

3.1.3 Questionnaire

The study instrument is a survey questionnaire which is constructed from related theories and previous studies. The questionnaire is written in Thai and to reach all respondents. The questionnaire consists of three parts as follows:

Part 1: General questions

Part 1.1: Screening question to identify HR/recruiting role

Part 1.2: General questions are asked to identify genders, ages,

occupation, education level, working experience, types of business and number of employees in the organization.

Part 2: 35 Questions based on variables affecting technology adoption to use AI in recruitment used the Likert scale to measure multi-items

Part 3: Opinions regarding advantages and limitations of implementing AI in recruitment process.

Part 4: Suggestion.

The answers of questions in part 2 indicate the respondents' responses on factors affecting user's intention to use AI in recruitment. The interval scale measure is implemented using a Five-point Likert Scales (Preedy & Watson, 2010):

5 means strongly agree

4 means agree

3 means neutral

2 means disagree

1 means strongly disagree.

The criteria of class interval were used to interpret the mean score of factors that influence user's intention to use AI based recruitment software

$$\text{Class interval} = \frac{(\text{Maximum} - \text{Minimum})}{\text{Class Number}}$$

$$= \frac{(5\text{-}1)}{5}$$

$$= 0.8$$

Mean = 1.00-1.80: Strongly Disagree (Not true at all)

Mean = 1.81-2.60: Disagree (True to a minimal degree)

Mean = 2.61-3.40: Neutral (True to a moderate degree)

Mean = 3.41-4.20: Agree (True to a high degree)

Mean = 4.21-5.00: Strongly Agree (Absolutely True)

3.2 Research Construct and Measurement

The measurement items employed in this study are derived from a thorough review of reference papers. These items are strategically chosen to encompass all the constructs outlined in the research framework, which comprises Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating conditions (FC), Privacy and security (PS), Trust in AI technology (TA), Perceived value

(PV), Perceived autonomy (PA) and Intention to use (IU). Each of these constructs is represented by five measurement items, providing a comprehensive approach to capturing the nuances of the research framework.

Table 3.1

Measurement Items

Construct	Measurement item	Source
Performance Expectancy	PE1: I think AI is useful in recruitment	(M. Alam et al., 2020; Venkatesh et al., 2003)
	PE2: I think that AI will make recruitment process faster	(M. Alam et al., 2020; Venkatesh et al., 2003)
	PE3: I think AI can increase efficiency of recruitment work	(M. Alam et al., 2020; Venkatesh et al., 2003)
	PE4: I think using AI can help analyze candidates more accurately	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
Effort Expectancy	EE1: I would find the AI based recruitment software easy to use	(M. Alam et al., 2020; Venkatesh et al., 2003)
	EE2: I think it would be easy to learn how to use the interface of AI based recruitment software	(M. Alam et al., 2020; Venkatesh et al., 2003)
	EE3: For me, it will not take long to be skillful in using AI in recruitment	(M. Alam et al., 2020; Venkatesh et al., 2003)
	EE4: I think AI in recruitment would be flexible for use.	(M. Alam et al., 2020; Venkatesh et al., 2003)
Social Influence	SI1: My decision to use AI in recruitment would be based on proportion of coworkers who use the software or system	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)

Table 3.1

Measurement Items (cont.)

Construct	Measurement item	Source
	SI2: Those who use AI in recruitment would have more advantages than those who do not	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
	SI3: With the rapid technology trend, AI integrated in recruitment is necessary for my company	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
	SI4: I think the introduction of AI in recruitment into our company will be trendy in my industry	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
Facilitating Conditions	FC1: I expect to call a technical support team in case of facing any problems	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
	FC2: I expect that the system would be available in both computer and mobile devices	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
	FC3: I think guidance would be available in AI based recruitment system	(M. Alam et al., 2020; Ha et al., 2020; Venkatesh et al., 2003)
Privacy and Security	PS1: I expect that AI based recruitment software will be safe and secure	(Tűrkeș et al., 2020)
	PS2: I expect AI based recruitment software will strictly comply data privacy policy regarding Personal Data Protection Act	(Tűrkeș et al., 2020)
	PS3: I feel safe and protected by the use of encryption	(Tűrkeș et al., 2020)

Table 3.1

Measurement Items (cont.)

Construct	Measurement item	Source
	PS4: I think AI software developer will protect and ensure safety of user’s personal data.	(Tűrkeș et al., 2020)
Trust in AI Technology	TA1: I trust that AI algorithm is reliable in screening candidates to match organization's requirement	(Cavus et al., 2021; Choung et al., 2022; Hsu, Chuan-Chuan Lin, & Chiang, 2013)
	TA2: I trust that AI based recruitment software has reliable database to complete recruitment	(Hsu et al., 2013)
	TA3: I think there will be a government organization to ensure AI based recruitment software is secured	(Cavus et al., 2021; Choung et al., 2022)
	TA4: I trust that AI software developer is honest and will not take advantage over user's information	(Choung et al., 2022)
Perceived Value	PV1: I think that using AI in recruitment is worth investing	(Sun, 2021)
	PV2: I feel that using AI can remain quality of recruitment process consistently.	(Sun, 2021)
	PV3: I realize that using AI in recruitment will give the organization the social approve	(Sun, 2021)
	PV4: I feel that using AI in recruitment will make impression on candidates	(Sun, 2021)
Perceived Autonomy	PA1: Using AI in recruitment will allow recruiters/ HR officers to have more freedom to develop preferred skills and tasks	(Tűrkeș et al., 2020)

Table 3.1

Measurement Items (cont.)

Construct	Measurement item	Source
	PA2: Using AI will give recruiters/ HR officers the opportunity to better coordinate with candidates	(Tűrkeș et al., 2020)
	PA3: Utilizing AI will provide recruiters and HR officers with more flexibility to manage other essential responsibilities more effectively	(Tűrkeș et al., 2020)
	PA4: I think AI in recruitment will reduce the number of decisions to get the optimal results	(Tűrkeș et al., 2020)
Intention to Use	IU1: Using AI based recruitment software is a good and modern idea	(Davis, 1989)
	IU2: I like the idea of using AI in recruitment	(Venkatesh et al., 2003)
	IU3: The AI based recruitment software makes me more interested	(R. D. Johnson et al., 2021)
	IU4: I have a high wiliness to use AI in recruitment	(Ha et al., 2020)

3.3 Content Validity

The questions in the survey are from the previous research and academic articles. Then, they passed the verification of content validity by 3 experts in HR and recruitment area using Index of Item Objective Congruence (IOC) (Turner & Carlson, 2003). In each item, the experts were asked to rate the content validity score:

The score means 1, if the expert is sure that this item measures the attribute.

The score means –1, if the expert is sure that this item does not measure the attribute.

The score means 0, if the expert is not sure whether the item measures or does not measure the expected attribute.

IOC score of qualified items should equal or be greater than 0.50

After that, the pilot test is conducted with 30 questionnaires and use Cronbach's alpha coefficient (α) for reliability analysis. The reliability test is conducted by SPSS to assess the Cronbach's alpha coefficient which measures questionnaire reliability. The variables is considered good if Cronbach's alpha is 0.7 or higher (Streiner, 2003). The value of Cronbach's alpha was between $0 \leq \alpha \leq 1$, the score that closest to 1 is the most reliable.

3.4 Sampling Plan

The target populations of this study were HR professionals from diverse industries in the Bangkok metropolitan region. The sample size has been determined using Structure Equation Modeling (SEM) guidelines (Hair, Black, Babin, & Anderson, 2010; Kline & St, 2022), which recommend a sample size that ranges from 5 to 10 times the total number of indicators and variables. It is crucial to ensure that the sample comprises at least 100 respondents. Thus, the minimum sample size required should have been at least 35 indicators multiplied by 5, resulting in 175 respondents. To enhance the research's reliability, data were gathered from 364 participants in this study. Furthermore, an intentional online sampling approach will be employed, involving the distribution of the survey questionnaire through various social media platforms such as LinkedIn, Facebook, and email.

3.5 Statistics for Data Analysis

The data gathered from the survey participants underwent processing through SPSS and SmartPLS 4 software (C. M. Ringle, Wende, Sven & Becker, Jan-Michael, 2022). The study outcomes were exclusively derived using the Partial Least Squares-Path Model (PLS-PM) in conjunction with Bootstrapping and Blindfolding algorithms. The statistical methods for data analysis and interpretation included descriptive statistics, reliability test and inferential statistics (Hair, Hult, Ringle & Sarstedt, 2014) as the following:

3.5.1 Descriptive Statistics

Descriptive statistics is used to analyze data collected from the questionnaires. The statistics for data analysis is used as follows:

Section 1: Personal information such as gender, age, education degree, occupation, and position, and business sector, employee size which would be analyzed by frequency and percentage.

Section 2: Factors influencing adoption of AI technology in recruitment in Likert scale questions which would be analyzed by using mean and standard deviation (S.D.).

3.5.2 Model Measurement Evaluation

Assessing the questionnaire as a reflective model involves evaluating the consistency between questionnaire items gauging latent variables. Since the latent variables cannot be measured directly, model measurement serves to evaluate the questionnaire's accuracy and reliability through the application of internal consistency reliability, indicator reliability, convergent validity and discriminant validity (Mohd Dzin & Lay, 2021; Usakli & Küçükergin, 2018) as follows:

3.5.2.1 Internal Consistency Reliability

To assess the accuracy of the collected data, the Cronbach's alpha and Composite Reliability (CR) are utilized. The tests verify the reliability of the questions, ensuring they are accurate and applicable across various situations and times.

(1) Cronbach's Alpha

Cronbach's Alpha (α) is defined below and it provides the value for Cronbach’s alpha coefficient.

$$\alpha = \frac{N}{N-1}\left(1 - \frac{\sum_{i=1}^{N} \sigma_{Y_i}^2}{\sigma_x^2}\right)$$

Where

N is the number of items.

σ_x^2 is the variance of the observed total test scores.

$\sigma_{Y_i}^2$ is the variance of component i.

The value of Cronbach's Alpha is $0 \leq \alpha \leq 1$, the higher value implies the higher reliability and the range of Cronbach's Alpha is between 0.7 and 0.9 to be considered as good (Streiner, 2003).

Table 3.2

Cronbach's Alpha Scores' Levels.

Cronbach's Alpha	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.7 \leq \alpha < 0.9$	Good
$0.6 \leq \alpha < 0.7$	Acceptable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Source: Streiner, 2003.

(2) Composite Reliability

Composite Reliability (CR), also known as construct reliability, is employed to assess the internal consistency of scale items, similar to Cronbach's alpha (Netemeyer, Bearden & Sharma, 2003).

$$CR=\frac{(\sum_{i=1}^{p}\lambda_i)^2}{(\sum_{i=1}^{p}\lambda_i)^2-\sum_{i=1}^{p}V(\delta_i)}$$

Where

λ_i is the factor loading for the i^{th} indicator.

$V(\delta)$ is the variance of the error term for the i^{th} indicator.

p is the count of indicators.

The composite reliability values of each factor are greater than 0.80, which is very high for the proposed construct (Henseler & Sarstedt, 2013; C. M. Ringle, Sarstedt & Straub, 2012).

3.5.2.2 Indicator Reliability

To ensure the reliability of the indicator, it is recommended that the external loadings surpass 0.708; however, a loading exceeding 0.5 is deemed acceptable if the measurement model meets the criteria for internal consistency and convergent validity (Ramayah, Hwa, Chuah, Ting & Memon, 2016).

3.5.2.3 Convergent Validity

Convergent validity is employed to assess the reliability and usability of measurement questions. Despite variations in question meanings, the underlying principle remains consistent. The Average Variance Extract (AVE) should exceed 0.5, indicating that the constructs can elucidate over 50% of the measurable variable (Hair et al., 2010; Sarstedt, 2008).

$$\text{AVE}=\frac{\sum_{i=1}^{p}\lambda_i^2}{\sum_{i=1}^{p}\lambda_i^2-\sum_{i=1}^{p}V(\delta_i)}$$

Where

λ_i is the factor loading for the i^{th} indicator.

$V(\delta)$ is the variance of the error term for the i^{th} indicator.

p is the count of indicators.

3.5.2.4 Discriminant Validity

Discriminant validity is employed to distinguish the items of a particular construct in a questionnaire from those of other constructs. The evaluation, following Fornell and Larcker's criteria (Fornell & Larcker, 1981), relied on ensuring that the square roots of Average Variance Extracted (AVE) were greater than the correlations with any other latent variables. An alternative method involves using the Heterotrait-Monotrait Ratio (HTMT) criterion, suggesting that variations in correlations among different constructs should not exceed 0.85 (Henseler, Ringle & Sarstedt, 2015).

