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A UTAUT-Based Framework for Analyzing Users' Intention to Adopt Artificial Intelligence in Human Resource Recruitment: A Case Study of Thailand

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Abstract: Recruitment is a fundamental aspect of Human Resource Management to drive organizational performance. Traditional recruitment processes, with manual stages, are time-consuming and inefficient. Artificial Intelligence (AI), which demonstrates its potential in various sectors such as healthcare, education, and notable cases of ChatGPT, is currently reshaping recruitment by automating tasks to improve efficiency. However, in Thailand, where there is a growing demand for talents, the application of AI in recruitment remains relatively limited. This study focuses on human resources (HR) and recruitment professionals in Thailand, aiming to understand their perspectives on the integration of AI in recruitment. It utilized the Unified Theory for Acceptance and Use of Technology (UTAUT) model, customized to suit the specific requirements of Thailand recruitment practices. The study explores the factors influencing users' intention to adopt AI in recruitment. Survey questionnaire items were created based on prior literature and refined with insights from HR and recruitment experts to ensure applicability in the context of recruitment in Thailand. A survey involving 364 HR and recruiting professionals in the Bangkok metropolitan area supplied comprehensive responses. The study reveals that several factors, including perceived value, perceived autonomy, effort expectancy, and facilitating conditions, significantly impact the intention to adopt AI for recruitment. While social influence and trust in AI technology do not have a direct influence on intention, social influence directly affects perceived value. Trust in AI technology positively influences Effort Expectancy. This study provides valuable benefits for HR and recruitment professionals, organizations, and AI developers by offering insights into AI adoption and sustainability, enhancing recruitment processes and promoting the effective use of AI tools in this sector.

Keywords: Artificial Intelligence; recruitment; technology adoption; UTAUT; talent acquisition; human resource; AI in recruitment; Thailand 4.0

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1. Introduction

Recruitment is a pivotal component of Human Resource Management (HRM) in identifying, evaluating, and selecting potential candidates to fill organizational positions, ensuring their seamless integration [1]. It significantly enhances performance, fosters employee growth, and decreases the turnover rate [2]. Traditional recruitment processes consist of multiple stages, including identifying applicants, attracting candidates, processing applications, and communicating with them. This process involves a time-consuming, location-bound, and costly process relying on face-to-face interactions and paper-based assessments [3,4]. Recruitment currently heavily relies on manual tasks like resume review, profile assessment, initial contact, prescreening interviews, and providing feedback to applicants [5]. The biggest challenge for recruiters is to find candidates who align with their company culture, which narrows down the already limited pool of potential hires [6].

The digital era has revolutionized recruitment, utilizing technologies, e.g., Artificial Intelligence (AI), to enhance management practices and decision-making [7]. Digital recruitment, or e-recruitment, utilizes websites and social media for cost-effective and efficient candidate engagement [8,9]. Online testing has gained popularity for evaluating applicants, ensuring selection based on both hard and soft skills [10]. AI has become pervasive in our lives, ranging from voice assistants like Google [11] and Alexa [12] to the integration of AI-driven conversational commerce [13]. Its presence is evident in diverse applications, including online banking [14], social network data analysis [15], or even the classification of unsuitable video content on the internet [16]. Moreover, AI's influence extends to education with ChatGPT [17], healthcare areas like resource management in a hospital [18], medical image diagnostics and virtual patient care through wearables [19,20], and the recruitment field is no exception.

AI streamlines various aspects of the hiring process, such as screening, interview scheduling, and candidate interactions, improving efficiency and the candidate experience tasks [21,22]. AI enhances the recruitment process by automating time-consuming tasks, from resume screening to candidate matching to the onboarding process [23,24]. This automation enables recruiters to concentrate more on strategic matters. A prime example is HireVue, a prominent AI platform that reduced recruitment time by 90% and boosted employment diversity by 16% through the use of voice and facial recognition, along with proprietary algorithms [25,26]. AI promotes fairness by considering all candidate traits equally and prioritizing job fitness over performance comparisons, excluding demographic information to eliminate bias [27]. It overcomes data processing issues, handles large datasets, and uses predictive algorithms to enhance decision-making [28].

The adoption of AI in recruitment in this study refers to the integration and use of Artificial Intelligence technologies in the various stages of the hiring process. These technologies encompass natural language processing (NLP), machine learning, pattern recognition, and chatbot to optimize and streamline recruitment tasks such as creating job postings (natural language processing), evaluating candidate profiles and screening applicants (machine learning and pattern recognition), and conducting preassessments (chatbot). The intention is to leverage AI-driven tools to improve the efficiency, objectivity, and effectiveness of the recruitment process.