3.5.2.5 Multicollinearity

Multicollinearity is a situation where independent variables in a statistical model display strong correlations, potentially resulting in unreliable and unstable estimates in regression model. In the assessment of the measurement model, the final step involved the examination of both the outer and inner VIF (Variance Inflation Factor) values. Multicollinearity becomes an issue when the variance inflation coefficient (VIF) surpasses 4.0 (Henseler & Sarstedt, 2013).

3.5.3 Structural Model Evaluation

To assess the structural model and quantify the concurrent impact among its latent variables, the data collected were organized in SPSS and subjected to analysis through the Structural Equation Modeling (SEM) method performed using SmartPLS 4 (C. M. Ringle, Wende, Sven, & Becker, Jan-Michael, 2022). Regression analysis was used to analyze the relationship between the independent and dependent variables. The utilization of PLS algorithms enabled the assessment of the structural connections between the model's components and the validation of research hypotheses. Partial Least Squares (PLS) regression models find common application in technology adoption modeling and have been the focus of numerous research investigation (Căpu**Ş**neanu et al., 2021; Gupta, Kiran & Sharma, 2023; T**ű**rke**Ș** et al., 2020; Uddin et al., 2020). Assessment of the structural model involves examining the relationship between independent and dependent variables. The evaluation includes conducting the coefficient determinant test and hypothesis testing through the analysis of total effects.

3.5.3.1 Coefficient Determminant

The coefficient determinant, denoted as R^2, is a method used to ascertain the variance in the endogenous variable explained by the exogenous variable. The R^2 value ranges from 0 to 1. The R^2, which serves as a comprehensive measure of effect size in the structural model, categorizes its values as "high" when exceeding 0.5, "moderate" when surpassing 0.30, and "weak" when surpassing 0.1 (Sarstedt, 2008).

3.5.3.2 Hypothesis Testing and Path Coefficient

In the process of hypothesis testing, the objective is to confirm the predicted path and assess the significance level for each path. It is crucial that the path coefficient, ranging from -1 to 1, aligns with expectations. A positive coefficient in the range of 0 to +1 signifies a positive relationship, while a negative coefficient in the range of-1 to 0 indicates a negative relationship. The significance level of the path is 0.05, meaning $p < 0.05$ (Sarstedt, Ringle & Hair, 2017).

CHAPTER 4
RESULTS AND DISCUSSION

This chapter reveals the discoveries regarding the factors influencing the intention of HR and recruiting professionals to adopt AI in recruitment. Employing both in-depth interviews and questionnaires, the study initially utilized data from previous studies to construct the research model. Survey questionnaire items were refined through literature review and in-depth interviews, tailored for relevance in the Thai recruitment context. A survey involving HR and recruiting professionals was conducted. The data analysis methodology employed Structural Equation Modeling with Partial Least Squares. The chapter presents the results of in-depth interviews, descriptive statistics, data interpretation, measurement model evaluation, and structural model evaluation.

4.1 In-Depth Interview Results

The In-depth interviews were conducted with 20 respondents including 7 jobseekers 5 hiring managers and 8 HR professionals from various business sectors. These participants varied in terms of age, encompassing both Generation Y and Generation Z, as well as gender and levels of technological experience. Among the 20 participants, 13 individuals had prior experience with AI in recruitment. Notably, within the group of HR and recruitment professionals, 7 out of 8 ever employed or tested AI-based recruitment software in their practices.

The result of the interviews, which aimed to validate the elements derived from UTAUT along with additional factors, was carried out as follows:

Performance Expectancy

Among 20 interviewees, all of them agreed that the level of performance expectancy directly influences the intention to incorporate AI in the recruitment process.

HM1: The integration of AI technology is inevitable, permeating every work process, including HR and recruitment. With the anticipation of robust AI capabilities, it becomes a valuable asset for all users, hiring managers or recruiters, facilitating the sourcing of potential candidates through access to extensive databases. This, in turn, enhances the efficiency of the recruitment process with minimal intervention from human recruiters.

HR2: In the case of a large corporation facing high demand of hiring, employing AI as a tool proves valuable for efficiently screening a high volume of resumes and providing automatic responses to candidates seeking basic company information. Automating these manual tasks is certain to significantly expedite the recruitment processes.

HR3: I believe that as machine learning experiences rapid growth, AI's ability to assess and match the right candidate for an organization will be greatly enhanced by evaluating combined data, including resumes, skill tests, and attitude assessments. This approach is expected to result in a more effective candidate selection process.

Effort Expectancy

The 19 out of 20 interview participants concurred that the perceived ease of use or effort expectancy plays a crucial role in influencing a user's intention to utilize AI tools in the recruitment process.

HR3: Beyond the capabilities of AI, an essential consideration for embracing new technologies or systems like HRS, payroll systems, or automated recruitment lies in their user-friendliness. Utilizing an AI tool in recruitment should not necessitate technical expertise; it ought to be as straightforward as employing general AI tools in everyday situations.

HR5: While I don't foresee AI replacing human recruiters entirely, it can serve as a valuable aid to them. In this context, any assisting tool should boast user-friendliness, featuring a well-designed interface and providing clear guidelines for new functionalities.

HR8: Certainly, when adopting a new system within an organization, simplicity becomes a crucial factor. The easier the system is to navigate, the more likely it is to be embraced. This holds true even for AI-based recruitment software.

Social Influence

From the interviews, a majority of 14 participants acknowledged that social influence emerges as a key factor influencing the intention to adopt AI-based recruitment systems.

J4: Certainly, knowing a success story of those who use AI in the recruitment and successfully match candidates with organizations would motivate me to utilize this tool. The benefits of using AI are evident and surpass those who refrain from its adoption.

HM2: Using AI in talent acquisition is in the current trend in my business sector and I firmly believe that HR professionals need to be proactive in adopting this tool. Without AI assistance, a recruitment team might lag behind competitors in the talent acquisition arena.

HR1: Naturally, if I become aware that recruiters from competing companies are utilizing AI, it would persuade me to adopt the tool to maintain competitiveness.

Facilitating Conditions

15 of the total 20 participants expressed a consensus that facilitating conditions have a direct impact on the intention to embrace AI in recruiting processes.

HM4: When introducing a new system such as AI in the hiring process, it is crucial to ensure that the system is equipped with ample facilitating conditions or has a technical support team readily available for assistance.

HR4: Before integrating AI into recruitment, it's essential to provide training to all users. Additionally, the system should have a readily accessible guideline to consult whenever necessary.

HR6: It would be advantageous if the AI tool in recruitment could be utilized on both office laptops and mobile devices, facilitating easy access whether in the office or during remote work from home.

Privacy and Security

The 18 out of 20 interviewees acknowledged that privacy and security play a crucial role in influencing the decision to adopt AI in the hiring process.

J2: For job seekers to utilize AI-based recruitment software, obtaining consent for data privacy before sharing information with employers or recruiters is crucial. Without data privacy and security measures, the credibility of the AI system is compromised.

HR2: Given the Personal Data Protection Act (PDPA) in Thailand, it is imperative for AI software to adhere to data privacy laws, ensuring the privacy and security of user's personal data. Compliance with these regulations should be a fundamental criterion for adopting such new technology.

HR7: As a fundamental requirement, the system must be encrypted and secured to prevent unauthorized organizations from accessing the user database.

Trust in AI Technology

15 our of 20 participants collectively agreed that the level of trust in AI technology significantly influences the intention to utilize AI in the recruitment process.

J6: A critical aspect to consider when integrating AI into the recruiting procedure is the reliability of the AI system. Users must ensure that AI developers do not exploit data from candidates or companies for other benefits.

HM3: A significant concern in recruiting new team members is the challenge HR faces in screening and matching the right-fit candidate according to requirements. If an AI algorithm can address this issue and effectively screen suitable candidates for an organization, it is likely to motivate HR to embrace such a new system.

HR5: An important consideration is the trust placed in AI algorithms and databases. AI databases are tailored to specific business sectors; for instance, recruiting IT specialists might require one platform, while recruiting manufacturing engineers might require another. Therefore, trust in AI database is crucial in deciding whether to effectively use AI in recruiting candidates.

Perceived Value

The majority of 14 participants recognized that the perceived value in AI can have an impact on their intention to use AI software in the recruiting process.

HM5: As the Managing Director and head of an organization, it is crucial to conduct a financial analysis before incorporating AI into the hiring process. We must carefully assess and compare it with alternative options like enhancing productivity or utilizing external recruiters. If the investment proves worthwhile, why hesitate to implement it?

HR7: For AI integration in talent acquisition to be embraced, it must consistently demonstrate its value in terms of functionality that aligns with identifying candidates who genuinely suit the organization.

HR8: An additional consideration for adopting AI is its social value. The integration of AI can contribute to social value, positioning the company as tech-driven or endorsing bias-free hiring software with the aim of fostering diversity.

Perceived Autonomy

The majority of 14 participants reached a consensus that perceived autonomy can influence a user's intent to adopt AI in the recruitment process.

HM2: With the application of advanced machine learning, artificial intelligence (AI) is poised to automate various manual tasks in the recruitment process, such as skill matching, candidate shortlisting, and evaluating resumes. This automation will result in significant time savings, enabling HR professionals and recruiters to focus more on strategic initiatives, thereby enhancing overall benefits for the company.

HR1: In the past, I used to dedicate an entire week to screening a hundred resumes and selecting a few candidates for the interview round. This process was notably unproductive. However, after experimenting with an AI recruiting platform, I found that it efficiently screened numerous resumes, providing summaries and ranking candidates based on our criteria. This not only reduces decision-making workload but also motivates me to use such a system due to the increased autonomy in decision-making.

HR4: Although I acknowledge that AI can handle a majority of recruiting tasks, I see this as an opportunity for human recruiters to be liberated from routine tasks. This newfound freedom allows them to invest more time in coordinating and engaging with candidates on a personal level, adding a distinct human touch. This human interaction can leave a lasting impression on candidates, making the recruitment process even more impactful.

In conclusion, the consensus among participants is clear. The majority of them agree that the 8 factors proposed can indeed impact the intention to use AI in recruitment practices. Furthermore, a prevalent understanding exists that AI is not positioned to replace human recruiters. Instead, it is widely perceived as a valuable aid for HR and recruitment professionals.

Table 4.1

In-Depth Interview Summary

No.	Age	Academic	Occupation/ Position	PE	EE	SI	FC	PS	PA	TA	PV
J1	37	Bachelor	Engineer	x	x	x	x	x	x		
J2	32	PhD	Market researcher	x	x	x	x	x	x	x	x
J3	36	Bachelor	Engineer	x	x	x	x	x	x		
J4	34	Bachelor	Business developer	x	x	x	x	x	x	x	x
J5	32	Master	Data scientist	x	x			x			x
J6	36	Master	Programmer	x	x	x	x	x	x	x	x
J7	23	Bachelor	Business analyst	x	x		x	x			
HM1	34	Master	Business development manager	x	x	x		x		x	x
HM2	37	Bachelor	Digital transformation head	x	x	x	x	x	x	x	
HM3	36	Master	Production manager	x	x				x	x	x
HM4	37	Master	Head of Marketing	x		x	x	x			
HM5	42	Bachelor	Managing Director	x	x		x	x	x	x	x
HR1	23	Bachelor	HR/Recruitment officer	x	x	x	x	x	x	x	
HR2	25	Bachelor	HR/Recruitment officer	x	x	x	x	x	x	x	x
HR3	24	Bachelor	HR/Recruitment officer	x	x		x			x	x
HR4	39	Master	HR Manager	x	x	x	x	x	x	x	x
HR5	33	Master	HR/Recruitment officer	x	x	x	x	x	x	x	x
HR6	30	Master	HR generalist	x	x	x	x	x	x	x	x
HR7	40	Master	People head Director level	x	x			x		x	x
HR8	39	Master	General manager - HR	x	x	x		x	x	x	x

4.2 Demographic Characteristics

The sample size was calculated using the method proposed by (Hair et al., 2010; Kline & St, 2022), which involves multiplying the number of indicators by a factor of 5 to 10. Thus, the minimum sample size required should have been at least 35 indicators multiplied by 5, resulting in 175 respondents. The survey was conducted from July 2022 to March 2023 involving a range of participants across different gender, age, and academic qualification categories with 364 respondents. Among the respondents, comprising 42% men and 58% women, who were HR and recruiting professionals in the Bangkok metropolitan area, there was a diversity in professional roles, with 131 (36%) in officer positions, 119 (33%) in managerial roles, 82 (23%) in supervisory positions, and 32 (9%) directorial positions. Additionally, 58% of these professionals held bachelor's degrees, 41% held master's degrees, and 1% held doctoral degrees.

The majority of respondents were in the age brackets of 25-34 years (45%) and 35-44 years (33%), with varying work experience durations, including 27% with 5-10 years, 25% with more than 15 years, and 21% with 10-15 years of experience.

These professionals operated in diverse business sectors, including information technology (18%), manufacturing (16%), services (12%), and others. Furthermore, the respondents represented various organization sizes, with 38% from organizations employing more than 500 individuals, 26% from those with 51-200 employees, and 21% from organizations with 201-500 employees. Notably, a significant proportion (82%) of the respondents were familiar with or had heard of AI-based recruitment software, while only 30% had actually used such software. The majority of respondents (65%) pointed that AI cannot replace human recruiters.

Table 4.2

Demographic Characteristics

Categories	Dimensions	N	%
Gender	Male	153	42%
	Female	211	58%
Age	Less than 25 years old	25	7%
	25-34 years old	165	45%
	35-44 years old	121	33%
	45-54 years old	45	12%
	upper 54 years old	8	2%
Education Level	Doctoral Degree	4	1%
	Master's Degree	148	41%
	Bachelor's Degree	212	58%
Position Level	Officer/ Staff	131	36%
	Supervisor / Team Leader	82	23%
	Manager / Department Head	119	33%
	Director/ Executive	32	9%
Work Experience	0-3 years	43	12%
	3-5 years	53	15%
	5-10 years	99	27%
	10-15 years	78	21%
	More than 15 years	91	25%
Organization Size (# of Employees)	Less than 25	13	4%
	26-50	43	12%
	51-200	93	26%
	201-500	78	21%
	More than 500	137	38%

Table 4.2

Demographic Characteristics (cont.)

Categories	Dimensions	N	%
Business Sector	Agro & Food Industry	19	5%
	Information Technology	67	18%
	Manufacturers	57	16%
	Medical and Healthcare	16	4%
	Financials	27	7%
	Consultancy	36	10%
	Services	43	12%
	Energy and Utilities	27	7%
	Consumer Products	33	9%
	Others	39	11%
Do you know AI based recruitment software before?	Yes	299	82%
	No	65	18%
Have you ever used AI based recruitment software before?	Yes	110	30%
	No	254	70%
Do you think AI based recruitment can replace human?	Yes	128	35%
	No	236	65%
Total		364	100%

4.3 Acceptance Factor Perception Levels

The data related to opinions regarding independent and dependent variables undergoes analysis employing descriptive statistics. This analysis includes data summarization based on the survey questions and the presentation of statistics such as the mean, standard deviation, and the interpretation of opinion levels in the subsequent manner:

Table 4.3

Acceptance Factor Perception Levels

Influencing factors	Item	Question item	Mean	Standard deviation	Mean score interpreted
Performance Expectancy	PE1	I think AI is useful in recruitment	4.31	0.68	Strongly Agree
	PE2	I think that AI will make recruitment process faster	4.32	0.70	Strongly Agree
	PE3	I think AI can increase efficiency of recruitment work	4.11	0.82	Agree
	PE4	I think using AI can help analyze candidates more accurately	3.74	0.86	Agree
Effort Expectancy	EE1	I would find the AI based recruitment software easy to use	4.19	0.72	Agree
	EE2	I think it would be easy to learn how to use the interface of AI based recruitment software	4.20	0.78	Agree
	EE3	For me, it will not take long to be skillful in using AI in recruitment	4.24	0.68	Strongly Agree
	EE4	I think AI in recruitment would be flexible for use.	3.78	0.93	Agree

Table 4.3

Acceptance Factor Perception Levels (cont.)

Influencing factors	Item	Question item	Mean	Standard deviation	Mean score interpreted
Social influence	SI1	My decision to use AI in recruitment would be based on proportion of coworkers who use the software or system	3.67	0.99	Agree
	SI2	Those who use AI based recruitment software would have more advantages than those who do not)	3.96	0.88	Agree
	SI3	With the rapid development of technology, the introduction of AI in recruitment into my company is necessary	4.17	0.79	Agree
	SI4	I think the introduction of AI in recruitment into our company will be trendy in my industry	3.46	1.03	Agree
Facilitating Conditions	FC1	I expect to call a technical support team in case of facing any problems while using AI driven recruitment system	4.05	0.89	Agree

Table 4.3

Acceptance Factor Perception Levels (cont.)

Influencing factors	Item	Question item	Mean	Standard deviation	Mean score interpreted
	FC2	I expect that the system would be available in both computer and mobile devices	4.40	0.72	Strongly Agree
	FC3	I think guidance would be available in AI based recruitment system	4.40	0.63	Strongly Agree
Privacy and Security	PS1	I expect that AI based recruitment software will be safe and secure	4.67	0.61	Strongly Agree
	PS2	I expect that AI based recruitment software will strictly comply data privacy policy regarding Personal Data Protection Act	4.72	0.58	Strongly Agree
	PS3	I feel safe and protected by the use of encryption	4.41	0.76	Strongly Agree
	PS4	I think AI based recruitment software developer will protect and ensure safety of user's personal data.	4.10	0.96	Agree

Table 4.3

Acceptance Factor Perception Levels (cont.)

Influencing factors	Item	Question item	Mean	Standard deviation	Mean score interpreted
Technology Trust in AI	TA1	I trust that AI algorithm is reliable in screening candidates to match organization's requirement	3.64	0.84	Agree
	TA2	I trust that AI based recruitment software has reliable database to complete main tasks of recruitment process	3.71	0.82	Agree
	TA3	I think there will be a trusted body or government organizations to ensure that AI based recruitment software is secured	3.24	1.16	Neutral
	TA4	I trust that AI based software developer is honest and will not take advantage over user's information	3.26	1.12	Neutral

Table 4.3

Acceptance Factor Perception Levels (cont.)

Influencing factors	Item	Question item	Mean	Standard deviation	Mean score interpreted
Perceived Value	PV1	I think that using AI in recruitment is worth investing	3.89	0.89	Agree
	PV2	I feel that using AI can remain quality of recruitment process consistently.	3.92	0.84	Agree
	PV3	I realize that using AI in recruitment will give the organization the social approve	3.93	0.94	Agree
	PV4	I feel that using AI in recruitment will make impression on candidates	3.79	0.97	Agree
Perceived Autonomy	PA1	Using AI in recruitment will allow recruiters or HR officers to have time for developing other skills	4.13	0.79	Agree
	PA2	Using AI in recruitment will give recruiters or HR officer the opportunity to better coordinate with candidates	3.64	1.09	Agree

Table 4.3

Acceptance Factor Perception Levels (cont.)

Influencing factors	Item	Question item	Mean	Standard deviation	Mean score interpreted
	PA3	Using AI in recruitment will give recruiters or HR officer more time to better deals with other necessary activities	4.07	0.89	Agree
	PA4	I think that AI in recruitment will reduce the number of decisions to get the optimal results	3.96	0.92	Agree
User's Intention	IU1	Using AI based recruitment software is a good and modern idea	4.42	0.68	Strongly Agree
	IU2	I like the idea of using AI in recruitment	4.29	0.78	Strongly Agree
	IU3	The AI based recruitment software makes me more interested	4.09	0.88	Agree
	IU4	I have a high wiliness to use AI in recruitment	3.85	0.95	Agree

4.3.1 Performance Expectancy

Participants strongly agreed on the usefulness of AI in recruitment (PE1, Mean = 4.31) and the fast recruitment proceeded by AI (PE2, Mean = 4.32). They expressed agreements on AI's potential to increase efficiency (PE3, Mean = 4.11) and analyze candidates accurately (PE4, Mean = 3.74).

4.3.2 Effort Expectancy

Survey participants agreed that AI-based recruitment software would be easy to use (EE1, Mean = 4.19) and it's easy to learn (EE2, Mean = 4.20). They expressed a strong agreement that becoming skillful in using AI won't take long (EE3, Mean = 4.24), and a general agreement on the flexibility of AI in recruitment (EE4, Mean = 3.78).

4.3.3 Social Influence

Survey participants agreed all items regarding social influence including coworkers influencing the decision to use AI (SI1, Mean = 3.67), recognizing advantages for individuals using AI in recruitment (SI2, Mean = 3.96), deeming the integration of AI into their company as necessary (SI3, Mean = 4.17), and acknowledging its trendiness in the industry (SI4, Mean = 3.46).

4.3.4 Facilitating Conditions

Participants demonstrated agreement in anticipating the availability of technical support (FC1, Mean = 4.05). They expressed strong agreement regarding system accessibility on various devices (FC2, Mean = 4.40), and the presence of guidance within AI-based recruitment systems (FC3, Mean = 4.40).

4.3.5 Privacy and Security

There are strong agreements on the expectation of safety and security (PS1, Mean = 4.67), strict compliance with data privacy policies (PS2, Mean = 4.72), and a feeling of safety through encryption (PS3, Mean = 4.41). Participants agree that AI developers will protect user’s personal data (PS4, Mean = 4.10).

4.3.6 Technology Trust in AI

Trust in AI algorithms for screening candidates (TA1, Mean = 3.64) and reliance on a reliable database in AI-based recruitment software (TA2, Mean = 3.71) received agreement. However, there were neutral stances on the expectation of trusted bodies ensuring software security (TA3, Mean = 3.24) and trust in developer honesty (TA4, Mean = 3.26).

4.3.7 Perceived Value

Agreement was observed regarding all measurement items in perceived value including the conviction that investing in AI for recruitment is worthwhile (PV1, Mean = 3.89), acknowledgment that AI can consistently maintain quality in recruitment (PV2, Mean = 3.92), recognition of the social approval linked to AI (PV3, Mean = 3.93), and the positive impressions on candidates associated with the use of AI in recruitment (PV4, Mean = 3.79).

4.3.8 Perceived Autonomy

Participants agreed that using AI in recruitment will allow recruiters or HR officers to have time for developing other skills (PA1, Mean = 4.13), AI in recruitment will give recruiters or HR officer the opportunity to better coordinate with candidates (PA2, Mean = 3.64), using AI in recruitment will give recruiters or HR officer more time to better deals with other necessary activities (PA3, Mean = 4.07) and reduces decision-making for optimal results (PA4, Mean = 3.96).

4.3.9 User's Intention

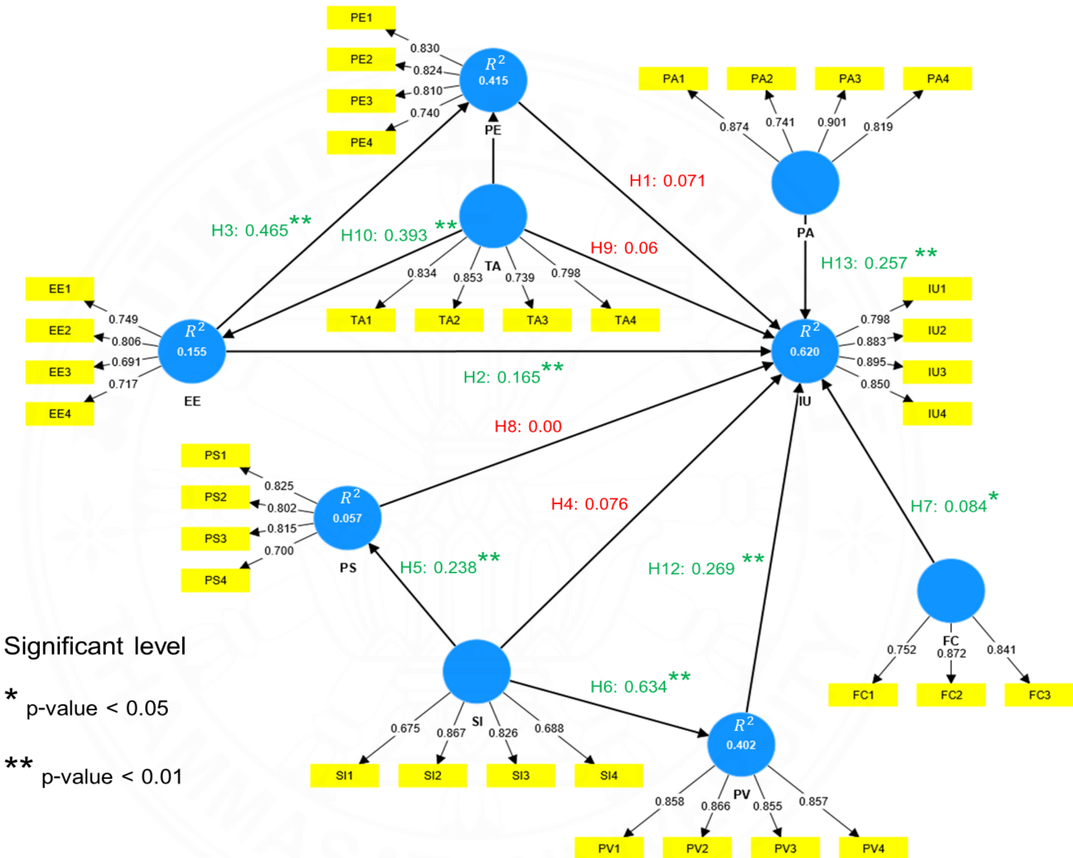
Strong agreements were seen in participants viewing AI-based recruitment software as a good and modern idea (IU1, Mean = 4.42) and expressing a liking for the idea to use AI in recruitment (IU2, Mean = 4.29). Agreements were also noted in AI generating interest (IU3, Mean = 4.09) and participants having a high intention to use AI in recruitment (IU4, Mean = 3.85).