Thailand, a newly industrialized country in Southeast Asia, aspires to transition from a developing nation to a developed one. Their goal is to raise the GDP per capita to USD 15,000 within the next two decades. To tackle economic challenges and an aging population, the current Thai Government has introduced a new national development strategy known as "Thailand 4.0" [29], a 20-year national strategy spanning from 2017 to 2036. This strategy aligns closely with the concept of Industry 4.0 and emphasizes advanced technology industries for sustainable economic growth [30], incorporating Sustainable Development Goal (SDG) 8 to sustain economic growth per capita considering the specific conditions of the country [31,32]. Thus, the demand for highly skilled professionals is increasing, leading to high competition in the job market. This drives companies to invest in technology to enhance their talent acquisition processes. Effective talent recruitment is critical for capitalizing on the opportunities presented by this digital era [30]. The potential to enhance the competitiveness of Thailand companies lies in the incorporation of AI technology into their recruitment processes. This integration also aligns with the principles of Sustainable Development Goal 9, which focuses on the significance of industry, innovation, and infrastructure in promoting sustainable economic growth and societal well-being, as well as advancing technological innovation and skill development [33].

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 resume judgments [34]. Challenges also arise in trustworthiness, data privacy, and the replacement of human recruiters [35,36]. 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 infrastructures [37].

This study is aimed at exploring the 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) [38] 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 [39]. Thus, this study is specially tailored to construct a fresh structural model by integrating UTAUT components with additional factors that are within the context of recruitment practices in Thai companies.

The study is designed to achieve these objectives: (1) gaining insights and analyzing the perspectives of HR and recruitment professionals in Thailand regarding the integration of AI technology in recruitment processes. and (2) examining professionals' viewpoints on AI in recruitment with the identification of influential factors related to AI use in recruitment.

The study's structure aligns with the intended purpose and objectives, comprising Section 2, which provides a concise literature review; Section 3, which explains the research approach and sources of data; Section 4, dedicated to presenting the empirical findings of the structural model measurement; Section 5, where the discussion and results are presented; and Section 6, which delves into the conclusion.

2. Literature Reviews

2.1. Recruitment Overview

Recruitment is a process involving a search to attract and appoint individuals to fulfill designated job roles, with the primary goal of identifying the most appropriate candidate for a specific position [40]. The recruitment process marks the initial interaction between an employee and an employer, representing the initial stage experienced by both parties. Its main objective is to match candidates with particular roles and ensure their seamless integration into the organization [1,41]. From the perspective of the employee, recruitment involves matching their skills with what the organization offers, and this alignment is highly valued by candidates during the recruitment process. To stay effective, organizations must regularly adjust their recruitment strategies by monitoring market conditions and evaluating how shifting demands affect their resource requirements [1,2,42].

Recruitment encompasses internal and external approaches. Internal recruitment focuses on talent development and is cost-effective due to its understanding of the candidate profile [43]. External recruitment addresses skills gaps by seeking candidates outside the organization, especially when internal candidates move to different roles, and emphasizes the importance of the cultural fit to reduce turnover [40,44]. The usual recruitment process includes job analysis, profile creation, scheduling, interviews, testing, shortlisting, contracts, and onboarding [45]. Traditional recruitment, as described by [4], follows a model with four primary tasks. First, it involves identifying applicants, where job requirements and descriptions are formulated to understand the needed skills and responsibilities. The second step is attracting applicants, traditionally achieved through advertising through various media to engage potential candidates. Processing incoming applicants is the third task, which includes sorting and screening applicants and communication with the hiring team. The final step is communicating with applicants, notifying them about the next steps or rejection. Similarly, according to [46], the typical recruitment steps include recruitment planning, strategic development, sourcing and attraction, screening, evaluation, and tracking. These steps involve identifying job vacancies, creating job descriptions with soft skill criteria, sourcing and screening candidates, shortlisting for interviews, and making the final selection [47]. However, conventional recruitment is commonly known as in-person and paper-based, with newspapers, manual job boards, and face-to-face interactions in specific locations being the primary methods for attracting candidates [40].

2.2. Digital Era and Artificial Intelligence in Recruitment

The digital era has brought about significant transformations in the domain of recruitment. The evolving digital technologies of the past few decades have played an increasingly prominent role for both employees and Human Resource Management (HRM) [40]. Electronic Human Resource Management involves information technology to streamline HR processes like recruitment, training, and compensation. Digital recruitment, also known as e-recruitment, uses websites and social media platforms to attract skilled job candidates and provides a cost-effective and efficient means of searching [8,9]. The use of an online assessment is on the rise for appraising candidates, guaranteeing a selection process that takes into account both technical and interpersonal skills [10]. Advantages of e-recruitment include wider exposure across local, national, and global markets; reduced advertising costs; 24/7 job postings; unlimited advertising content; and improved online communication [48]. As the competition for skilled employees intensifies, automation is crucial for expediting the recruitment process [49].