4.4 Model Measurement Evaluation

The results of employing PLS-SEM modeling, a statistical method used for scrutinizing relationships between variables in the study, are depicted in Figure 4.1. As depicted in the diagram, the connection of each hypothesis is represented by a path coefficient, highlighted in green to indicate significance level (* p-value < 0.05,** p-value < 0.01) and in red to indicate insignificance. This visual presentation enhances the understanding of insights and discoveries stemming from PLS-SEM, contributing to a more profound comprehension of the study's outcomes.

Figure 4.1

PLS-SEM Result with path coefficients



4.4.1 Internal Consistency Reliability

According to the results provided in Table 4.4, it can be inferred that the measurement scales for PE, EE, SI, FC, PS, TA, PV, PA, and IU demonstrate reliability. This conclusion is drawn from the fact that the Cronbach's alpha values for each variable exceeded 0.7, which is considered good for constructs validated in this study (Streiner, 2003). Additionally, the composite reliability values of each factors are greater than 0.80, which is very high for the proposed construct (Henseler & Sarstedt, 2013; C. M. Ringle, Sarstedt, & Straub, 2012). Therefore, the suggested model meets the requirement for reliability test.

Table 4.4

Reliability and Validity Construction

Factors	Item	Outer loading	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
EE	EE1	0.749	0.726	0.83	0.551
	EE2	0.806			
	EE3	0.691			
	EE4	0.717			
FC	FC1	0.752	0.76	0.863	0.678
	FC2	0.872			
	FC3	0.841			
IU	IU1	0.798	0.879	0.917	0.735
	IU2	0.883			
	IU3	0.895			
	IU4	0.850			
PA	PA1	0.874	0.854	0.902	0.699
	PA2	0.741			
	PA3	0.901			
	PA4	0.819			
PE	PE1	0.830	0.814	0.878	0.643
	PE2	0.824			
	PE3	0.810			
	PE4	0.740			
PS	PS1	0.825	0.793	0.866	0.619
	PS2	0.802			
	PS3	0.815			
	PS4	0.700			
PV	PV1	0.858	0.881	0.918	0.738
	PV2	0.866			

Table 4.4

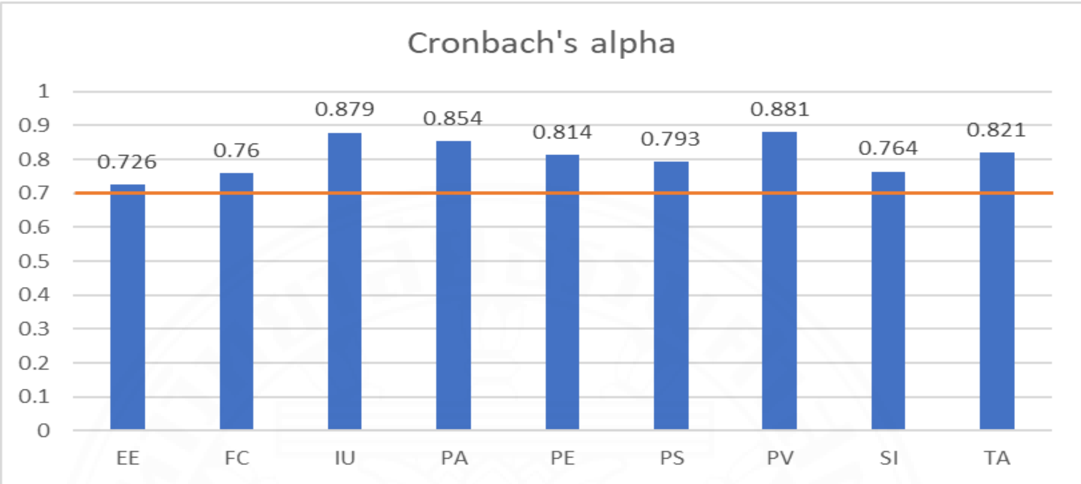
Reliability and Validity Construction (cont.)

Factors	Item	Outer loading	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
	PV3	0.855			
	PV4	0.857			
SI	SI1	0.675	0.764	0.851	0.591
	SI2	0.867			
	SI3	0.826			
	SI4	0.688			
TA	TA1	0.834	0.821	0.882	0.651
	TA2	0.853			
	TA3	0.739			
	TA4	0.798			

Cronbach's Alpha, which varies between 0 and 1, signifies greater reliability as its value increases. For assessing convergent validity in a construct model, it is recommended that the indicators for variables should be equal to or greater than 0.6, and with a range of 0.7 or higher is typically considered good (Streiner, 2003). All factors, namely EE (0.726), FC (0.76), IU (0.879), PA (0.854), PE (0.814), PS (0.793), PV (0.881), SI (0.764), TA (0.821) were assessed at a good level as all values are above 0.7 (see Figure 4.2). Consequently, the suggested model meets the requirement for good reliability.

Figure 4.2

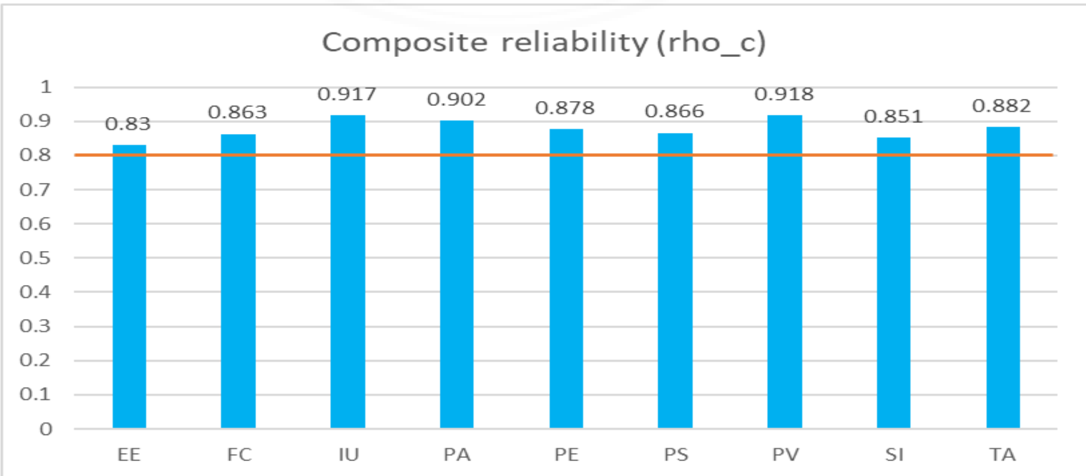
Cronbach's Alpha for Variables with a Minimum Threshold Exceeding 0.7



In addition, the evaluation of the reliability test was conducted using the composite reliability indicator (CR), with a threshold of CR > 0.8 which is very high for the proposed construct (Henseler & Sarstedt, 2013; C. M. Ringle et al., 2012). In this study finding, the composite reliability indicator (CR) demonstrates a range of values spanning from 0.83 to 0.918 as shown in Figure 4.3.

Figure 4.3

Composite Reliability of Variables with a Minimum Threshold Exceeding 0.8



4.4.2 Indicator Reliability

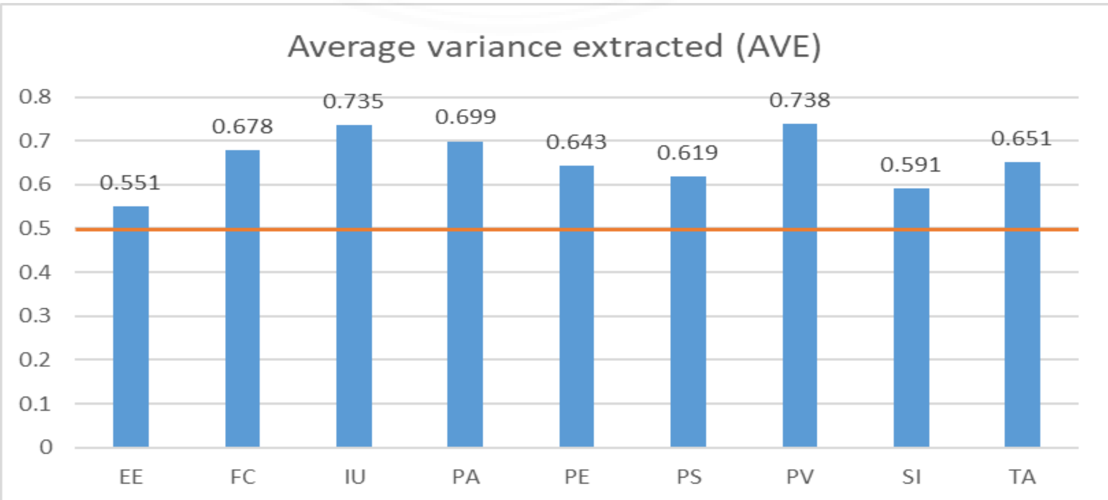
In Table 4.4, all items exhibit outer loadings within the range of 0.675 to 0.901. Among the 35 items, 33 have outer loadings equal to or exceeding 0.7. Only items EE3, SI1, and SI4 have outer loadings at 0.691, 0.675, and 0.688, respectively, slightly lower than 0.7 but still greater than 0.6. When comparing these results to other metrics such as AVE surpassing 0.5, Cronbach's alpha exceeding 0.7, and composite reliability surpassing 0.8, it can be inferred that the construct model meets the criteria for indicator reliability (Ramayah et al., 2016).

4.4.3 Convergent Validity

Furthermore, the Average Variance Extracted (AVE) remains the favored measure for evaluating both convergent and divergent validity. In reflective models, when the AVE values for latent factors exceed the recommended minimum threshold of 0.5, it affirms the presence of convergent validity. Given that all AVE values surpass the minimum threshold of 0.5, it can be inferred that the construct model meets the criteria for convergent validity (Sarstedt, 2008). In the structural model, the AVE falls within the range of 0.551 to 0.738, all surpassing the 0.5 threshold as depicted in Figure 4.4. Thus, the confirmation of convergent validity for the proposed construct model is affirmed.

Figure 4.4

Average Variance Extracted of Variables with a Minimum Threshold Exceeding 0.5



4.4.4 Discriminant Validity

By examining Table 4.5, it is evident that according to Fornell and Larcker's criteria (Fornell & Larcker, 1981), the constructs demonstrate discriminant validity the square root of AVE values on the diagonal for constructs exceeds the correlations between constructs (Fornell & Larcker, 1981; Henseler, 2010). The square root of the AVE for IU, measuring 0.857, surpasses both the vertical (0.694, 0.626, 0.319, 0.714, 0.598, 0.532) and horizontal (0.581, 0.372) correlation values. As a result, the construct model fulfills the condition of discriminant validity.

Table 4.5

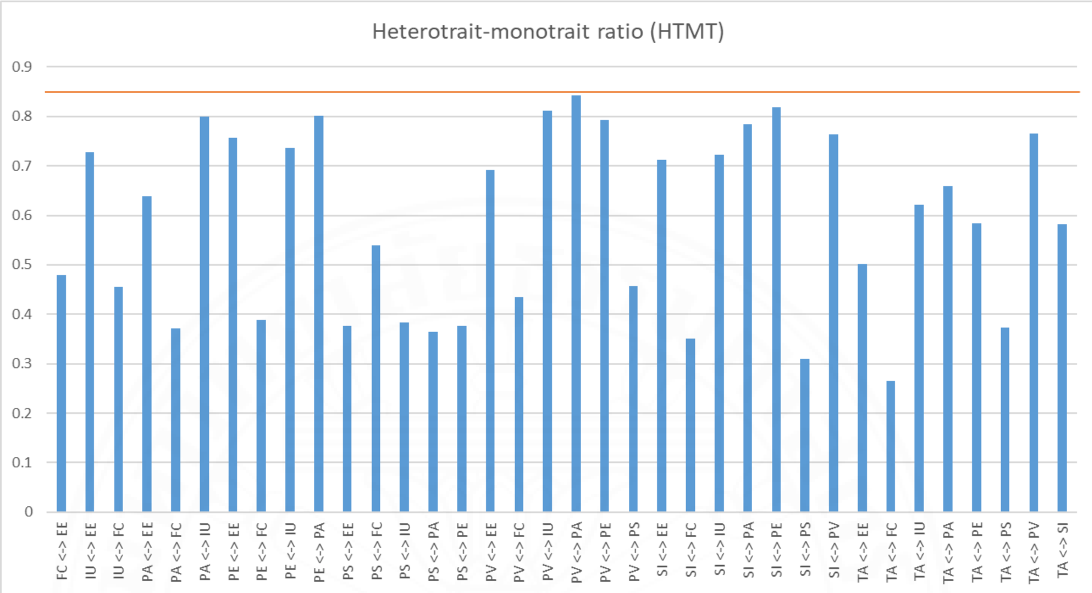
Fornell–Larcker criterion

	EE	FC	IU	PA	PE	PS	PV	SI	TA
EE	0.742								
FC	0.356	0.823							
IU	0.581	0.372	0.857						
PA	0.507	0.305	0.694	0.836					
PE	0.583	0.305	0.626	0.67	0.802				
PS	0.286	0.426	0.319	0.3	0.3	0.787			
PV	0.555	0.354	0.714	0.731	0.671	0.377	0.859		
SI	0.539	0.264	0.598	0.639	0.66	0.238	0.634	0.769	
TA	0.393	0.213	0.532	0.555	0.482	0.294	0.655	0.463	0.807

The standardized average residual square root (SRMR) serves as a measure of the appropriateness of the model under consideration. When the distinction between the observed correlation matrix and the expected correlation matrix is under 0.08 (L. t. Hu & Bentler, 1999), it demonstrates the model's appropriateness. In this study, the average difference (SRMR) was 0.075, which is below 0.08, the proposed model is both effective and pertinent.

Figure 4.5

Heterotrait–Monotrait Ratio with a Baseline below 0.85



Discriminant validity can also be assessed through the Heterotrait–Monotrait Ratio (HTMT), which stipulates that the disparities between Heterotrait and Monotrait correlations should not exceed 0.85 (Henseler et al., 2015). As observed in Figure 4.5, the variances between Heterotrait and Monotrait correlations among the model's latent variables fall below the threshold of 0.85.

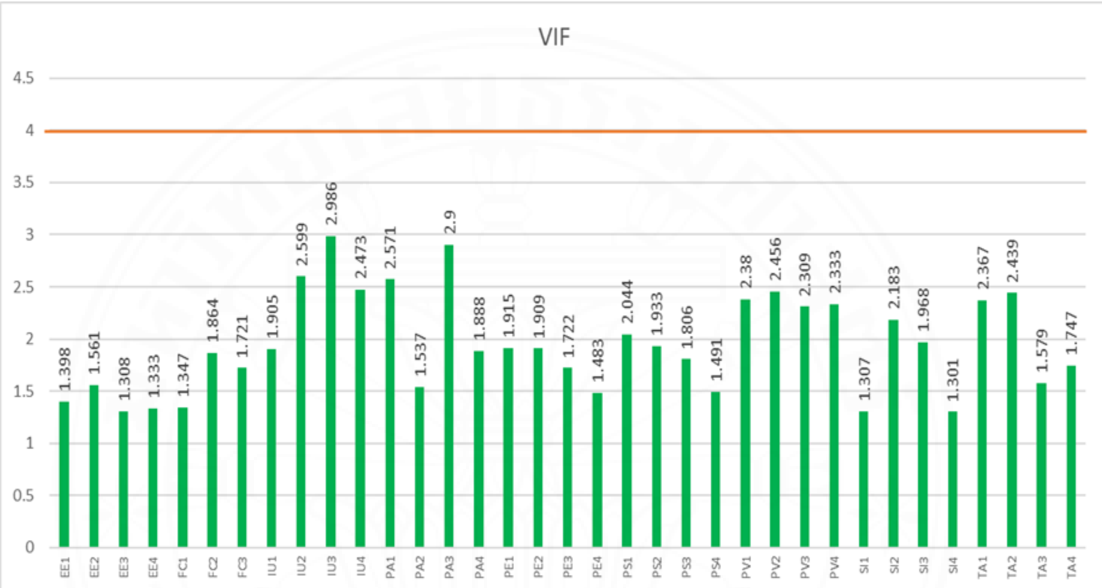
4.4.5 Multicollinearity

Multicollinearity is a situation where independent variables in a statistical model display strong correlations, potentially resulting in unreliable and unstable estimates in regression model. In the assessment of the measurement model, the final step involved the examination of both the outer and inner VIF (Variance Inflation Factor) values. Multicollinearity becomes an issue when the variance inflation coefficient (VIF) surpasses 4.0. In the structural model, there is no concern about multicollinearity, as the VIF values for all 35 items are below the 4.0 threshold, denoted as Figure 4.6 (Henseler & Sarstedt, 2013). This indicates that the variables in the model are not excessively interrelated, rendering the data suitable for further structural analysis. In Figure 4.6, the highest VIF values from each element were EE2

(1.561), FC2 (1.864), IU3 (2.986), PA3 (2.9), PE2 (1.909), PS1 (2.044), PV2 (2.456), SI2 (2.183), TA2 (2.439), which are all below 4.0.

Figure 4.6

Variance Inflation Factor with a Baseline under 4



4.5 Structural Model Analysis

Table 5 displays the outcomes of correlations among construct variables, Path coefficients (β), T-Statistics, and associated p-values. These results are obtained through the use of PLS algorithms, which enable the examination of structural relationships among model constructs and the testing of research hypotheses. The analysis also includes Bootstrapping and Blindfolding procedures performed within SmartPLS4.

Table 4.6

Summary of path coefficients and testing results

Hypothesis	Correlation	Path coefficients	T statistics	p-values	Meaning
H1	PE -> IU	0.071	1.065	0.287	Not Supported
H2	EE -> IU	0.165	3.208	0.001	Supported
H3	EE -> PE	0.465	10.996	0.000	Supported
H4	SI -> IU	0.076	1.203	0.229	Not Supported
H5	SI -> PS	0.238	4.208	0.000	Supported
H6	SI -> PV	0.634	18.272	0.000	Supported
H7	FC -> IU	0.084	2.217	0.027	Supported
H8	PS -> IU	0.000	0.006	0.995	Not Supported
H9	TA -> IU	0.060	1.279	0.201	Not Supported
H10	TA -> EE	0.393	7.725	0.000	Supported
H11	TA -> PE	0.300	6.777	0.000	Supported
H12	PV -> IU	0.269	4.132	0.000	Supported
H13	PA -> IU	0.257	3.877	0.000	Supported

Table 4.6 presents the outcomes of hypothesis testing, revealing that hypotheses H2, H3, H5, H6, H7, H10, H11, H12, and H13 were statistically significant at the 0.01 probability level, while H7 reached significance at the 0.05 level (with provided path coefficients and p-values). In contrast, H1, H4, H8, and H9 were found to be statistically insignificant at the 0.05 significance level with p-values of 0.287, 0.229, 0.995, and 0.201, respectively. Thus, this study supports hypotheses H2, H3, H5, H6, H7, H10, H11, H12, and H13 regarding significant and positive effects, while H1, H4, H8, and H9 do not receive support.

Path coefficients (β) reveal relationships within a structural model organization. Significantly, perceived value (PV) positively affects the intention to use AI-based recruitment software with a coefficient of 0.269. Additionally, perceived autonomy (PA) directly impacts the intention to use with a coefficient of 0.257. Positive contributions to the intention to use AI in recruitment are made by the effort expectancy (EE), which has a path coefficient of 0.165, and facilitating conditions (FC) also directly affect user's intent to accept AI-based recruitment software, with a path coefficient of 0.084.

In the case of other indirect factors, social influence (SI) significantly affects the perceived value (PV) with a path coefficient of 0.634, which in turn directly influences the intention to use AI-based recruitment systems. Trust in AI technology (TA) has a positive effect on the effort expectancy (EE) with a path coefficient of 0.393. Despite the substantial influence of the effort expectancy (EE) on performance expectancy (PE), as reflected in a path coefficient of 0.465, performance expectancy (PE) does not significantly impact user's intention to adopt AI in the recruitment process.

The study also highlights the complex social influence factor, as seen in its impact on privacy and security with a path coefficient of 0.238. This underscores the role of the social context in shaping user's perceptions of AI adoption. However, privacy and security (PS) do not have a direct effect on IU, as indicated by a coefficient of 0.00.

Figure 4.7

Path Coefficients for all Variables

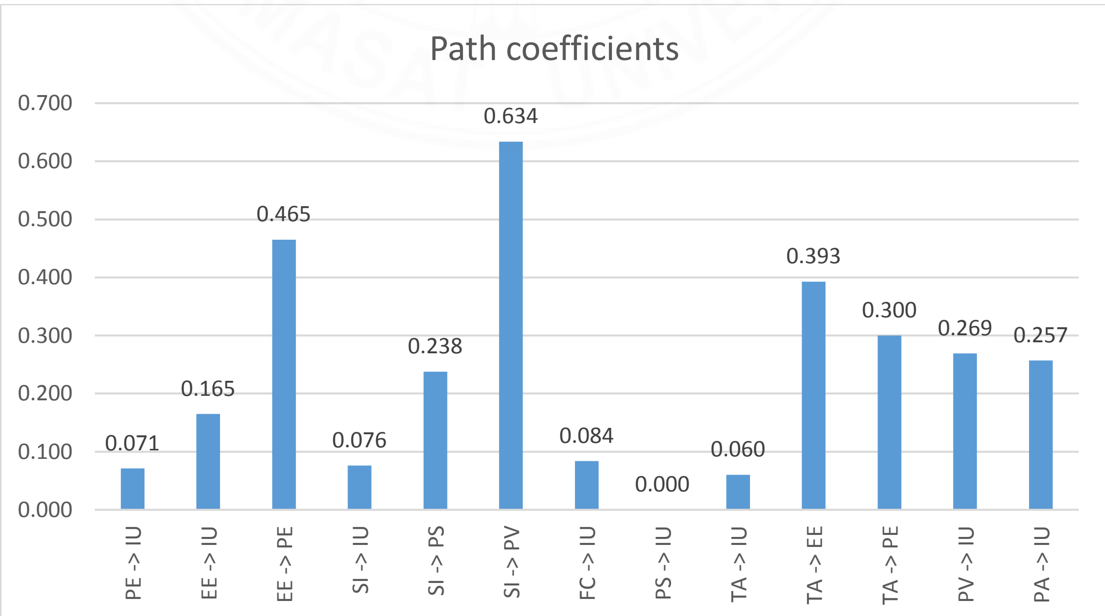


Table 4.7

Magnitude of coefficients of determination R-squared (R^2).

	R-square	R-square adjusted
IU	0.620	0.612
PE	0.415	0.412
PV	0.402	0.400
EE	0.155	0.152
PS	0.057	0.054

The overall indicator of the effect size in the structural model, R^2, can be categorized as "high" (R^2 > 0.5), "moderate" (R^2 > 0.30), or "weak" (R^2> 0.1) (Sarstedt, 2008). The R-squared (R^2) value for intention to use AI-based recruitment software (IU) is impressively high at 0.620, indicating that approximately 62% of the variance is explained by all eight factors (PE, EE, SI, FC, PS, TA, PV, and PA) working in concert. Among these factors, effort expectancy (EE) and trust in AI technology (TA) collectively contribute to around 41.5% of the variability in performance expectancy (PE). In the case of perceived value (PV), social influence (SI) alone significantly accounts for 40.2% of the variance in perceived value (PV). The adjusted R-squared, being nearly identical to the R-squared, indicates that the added predictors have an insignificant contribution to additional explanatory value (Tűrkeș et al., 2020).