Artificial Intelligence (AI) permeates various aspects of our lives, including voice assistants like Siri and Alexa, robotics, loan and credit card processing, online banking, and social networks, offering potential improvements in efficiency and convenience well-being [14]. In recent years, as the global economy has expanded, talent recruitment has become highly competitive, prompting the widespread adoption of AI in the recruitment field [23]. This integration has notably improved candidate selection from a vast pool of candidates [50]. AI's capabilities include initial resume screening, identifying promising candidates, and matching them with suitable positions. Virtual assistants engage candidates through various communication platforms services [23]. AI ensures bias-free, precise job descriptions and automates the entire recruitment process, from creation to onboarding, reducing the need for human involvement [24].

The leading AI recruitment platforms play vital roles in different recruitment stages. In job postings, Textio employs Natural Language Processing (NLP) to refine language, reducing bias and enhancing response rates, with organizations like Atos and McDonald's utilizing its software [47]. Knockri, a Canadian company, has developed bias-free hiring software that aims to boost diversity by employing AI and NLP technology. This software incorporates video interviews, audio assessments, and written evaluations in the recruitment process. It assesses the content of these behavioral evaluations using NLP and AI algorithms. The company's algorithm assesses a candidate's qualifications solely based on their skills, ensuring there is no discrimination [33]. For sourcing candidates, Arya enhances talent searching by efficiently sourcing candidates from over 50 social platforms while fostering interactions between candidates and recruitment teams [51]. In the screening phase, Pomato uses machine learning and pattern recognition to shortlist candidates, and Textkernel and SAP's Resume Matcher to process applications and rank applicants based on job requirement teams [51,52]. For candidate preassessments, GoBe, a recruitment chatbot, manages the initial assessments, and Mya Systems streamlines the hiring process using conversational AI, benefiting organizations like L'Oréal and Deloitte [26,34]. These platforms enhance recruitment sustainability, improving efficiency and objectivity.

The intense competition for talent leads to challenges in traditional recruitment processes due to time and effort requirements. Utilizing AI can improve recruitment efficiency, as seen in companies like L'Oreal, Unilever, IKEA, and Amazon [40]. Thus, with AI implementation, recruitment processes can be significantly automated, reducing the need for human involvement. AI can now 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 [25]. AI-driven recruitment not only widens a company's scope but also deeply assesses candidate–job compatibility. Nvidia uses AI chips to analyze behavior and speech, aligning candidates with suitable roles. Companies like eBay, IBM, Intel, and Verizon employ AI-powered tools like Hiretual to evaluate candidates' availability, skills, and market value, comparing them against a vast database of over 700 million professional profiles from 30 web-based platforms [53].

2.3. The Unified Theory for Acceptance and Use of Technology (UTAUT)

The Unified Theory for Acceptance and Use of Technology (UTAUT) [38], developed by Venkatesh and colleagues in 2003, serves as the foundational structure for illustrating technology adoption within the realms of employees, employers, and managers. The UTAUT model has found extensive applications in various technology adoption studies. It predicts behavioral intention to use new technology. The UTAUT model explains why users adopt an information system and how their usage unfolds. It identifies four key factors: Performance Expectancy (confidence in the system enhancing job performance), effort expectancy (ease of use), social influence (importance placed by others), and facilitating conditions (belief in organizational support). These factors predict behavioral intention (intent to use) and Usage Behavior in adopting new technology. Gender, age, prior experience, voluntariness, and other variables are also considered in the model [38,54].

The Unified Theory for Acceptance and Use of Technology (UTAUT) model ensures 70% accuracy in analyzing behavior related to information technology usage. Additionally, it is considered a reliable model, with an average explanatory capability ranging from 40% to 50% [39].