4.6 Discussion

This independent study delves into the determinants impacting the intention of HR and recruiting professionals to adopt AI integration in their recruitment procedures. To adapt to Thailand's unique AI adoption landscape, the study extended the Unified Theory of Acceptance and Use of Technology (UTAUT) model, creating a new conceptual framework that includes eight independent variables. These variables comprise Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating conditions (FC) from the UTAUT model, and additional elements: Privacy and security (PS), Trust in AI technology (TA), Perceived value (PV), and Perceived autonomy (PA). A thorough survey involving 364 HR and recruiting professionals in the Bangkok metropolitan area formed the empirical foundation of this study.

Using Structural Equation Modeling (PLS-SEM), the study tested various hypotheses. The structural model accounts for 62% of the variation in the intention to adopt AI-based recruitment software, indicating that approximately 62% of the variance in this intention can be explained by the proposed model. In line with the findings, the intention towards adoption of AI in recruitment is positively affected by variables that demonstrated statistical significance, including:

1) Perceived value, which has a direct impact on the intention to use AI in recruitment, PV -> IU (β =, 0.269, p-value = 0.000 < 0.01 confidence level).

2) Perceived autonomy positively affects the intention to use AI in recruitment, PA -> IU (β =, 0.257, p-value = 0.001 < 0.01 confidence level).

3) Effort expectancy positively contributes to shaping the intention to use AI in recruitment, EE -> IU (β = 0.165, p-value = 0.001 < 0.01 confidence level).

4) Facilitating conditions also directly influence the intention to use AI in recruitment, FC -> IU (β = 0.084, p-value = 0.027 < 0.05 confidence level).

For other indirect variables, it is worth highlighting the impact of social influence (SI) on perceived value (PV), where a substantial path coefficient (β = 0.634) is observed, and the associated p-value (0.000) indicates statistical significance at a confidence level below 0.01. This suggests that social influence has a clear and positive impact on perceived value, which, in turn, plays a direct role in shaping individuals' intentions to adopt AI-based recruitment systems, underlining the influence of colleagues in shaping how AI adoption is viewed.

Similarly, trust in AI technology (TA) is found to have a positive effect on effort expectancy (EE), and this relationship is statistically significant with a low p-value (0.001) at a confidence level below 0.01. This implies that individuals' trust in AI technology directly influences their expectations regarding the ease of using AI systems.

Furthermore, social influence is a crucial driver, explaining 40.2% of the variance in Perceived Value. The combined impact of effort expectancy (EE) and trust in AI technology (TA) accounts for approximately 41.5% of the fluctuations in performance expectancy (PE). Despite the substantial influence of the effort expectancy (EE) on performance expectancy (PE), as reflected in a path coefficient of 0.465, performance expectancy (PE) does not significantly impact user's intention to adopt AI in the recruitment process. Similarly, privacy and security (PS) do not have a direct effect on the intention to use AI recruitment software (IU), as indicated by a coefficient of 0.00.

Although privacy and security may not directly impact the intention to use AI in the hiring process, respondents exhibited strong expectations regarding safety and data privacy in AI-based recruitment. However, they were somewhat uncertain about external oversight and the honesty of AI developers. Nevertheless, it remains crucial to establish a strong foundation for privacy and security when implementing AI platforms in recruitment, in accordance with Thailand's PDPA law. This compliance is essential for both employing organizations and AI developers to ensure trust and reliability in adhering to this legislation.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

This chapter presents conclusions based on the study results. It outlines implications to both theory and practice and addresses limitations, providing recommendations for future research studies.

5.1 Theoretical Implications

In this independent study, an examination is conducted into the factors influencing the intention of HR and recruiting professionals to adopt AI in recruitment. The findings reveal both novel and existing factors that contribute to AI adoption in the recruitment process as follows:

1) Perceived Value Factor: This factor has a direct impact on the willingness to adopt AI in recruitment. Despite numerous studies on technology adoption emphasizing the pivotal role of perceived value in the intention to adopt new technologies, such as sustainable e-learning systems (Liao, Wu, Le, & Phung, 2022), AI smart product (Sohn & Kwon, 2020) and digital payment systems (Gupta et al., 2023). There was an absence of research acknowledging this factor in the context of AI adoption in recruitment. Therefore, this represents a novel insight within the realm of AI adoption in the recruitment.

2) Perceived Autonomy Factor: With automated recruitment processes, HR and recruiters can gain flexibility in managing other crucial responsibilities, leading to a reduction in the number of decisions to achieve optimal outcomes. This factor represents a new finding with a direct impact on user's intention to use AI-based recruitment.

3) Social Influence Factor: For this study, social influence positively impacts perceived value which directly affects the intention to use AI based recruitment system. This is a novel technology acceptance in AI-based recruitment system.

4) Trust in AI Technology Factor: has a positive effect on effort expectancy, which directly influences user's intent in using AI in recruitment. In this study findings, this connection represents a newly identified technology adoption framework in AI acceptance in recruitment.

5) Effort Expectancy Factor: In this study, effort expectancy positively contributes to the willingness to embrace AI. This observation resonates with the research conducted by (Ochmann & Laumer, 2020) regarding AI recruitment acceptance in candidates' views, and AI Recruitment Interview System (Byoung-Chol & Bo-Young, 2021). Thus, this study reaffirms existing evidence, highlighting that effort expectancy directly influences user's intention to use AI-based recruitment systems.

6) Facilitating Condition Factor: The independent study underscores that facilitating conditions have a direct impact on user's intent to accept AI-based recruitment software, aligning with the findings of (M. Alam et al., 2020) and (Byoung-Chol & Bo-Young, 2021) in the area of AI adoption in recruitment. Consequently, this research affirms prior studies on AI acceptance in recruitment.

5.2 Managerial Implications

AI-driven recruitment is a key driver for Thailand's economic advancement in line with the Thailand 4.0 initiative. Government initiatives emphasize the transformative role of AI, with a potential economic benefit of THB 2.6 trillion by 2030. Investing in digital skills can generate THB 1.0 trillion by 2030, fostering job creation and productivity (Partnership, 2023). In the competitive recruitment, AI-based recruitment emerges as a strategic tool, contributing to economic growth. The study provides insights for stakeholders as follows:

5.2.1 Organizations

This independent study provides practical guidance for companies that plan to adopt AI in recruitment as follows:

1) Recognized benefits: AI recruitment demonstrates the potential for cost savings of 30% in hiring costs per recruitment. Forbes notes that candidates chosen by AI have a 14% higher likelihood of success in interviews. 67% of hiring decision-makers recognize AI's benefit as time savings, and 43% believe it can mitigate human biases ("AI Recruitment Statistics," 2023). According to this study, HR and recruiters are more likely to adopt AI- based recruitment system when they perceive benefits from the system. Thus, companies need to effectively demonstrate these perceived benefits to their employees as part of AI implementation.

2) Supportive infrastructure: Organizations can support AI integration by providing resources, but infrastructure challenges hinder many Thai companies. The Cisco AI Readiness Index reveals that 62% lack readiness in preventing AI model attacks (Cisco, 2023). Facilitating conditions play a pivotal role in user's intention to adopt AI in recruitment. To promote AI-based recruitment, business leaders need to evaluate and prepare necessary infrastructure for optimal utilization.

3) Security and privacy protocol enforcement: Enforcing security and privacy protocols is vital due to the rising cybercrime threat in Thailand. In a year, 218,210 cyber threat complaints occurred, resulting in 31.5 billion baht in damage (VNA, 2023). Failure to address privacy and security concerns can harm both financial value and company reputation. Therefore, companies must enforce privacy and security policies to mitigate such risks before integrating AI into recruitment.

5.2.2 AI Developers and Providers

The findings of this study provide valuable insights that these technology providers can leverage to align their products with the identified factors, enabling them to better cater to the needs and expectations of their target users.

1) Privacy and security risk mitigation: Since June 2022, Thailand's Personal Data Protection Act has been effective, but cybersecurity threat persists. A report in August 2023 revealed that Thai organizations face cyber-attacks, averaging 2,388 attacks per week (Leesa-nguansuk, 2023). This underscores a lack of robust cybersecurity among Thai companies. For AI developers, establishing a strong cybersecurity is crucial to foster user's trust and prevent exposure of candidate and company data to cybercriminals.

2) User-friendly expectations: The study emphasizes the importance of user-friendliness in AI-based recruitment. An intuitive interface enhances adoption by boosting productivity and ensuring positive user experiences. A user-friendly system encourages acceptance. Prioritizing user-friendliness not only streamlines recruitment but also contributes to the integration of AI in recruitment.

3) The impact of social influence on the perceived value: The study highlights the impact of social influence on the perceived value of AI in recruitment, influencing AI software company's product success and marketing strategy. Positive social influence enhances the perceived value, fostering credibility in the market. Strengthening social influence can create positive feedback that benefits the product's reputation and marketing efforts.

5.2.3 HR and Recruiting Professionals

HR professionals and recruiters derive significant benefits from the perceived autonomy and values provided by AI-based recruitment software.

1) Perceived autonomy: AI enhances efficiency by automating tasks, allowing users to focus on strategic works and improving decision-making. AI is meant to assist, not replace human recruiters. AI is advantageous for managing larger candidate pools in growing organizations. The study suggests HR professionals are more inclined to adopt AI when they feel a sense of autonomy over the system.

2) Recognized values: AI in recruitment adds significant value to HR and recruiters by streamlining the hiring process through advanced algorithms. These efficiently analyze resumes, identify top candidates, and predict success based on historical data, resulting in cost savings per hire. This can reduce human error and accelerates the hiring process. The study highlights HR professionals and recruiters' intent to adopt AI when recognizing these benefits.

5.3 Limitations and Recommendations

The study, while providing valuable insights, is not exempt from its limitations. One noteworthy constraint is that only 30% of the surveyed individuals had hands-on experience with AI-based recruitment software, and in general the majority of HR and recruiting professionals do not possess extensive expertise in the domain of AI or sophisticated IT. Future research studies should aim to bridge this gap by either offering education in the application of AI specifically in recruitment or by involving individuals with practical experience and expertise in utilizing such technology. These will shed light on the motivations and impediments that influence professionals when transitioning to AI-based recruitment tools. Furthermore, it is important to recognize that UTAUT has its own set of limitations, like other theories. UTAUT was initially designed to explain the adoption of general information technology, which may not effectively address the distinct characteristics and challenges specific to AI. To address this, future studies should be conducted after AI implementation in a variety of organizational settings. This approach will allow researchers to identify more specific factors related to AI's distinct use cases, leading to the development of a more practical and tailored conceptual model.

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APPENDICES

APPENDIX A

ONLINE QUESTIONNAIRES (ENGLISH VERSION)

A STUDY OF FACTORS INFLUENCING EMPLOYEES' ACCEPTANCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN RECRUITMENT

This questionnaire is a part of an independent research study in the Master of Business Administration program, specializing in Business Innovation, at Thammasat University. The research aims to study factors influencing the acceptance of AI technology in human resource recruitment.

The questionnaire is divided into four parts:

Part 1: General questions

Part 1.1: Screening question to identify HR/recruiting role

Part 1.2: General information of the questionnaire respondents.

Part 2: Questions based on variables affecting technology adoption to use AI in recruitment

Part 3: Opinions regarding advantages and limitations of implementing AI in recruitment process

Part 4: Suggestion.

Please note that the information obtained from this questionnaire will be kept confidential and used solely for the purpose of this research. Participants are kindly requested to provide truthful responses. The researcher sincerely appreciates the time and effort contributed by all participants in completing this questionnaire.

The researcher is more than willing to address any questions and welcomes feedback.

You can contact the researcher at piriyapong.won@dome.tu.ac.th

Part 1: General questions

Part 1.1: Screening question to identify HR/recruiting role

1. Currently, are you working in human resources professional or recruiter role?

☐ Yes

☐ No

2. Where is your workplace located?

☐ Bangkok and metropolitan areas

☐ Others

Part 1.2: General information of the questionnaire respondents

1. What is your gender?

☐ Male

☐ Female

2. How old are you??

☐ Lower than 25

☐ 25-34

☐ 35-44

☐ 45-54

☐ 54 up

3. What is your academic background?

☐ Diploma

☐ Bachelor’s Degree

☐ Master’s Degree

☐ Doctoral Degree

4. What is your current position?

☐ Officer/ Staff

☐ Supervisor / Team Leader

☐ Manager / Department Head

☐ Director/ Executive

5. How many years of work experience do you have?

☐ 0-3 years

☐ 3-5 years

☐ 5-10 years

☐ 10-15 years

☐ 15 years or more

6. What is the business type of your organization??

☐ Agro & Food Industry

☐ Information Technology

☐ Manufacturers

☐ Medical and Healthcare

☐ Financials

☐ Consultancy

☐ Services

☐ Energy and Utilities

☐ Consumer Products

☐ Others

7. How many employees does your organization have (Organization size)?

☐ Less than 25

☐ 26-50

☐ 51-200

☐ 201-500

☐ More than 500

8. Are you familiar with or have you ever heard of AI-based recruitment software?

☐ Yes

☐ No

9. Have you ever used AI-based recruitment software, such as Automated resume parsing, communication with applicants through Chatbot, automated applicant scheduling, or AI-based candidate scoring?

☐ Yes

☐ No

Part 2: Questions based on variables affecting technology adoption to use AI in recruitment

Please assess your level of agreement with the provided statements using a scale of 1 to 5, where 1 represents 'Strongly Disagree' and 5 represents 'Strongly Agree.

5 = Strongly Agree

4 = Agree

3 = Neutral

2 = Disagree

1 = Strongly Disagree

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Performance Expectancy					
PE1: I think AI is useful in recruitment					
PE2: I think that AI will make recruitment process faster					

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
PE3: I think AI can increase efficiency of recruitment work					
PE4: I think using AI can help analyze candidates more accurately					
Effort Expectancy					
EE1: I would find the AI based recruitment software easy to use					
EE2: I think it would be easy to learn how to use the interface of AI based recruitment software					
EE3: For me, it will not take long to be skillful in using AI in recruitment					
EE4: I think AI in recruitment would be flexible for use.					
Social Influence					
SI1: My decision to use AI in recruitment would be based on proportion of coworkers who use the software or system					

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
SI2: Those who use AI in recruitment would have more advantages than those who do not					
SI3: With the rapid technology trend, AI integrated in recruitment is necessary for my company					
SI4: I think the introduction of AI in recruitment into our company will be trendy in my industry					
Facilitating Conditions					
FC1: I expect to call a technical support team in case of facing any problems					
FC2: I expect that the system would be available in both computer and mobile devices					

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
FC3: I think guidance would be available in AI based recruitment system					
Privacy and Security					
PS1: I expect that AI based recruitment software will be safe and secure					
PS2: I expect AI based recruitment software will strictly comply data privacy policy regarding Personal Data Protection Act					
PS3: I feel safe and protected by the use of encryption					
PS4: I think AI software developer will protect and ensure safety of user’s personal data.					
Trust in AI Technology					
TA1: I trust that AI algorithm is reliable in screening candidates to match organization's requirement					

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
TA2: I trust that AI based recruitment software has reliable database to complete recruitment					
TA3: I think there will be a government organization to ensure AI based recruitment software is secured					
TA4: I trust that AI software developer is honest and will not take advantage over user's information					
Perceived Value					
PV1: I think that using AI in recruitment is worth investing					
PV2: I feel that using AI can remain quality of recruitment process consistently.					
PV3: I realize that using AI in recruitment will give the organization the social approve					

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
PV4: I feel that using AI in recruitment will make impression on candidates					
Perceived Autonomy					
PA1: Using AI in recruitment will allow recruiters/ HR officers to have more freedom to develop preferred skills and tasks					
PA2: Using AI will give recruiters/ HR officers the opportunity to better coordinate with candidates					
PA3: Utilizing AI will provide recruiters and HR officers with more flexibility to manage other essential responsibilities more effectively					
PA4: I think AI in recruitment will reduce the number of decisions to get the optimal results					

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Intention to Use					
IU1: Using AI based recruitment software is a good and modern idea					
IU2: I like the idea of using AI in recruitment					
IU3: The AI based recruitment software makes me more interested					
IU4: I have a high wiliness to use AI in recruitment					

Part 3: Opinions regarding advantages and limitations of implementing AI in recruitment process

1. In your opinion, in which stages do you think AI can be most effectively applied in the recruitment process (Multiple answers are acceptable)?

    ☐ Job post/ advertisement

    ☐ Candidate sourcing

    ☐ Resume screening

    ☐ Scheduling for interview

    ☐ Evaluation and selection

    ☐ Others [...]

2. What do you think are the limitations of AI-powered recruitment software? (Multiple answers are acceptable)?

☐ Lack of interaction with applicants

☐ Reliability in data processing

☐ Inability to assess applicants' problem-solving skills

☐ Inability to assess personality or soft skills of applicants

☐ A possibility of overlooking resumes with potential if they are not directly related to the qualifications the organization is seeking

☐ Others [..]

3. Do you think that AI-powered recruitment software can replace human recruiters??

☐ Yes

☐ No

Part 4: Suggestion

Please specify any other suggestions or comments you may have (if any).

[..]

APPENDIX B
ONLINE QUESTIONNAIRES (THAI VERSION)

ปัจจัยที่ส่งผลต่อการยอมรับเทคโนโลยีของผู้ใช้งานต่อการนำปัญญาประดิษฐ์หรือ AI มาใช้ในงานสรรหาบุคลากร: ในบริบทของประเทศไทย

แบบสอบถามนี้เป็นส่วนหนึ่งของงานวิจัยค้นคว้าอิสระในหลักสูตรบริหารธุรกิจมหาบัณฑิต สาขาวิชานวัตกรรมทางธุรกิจ มหาวิทยาลัยธรรมศาสตร์ โดยมีวัตถุประสงค์ของการทำวิจัย เพื่อศึกษาปัจจัยที่ส่งผลต่อการยอมรับเทคโนโลยี AI ในงานสรรหาบุคลากร

โดยแบบสอบถามแบ่งออกเป็น 4 ส่วนเป็นดังนี้.

ส่วนที่ 1: คำถามทั่วไป

ส่วนที่ 1.1: คำถามคัดกรองเพื่อระบุบทบาทด้านการจัดหางาน/สรรหาบุคลากร

ส่วนที่ 1.2: ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม.

ส่วนที่ 2: คำถามเกี่ยวกับตัวแปรที่มีผลต่อการนำเทคโนโลยีในการใช้ AI ในกระบวนการสรรหา

ส่วนที่ 3: ความคิดเห็นเกี่ยวกับข้อได้เปรียบและข้อจำกัดของการใช้ AI ในกระบวนการสรรหา

ส่วนที่ 4: ข้อเสนอแนะ.

ทั้งนี้ข้อมูลที่ได้รับจากแบบสอบถามนี้จะถูกเก็บเป็นความลับเพื่อใช้ในการวิจัยครั้งนี้เท่านั้น ผู้วิจัยจึงขอความกรุณาผู้ตอบแบบสอบถามตามความเป็นจริง และขอขอบพระคุณผู้ตอบแบบสอบถามทุกท่านที่เสียสละเวลาในการตอบแบบสอบถามมา ณ โอกาสนี้ผู้วิจัยยินดีเป็นอย่างยิ่งที่จะตอบคำถามข้อสงสัยและรับฟังข้อเสนอแนะโดยสามารถติดต่อผู้วิจัยได้ที่ piriyapong.won@dome.tu.ac.th

ส่วนที่ 1: คำถามทั่วไป

ส่วนที่ 1.1: คำถามคัดกรองเพื่อระบุบทบาทด้านการจัดหางาน/สรรหาบุคลากร

1 ปัจจุบันท่านทำงานเกี่ยวกับทรัพยากรบุคคลหรือการสรรหาบุคลากรหรือไม่

☐ ใช่

☐ ไม่ใช่

2 บริษัทหรือองค์กรท่านตั้งอยู่ที่

☐ กรุงเทพและปริมณฑล

☐ ที่อื่น

ส่วนที่ 1.2: ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม

1 เพศ

☐ หญิง

☐ ชาย

2 อายุ

☐ ต่ำกว่า 25 ปี

☐ 25-34 ปี

☐ 35-44 ปี

☐ 45-54 ปี

☐ 54 ปีขึ้นไป

3 ระดับการศึกษาของท่าน

☐ อนุปริญญา

☐ ปริญญาตรี

☐ ปริญญาโท

☐ ปริญญาเอก

4 ระดับตำแหน่งงานของท่าน

☐ เจ้าหน้าที่

☐ หัวหน้างาน

☐ ผู้จัดการ

☐ ผู้บริหารระดับสูง

5 ประสบการณ์ในการทำงาน

☐ 0-3 ปี

☐ 3-5 ปี

☐ 5-10 ปี

☐ 10-15 ปี

☐ 15 ปีขึ้นไป

6 ประเภทธุรกิจขององค์กรท่าน

☐ กลุ่มเกษตรและอุตสาหกรรมอาหาร

☐ กลุ่มสินค้าอุปโภคบริโภค

☐ กลุ่มธุรกิจการเงิน

☐ กลุ่มเทคโนโลยีสารสนเทศ

☐ กลุ่มโรงงานอุตสาหกรรม

☐ กลุ่มพลังงานและสาธารณูปโภค

☐ กลุ่มธุรกิจที่ปรึกษา

☐ กลุ่มการแพทย์และสุขภาพ

☐ กลุ่มธุรกิจบริการ

☐ อื่นๆ

7 จำนวนพนักงานในองค์กรท่าน

☐ น้อยกว่าหรือเท่ากับ 25 คน

☐ 26-50 คน

☐ 51-200 คน

☐ 201-500 คน

☐ มากกว่า 500

8 ท่านรู้จักหรือเคยได้ยินซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI หรือไม่

☐ รู้จัก/ เคยได้ยิน

☐ ไม่รู้จัก/ ไม่เคยได้ยิน

9 ท่านเคยใช้ซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI หรือไม่ เช่น การวิเคราะห์ resume ด้วย AI (Resume parsing), การสื่อสารกับผู้สมัครด้วย Chatbot, การนัดหมายผู้สมัครอัติโนมัติ (Auto scheduling) หรือการ ให้คะแนนผู้สมัครด้วย AI (Candidate best-fit scoring)

☐ เคย

☐ ไม่เคย

ส่วนที่ 2: คำถามเกี่ยวกับตัวแปรที่มีผลต่อการนำเทคโนโลยีในการใช้ AI ในกระบวนการสรรหา

คำชี้แจง โปรดเลือกระดับคะแนนที่ตรงกับความเห็นของท่านมากที่สุด โดยมีเกณฑ์การพิจารณา ดังนี้

5 คะแนน หมายถึง เห็นด้วยอย่างยิ่ง

4 คะแนน หมายถึง เห็นด้วย

3 คะแนน หมายถึง เฉยๆ

2 คะแนน หมายถึง ไม่เห็นด้วย

1 คะแนน หมายถึง ไม่เห็นด้วยอย่างยิ่ง

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
ความคาดหวังในประสิทธิภาพ					
1. ท่านเห็นว่า AI เป็นประโยชน์ต่องานสรรหาบุคลากร					
2. ท่านเห็นว่า AI จะทำให้การสรรหาบุคลากรได้รวดเร็วกว่าเดิม					

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
3. ท่านคิดว่า AI จะช่วยเพิ่มประสิทธิภาพในการสรรหาบุคลากร					
4. ท่านคิดว่า AI จะช่วยในการวิเคราะห์ผู้สมัครงานให้มีความถูกต้องแม่นยำมากขึ้น					
ความคาดหวังในการพยายามใช้เทคโนโลยี					
1. ท่านคิดว่าซอฟต์แวร์สรรหาพนักงานด้วยระบบ AI ใช้งานง่าย (เช่น ง่ายสำหรับผู้สมัครงานในการกรอกข้อมูล หรือติดตามสถานะ, ง่ายสำหรับพนักงานสรรหาในการ Sourcing/ Screening เป็นต้น)					
2. ท่านคาดหวังว่าระบบ Interface เชื่อมต่อระหว่างท่านกับซอฟต์แวร์สรรหาพนักงานด้วยระบบ AI สามารถเรียนรู้ได้ง่าย					
3. ท่านคิดว่าท่านสามารถเรียนรู้การใช้ซอฟต์แวร์สรรหาพนักงานด้วยระบบ AI ได้อย่างชำนาญในเวลาไม่นาน					
4. ท่านคิดว่าระบบ AI ยืดหยุ่นต่อการใช้งานในการสรรหาบุคลากร					