3. Theoretical Background

The Theory of Reasoned Action (TRA), introduced by Icek Ajzen and Martin Fishbein in 1975, emphasizes that human behavior is influenced by the intention to engage in that behavior, which is shaped by one's attitude and subjective norms [55]. In 1989, the Technology Acceptance Model (TAM) was developed as a framework for understanding technology acceptance behavior. It builds upon the TRA, focusing on perceived usefulness (PU), perceived ease of use (PEOU), attitude, and intention to use [56]. Expanding on TRA, Icek Ajzen introduced the Theory of Planned Behavior (TPB) in 1991, emphasizing that actual behavior is guided by Behavioral Intention, which is influenced by attitude, subjective norms, and perceived behavioral control [57]. Thompson and colleagues introduced the Model of Personal Computer Utilization (MPCU) in 1991, modifying an existing behavior model to forecast personal computer usage based on attitudes, social norms, habits, and anticipated outcomes [58]. The Motivational Model (MM), introduced in 1992, focuses on intrinsic and extrinsic motivations as drivers of technology usage, highlighting the importance of perceived benefits and enjoyment computers [59]. The Innovation Diffusion Theory (IDT), introduced in 1995, concentrates on the spread of innovations in a social system, considering factors like the innovation–decision process, the characteristics of the innovation, and the characteristics of adopters [60]. In 1999, the Social Cognitive Theory (SCT) applied Bandura's theory to study computer self-efficacy, outcome expectations, emotions, and anxiety's impacts on computer use, highlighting the relationship between self-efficacy, emotions, and computer use [61,62].

The Unified Theory for Acceptance and Use of Technology (UTAUT) [38] integrates various technology adoption models, including the Technology Acceptance Model (TAM) [56], Theory of Reasoned Action (TRA) [55], Theory of Planned Behavior (TPB) [57], Model of PC Utilization (MPCU) [58], Motivational Model (MM) [59], Social Cognitive Theory (SCT) [61,62], and Innovation Diffusion Theory (IDT) [60]. UTAUT addresses TAM's limitations and provides insights into users' intentions to adopt technology.

3.1. Development of Influencing Factors toward the Intention to Use AI in Recruitment

The UTAUT-based model has been widely used in diverse research domains, covering the adoption of various technologies like mobile technology services [63–65], medical technology [66], corporate ERP management [67], education technology [68], IoT adoption [69], AI-driven customer relationship management systems [70], AI-powered intelligent products [71], AI in public technology services [72], and AI in HR and recruitment areas [39,73–75]. Consequently, the UTAUT was chosen as the foundational model for this study. To address the present AI adoption scenario, particularly within Thailand's expanding technology-centric economy, supplementary factors were incorporated in addition to those initially outlined in the UTAUT model. The users' intention to adopt AI integration in recruitment correlates with these following factors:

3.1.1. Performance Expectancy

Performance Expectancy signifies the users' perception of how using the particular system will impact their job performance specifically. It is closely related to the concept of perceived usefulness in the Technology Acceptance Model (TAM) [38]. In prior studies, researchers identified a noteworthy impact of performance expectancy on Behavioral Intention across various areas, including a study in e-HRM from Fortune Global 500 firms in Malaysia [76], the adoption of mobile Health Services in a developing country [63], and AI based recruitment adoption among HR staffs in Bangladesh [73]. Hence, individuals' perception of performance expectancy or how effective new technology, such as AI in talent recruitment, can be, impacts their willingness to use it. The first hypothesis was developed as follows:

Hypothesis 1 (H1). *Performance expectancy (PE) significantly influences the user's intention to use AI in recruitment (IU).*

3.1.2. Effort Expectancy

When users believe that a new system simplifies tasks and requires less effort to operate, they are more inclined to embrace it. This factor assesses how user-friendly the technology is and is associated with the notion of "perceived ease of use" in the TAM [38,58]. 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 [38,69]. 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 [77]. Likewise, research conducted among human resources personnel in the Indian IT industry revealed that a favorable perception of ease of use had a positive impact on employees' willingness to embrace AI [78,79]. 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 use AI in recruitment:

Hypothesis 2 (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 is evident that effort expectancy significantly influences performance expectancy [65,80]. Thus, the third hypothesis regarding this association can be constructed, suggesting that the impact of effort expectancy on performance expectancy is substantial:

Hypothesis 3 (H3). *Effort expectancy (EE) significantly influences performance expectancy (PE).*

3.1.3. 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 [38,81]. It has been noted that social influence holds a vital role in technology use across different areas, including mobile technology in healthcare [63], AI-based talent acquisition of job applicants [74], and adopting ERP in corporations [77]. Based on earlier research, HR and recruiting professionals can gain access to guidance, advice, and valuable information regarding AI software in recruitment, enhancing their confidence in making decisions to use the system, thereby assessing the fourth hypothesis:

Hypothesis 4 (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 [65]. Thus, the fifth hypothesis suggesting that social influence has a direct impact on privacy and security can be developed:

Hypothesis 5 (H5). *Social influence (SI) significantly influences privacy and security (PS).*