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
อิทธิพลทางสังคม					
1. ท่านเห็นว่าจำนวนเพื่อนร่วมงานและคนรู้จักที่ใช้ซอฟต์แวร์สรรหาพนักงานด้วยระบบ AI มีผลต่อการตัดสินใจของท่านในการใช้งานซอฟต์แวร์					
2. ท่านคิดว่าผู้คนที่ใช้ระบบ AI ในการสรรหาบุคลากรจะทำให้พวกเขามีข้อได้เปรียบมากกว่าคนที่ไม่ได้ใช้งาน					
3. ด้วยเทคโนโลยีที่เติบโตแบบก้าวกระโดด ระบบ AI จึงจำเป็นต่อเทคโนโลยีการสรรหาบุคลากร					
4. ท่านคิดว่าระบบ AI ในการสรรหาบุคลากรเป็นเรื่องที่กำลังพูดถึงอย่างมากในกลุ่มธุรกิจที่ท่านทำงานอยู่					
สภาพแวดล้อมที่สนับสนุนการใช้งาน					
1. หากท่านได้ใช้งาน AI ในการสรรหาบุคลากรท่านคาดหวังว่าท่านจะต้องโทรหรือติดต่อทีมงาน customer service ช่วยเหลือด้านการใช้โปรแกรมได้ทันท่วงที					

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
2. ท่านคาดหวังว่าซอฟต์แวร์สรรหาพนักงานด้วยระบบ AI ใช้งานได้กับทั้งคอมพิวเตอร์ส่วนบุคคลและมือถือ					
3. ท่านคาดหวังว่าในซอฟแวร์สรรหาบุคลากรด้วยระบบ AI จะมีฟังก์ชันข้อแนะนำการใช้งาน					
ความเป็นส่วนตัวและความปลอดภัยในการใช้เทคโนโลยี					
1. ท่านคาดหวังว่าซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI มีการป้องกันความปลอดภัยของข้อมูล					
2. ท่านคาดหวังว่าซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI ได้ดำเนินตามนโยบายปกป้องข้อมูลส่วนบุคคล (PDPA) อย่างเคร่งครัด					
3. ท่านจะรู้สึกปลอดภัยในการใช้งาน เมื่อระบบซอฟต์แวร์สรรหาบุคลากรด้วย AI มีการให้เข้ารหัสส่วนตัวเพื่อใช้งาน					
4. ท่านคาดหวังว่าบริษัทที่พัฒนาซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI จะปกป้องข้อมูลผู้ใช้งานได้อย่างปลอดภัย					

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
ความไว้วางใจในเทคโนโลยี AI					
1. ท่านคิดว่าอัลกอรีทึมของ AI เชื่อถือได้ในการคัดกรองบุคลากรตามที่องค์กรต้องการ					
2. ท่านเชื่อว่าฐานข้อมูลของซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI เชื่อถือได้					
3. ท่านเชื่อว่าจะมีหน่วยงานรัฐที่มีอำนาจควบคุมองค์กรและบริษัทที่ให้บริการระบบ AI อย่างปลอดภัย					
4. ท่านเชื่อว่าระบบ AI จะไม่นำข้อมูลของผู้สมัครไปใช้เพื่อหาประโยชน์ด้านอื่น					
คุณค่าที่รับรู้					
1. ท่านเห็นว่าการใช้ AI ในการสรรหาบุคลากรจะทำให้เกิดความคุ้มค่าในการลงทุน					
2. ท่านเห็นว่าการนำ AI มาใช้จะสามารถรักษาระดับคุณภาพในงานสรรหาบุคลากรได้อย่างต่อเนื่อง					
3. ท่านรู้สึกว่าการใช้ AI ในการสรรหาบุคลากรจะเป็นการสร้างภาพลักษณ์ที่ดีในสังคมให้กับองค์กรมากขึ้น					

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
4. ท่านเห็นว่าการใช้ AI ในการสรรหาบุคลากรจะทำให้เกิดความประทับใจต่อผู้สมัครงาน					
การรับรู้ถึงการมีอิสระ					
1. การใช้ AI ในงานสรรหาบุคลากรจะทำให้พนักงานสรรหาหรือพนักงานฝ่ายบุคลลมีเวลาในการพัฒนาทักษะด้านอื่นๆ ได้					
2. ท่านเห็นว่าการใช้ AI ในงานสรรหาบุคลากรจะทำให้พนักงานสรรหาหรือพนักงานฝ่ายบุคลได้มีโอกาสปฏิสัมพันธ์กับผู้สมัครงานหรือพนักงานได้มากขึ้น					
3. ท่านเห็นว่าการใช้ AI ในงานสรรหาบุคลากรจะทำให้พนักงานสรรหาหรือพนักงานฝ่ายบุคลลมีเวลาไปทำกิจกรรมอื่นๆ ที่เป็นประโยชน์ต่อองค์กรได้					
4. ท่านเห็นว่าการใช้ AI ในงานสรรหาบุคลากรจะทำให้ลดจำนวนงานที่ต้องตัดสินใจได้					

คำถาม	ไม่เห็นด้วยอย่างยิ่ง (1)	ไม่เห็นด้วย (2)	เฉยๆ (3)	เห็นด้วย (4)	เห็นด้วยอย่างยิ่ง (5)
ความตั้งใจที่จะใช้ซอฟแวร์สรรหาบุคลากรด้วยระบบปัญญาประดิษฐ์					
1. การใช้ AI ในการสรรหาบุคลากรเป็นแนวคิดที่ดี และทันสมัย					
2. ท่านชอบไอเดียในการใช้งาน AI ในการสรรหาบุคลากร					
3. ท่านเริ่มมีความสนใจการใช้ AI กับการสรรหาบุคลากรมากขึ้น					
4. ท่านมีความมุ่งมั่นสูงในการที่จะใช้ AI ในการสรรหาบุคลากร					

ส่วนที่ 3: ความคิดเห็นเกี่ยวกับข้อได้เปรียบและข้อจำกัดของการใช้ AI ในกระบวนการสรรหา

1. ท่านคิดว่า AI สามารถนำไปประยุกต์กระบวนการสรรหาบุคลากรขั้นตอนไหนได้อย่างมีประสิทธิภาพมากที่สุด (ตอบได้มากกว่า 1 ข้อ)

☐ ประกาศหาตำแหน่งงาน

☐ ค้นหาผู้สมัคร

☐ คัดกรอง Resume

☐ นัดตารางสัมภาษณ์

☐ ประเมินและคัดเลือกผู้สมัคร

☐ อื่นๆ

2. ท่านคิดว่าอะไรคือข้อจำกัดของซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI (ตอบได้มากกว่า 1 ข้อ)

☐ ขาดปฏิสัมพันธ์กับผู้สมัคร

☐ ความน่าเชื่อถือในการประมวลผล

☐ ไม่สามารถประเมินทักษะในการแก้ปัญหา (Problem solving skill) ของผู้สมัครได้

☐ ไม่สามารถประเมินบุคลิกภาพหรือ soft skill ของผู้สมัครได้

☐ มีโอกาสที่จะละเลย resume ของผู้สมัครที่มีศักยภาพได้หาก resume ไม่สัมพันธ์กับคุณสมบัติที่องค์กรต้องการ

3. ท่านคิดว่าซอฟต์แวร์สรรหาบุคลากรด้วยระบบ AI สามารถทดแทนพนักงานสรรหาได้หรือไม่

☐ ได้

☐ ไม่ได้

ส่วนที่ 4: ข้อเสนอแนะ

กรุณาระบุข้อเสนอแนะหรือข้อคิดเห็นอื่นๆ (ถ้ามี)

[...]

APPENDIX C
IOC: INDEX OF ITEM-OBJECTIVE CONGRUENCE

The survey questions underwent content validity verification by three HR and recruitment experts using the Index of Item Objective Congruence (IOC). The result reveals that IOC score of all items exceeds 0.50, thus confirming content validity as illustrated by the following result:

Construct	Measurement item	Experts' Opinions			IOC
		Expert 1	Expert 2	Expert 3	
Performance Expectancy	PE1: I think AI is useful in recruitment	1	1	1	1
	PE2: I think that AI will make recruitment process faster	1	1	1	1
	PE3: I think AI can increase efficiency of recruitment work	1	1	1	1
	PE4: I think using AI can help analyze candidates more accurately	1	1	1	1
Effort Expectancy	EE1: I would find the AI based recruitment software easy to use	1	1	1	1
	EE2: I think it would be easy to learn how to use the interface of AI based recruitment software	1	1	0	0.67
	EE3: For me, it will not take long to be skillful in using AI in recruitment	1	1	0	0.67
	EE4: I think AI in recruitment would be flexible for use.	1	1	1	1

Construct	Measurement item	Experts' Opinions			IOC
		Expert 1	Expert 2	Expert 3	
Social Influence	SI1: My decision to use AI in recruitment would be based on proportion of coworkers who use the software or system	1	0	1	0.67
	SI2: Those who use AI in recruitment would have more advantages than those who do not	1	1	1	1
	SI3: With the rapid technology trend, AI integrated in recruitment is necessary for my company	1	1	1	1
	SI4: I think the introduction of AI in recruitment into our company will be trendy in my industry	1	1	1	1
Facilitating Conditions	FC1: I expect to call a technical support team in case of facing any problems	1	1	1	1
	FC2: I expect that the system would be available in both computer and mobile devices	1	1	1	1
	FC3: I think guidance would be available in AI based recruitment system	1	1	1	1
Privacy and Security	PS1: I expect that AI based recruitment software will be safe and secure	1	1	1	1

Construct	Measurement item	Experts' Opinions			IOC
		Expert 1	Expert 2	Expert 3	
	PS2: I expect AI based recruitment software will strictly comply data privacy policy regarding Personal Data Protection Act	1	1	1	1
	PS3: I feel safe and protected by the use of encryption	1	1	1	1
	PS4: I think AI software developer will protect and ensure safety of user’s personal data.	0	1	1	0.67
Trust in AI Technology	TA1: I trust that AI algorithm is reliable in screening candidates to match organization's requirement	1	1	1	1
	TA2: I trust that AI based recruitment software has reliable database to complete recruitment	1	1	1	1
	TA3: I think there will be a government organization to ensure AI based recruitment software is secured	1	1	1	1
	TA4: I trust that AI software developer is honest and will not take advantage over user's information	1	1	1	1

Construct	Measurement item	Experts' Opinions			IOC
		Expert 1	Expert 2	Expert 3	
Perceived Value	PV1: I think that using AI in recruitment is worth investing	1	1	1	1
	PV2: I feel that using AI can remain quality of recruitment process consistently.	1	1	1	1
	PV3: I realize that using AI in recruitment will give the organization the social approve	1	1	1	1
	PV4: I feel that using AI in recruitment will make impression on candidates	0	1	1	0.67
Perceived Autonomy	PA1: Using AI in recruitment will allow recruiters/ HR officers to have more freedom to develop preferred skills and tasks	0	1	1	0.67
	PA2: Using AI will give recruiters/ HR officers the opportunity to better coordinate with candidates	1	1	1	1
	PA3: Utilizing AI will provide recruiters and HR officers with more flexibility to manage other essential responsibilities more effectively	1	0	1	0.67
	PA4: I think AI in recruitment will reduce the number of decisions to get the optimal results	1	1	1	1

Construct	Measurement item	Experts' Opinions			IOC
		Expert 1	Expert 2	Expert 3	
Intention to Use	IU1: Using AI based recruitment software is a good and modern idea	1	1	1	1
	IU2: I like the idea of using AI in recruitment	1	1	1	1
	IU3: The AI based recruitment software makes me more interested	1	1	1	1
	IU4: I have a high wiliness to use AI in recruitment	1	1	1	1

APPENDIX D
RELIABILITY AND VALIDITY OF PILOT SURVEY

The pilot survey questions with 30 participants underwent reliability and convergent validity tests, using Cronbach's alpha, composite reliability and the Average Variance Extract (AVE). The outcome is as follows:

Factors	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
EE	0.734	0.835	0.563
FC	0.846	0.907	0.766
IU	0.961	0.972	0.896
PA	0.874	0.916	0.733
PE	0.873	0.914	0.726
PS	0.782	0.86	0.607
PV	0.898	0.929	0.768
SI	0.77	0.856	0.605
TA	0.807	0.875	0.64

According to the results above, this can be inferred that the measurement scales for PE, EE, SI, FC, PS, TA, PV, PA, and IU exhibit reliability (alpha < 0.7, composite reliability < 0.80) and convergent validity (Average Variance Extracted (AVE) > 0.5).

LIST OF PUBLICATION

1. Wongras, P. and Tanantong, T. (2023). *An Extended UTAUT Model for Analyzing Users' Acceptance Factors for Artificial Intelligence Adoption in Human Resource Recruitment: A Case Study of Thailand. Preprints.* https://doi.org/10.20944/preprints202311.1612.v1.

BIOGRAPHY

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Work Position	Senior Engineering Manager, Harmless Harvest
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