Furthermore, social influence was found to have a direct impact on perceived value [82] in prior research within the realm of mobile payment adoption. It is essential to consider that social influence significantly affects perceived value. Thus, the sixth hypothesis can be tested:

Hypothesis 6 (H6). *Social influence (SI) significantly influences perceived value (PV).*

3.1.4. Facilitating Conditions

Facilitating conditions relate to how people perceive the available resources and support for executing a specific behavior [81]. To embrace new technology, it is essential to integrate the new technology into both the organizational and technical infrastructure of the technology itself [77]. A study of ERP acceptance in an organization presented that the perception of organizational support in providing necessary infrastructure increases the likelihood of system adoption and implementation [67]. Additionally, support in facilitating conditions plays a crucial role in the adoption of new technological systems in various domains, such as chatbot acceptance for public transport [72], the implementation of e-commerce platforms by SMEs [83], and the adoption of IT tools by medical doctors [66]. Consequently, it is hypothesized that the facilitating conditions can directly influence the intention of HR and recruitment specialists to use AI in talent acquisition, thus developing the seventh hypothesis:

Hypothesis 7 (H7). *Facilitating conditions (FCs) significantly influence the user's intention to use AI in recruitment (IU).*

3.1.5. 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 their safety, which are referred to as "security concerns". This essentially recognizes the significance of safeguarding private information and classifies this as a security issue [84]. 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 [85]. Secure systems with privacy safeguards show a positive impact on technology adoption across various domains, including mobile payment [65], mobile self-checkout [80], and AI adoption in Customer Relationship Management (CRM) application [85]. In Thailand, the Personal Data Protection Act of Thailand (PDPA) aims to protect the personal information of both individuals and organizations, outlining regulations for "personal data processing" [86], and the act became fully enforceable in June 2022 [87]. To prepare for AI integration, Microsoft Thailand recommended integrating AI regulations into the PDPA, enhancing the 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 [37]. Through the information provided, the 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:

Hypothesis 8 (H8). *Privacy and security (PS) significantly influence the user's intention to use AI in recruitment (IU).*

3.1.6. 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 [88]. 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 [89,90]. 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 have released guidelines emphasizing the need to design AI systems with trustworthiness as a core principle [89]. A study on technology acceptance showed 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 [90]. Trust plays a crucial role in shaping user behavior and has been integrated into models for accepting technology to forecast future actions [91]. In a study on biometric acceptance, trust emerged as the most influential factor in predicting the intention to use an AI system [92]. Moreover, trust plays a critical role in shaping users' willingness to embrace emerging technologies, including AI-driven CRM [85], AI-integrated HR systems [75], sustainable mobile banking app acceptance [93], or transportation services powered by AI chatbots [72].

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

Hypothesis 9 (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 [65], information systems [90], and e-document authority [94]. In a study regarding the expanded Technology Acceptance Model (TAM) [89], it demonstrated that trust has a positive correlation with perceived usefulness. Consequently, it is relevant to assess these relationships, leading to the formulation of the tenth and eleventh hypotheses accordingly:

Hypothesis 10 (H10). *Trust in AI technology (TA) significantly influences effort expectancy (EE).*

Hypothesis 11 (H11). *Trust in AI technology (TA) significantly influences performance expectancy (PE).*

3.1.7. Perceived Values

The term of perceived value, initially introduced by Dodds and Monroe [95], centers around the balance between how customers perceive the 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 [96,97]. 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 its functional, social, and knowledge-related values [97]. Furthermore, additional research studies have 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 [82] and the adoption of assistance products such as smart speakers, voice assistance, and home appliances [71]. Therefore, considering the evidence presented, it is clear that the perceived value plays a pivotal role in motivating users to adopt AI-integrated recruitment software. Therefore, the twelfth hypothesis can be assessed:

Hypothesis 12 (H12). *Perceived value (PV) significantly influences the user's intention to use AI in recruitment (IU).*

3.1.8. 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 [98]. 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, thoughts, and actions that have a direct impact on the perception of intelligent personal assistants that also directly influences the use intention [99]. Similarly, from other studies, perceived autonomy has been found to have a notable influence on the adoption of the IoT [54] and the utilization of online courses [100]. Therefore, perceived autonomy positively affects the intention to use AI in the hiring process. The thirteenth hypothesis can be tested as follows:

Hypothesis 13 (H13). *Perceived autonomy (PA) significantly influences the user's intention to use AI in recruitment (IU).*

3.2. Proposed Structural Model

Based on prior research and the established hypotheses above, the structural model is developed and depicted in Figure 1.

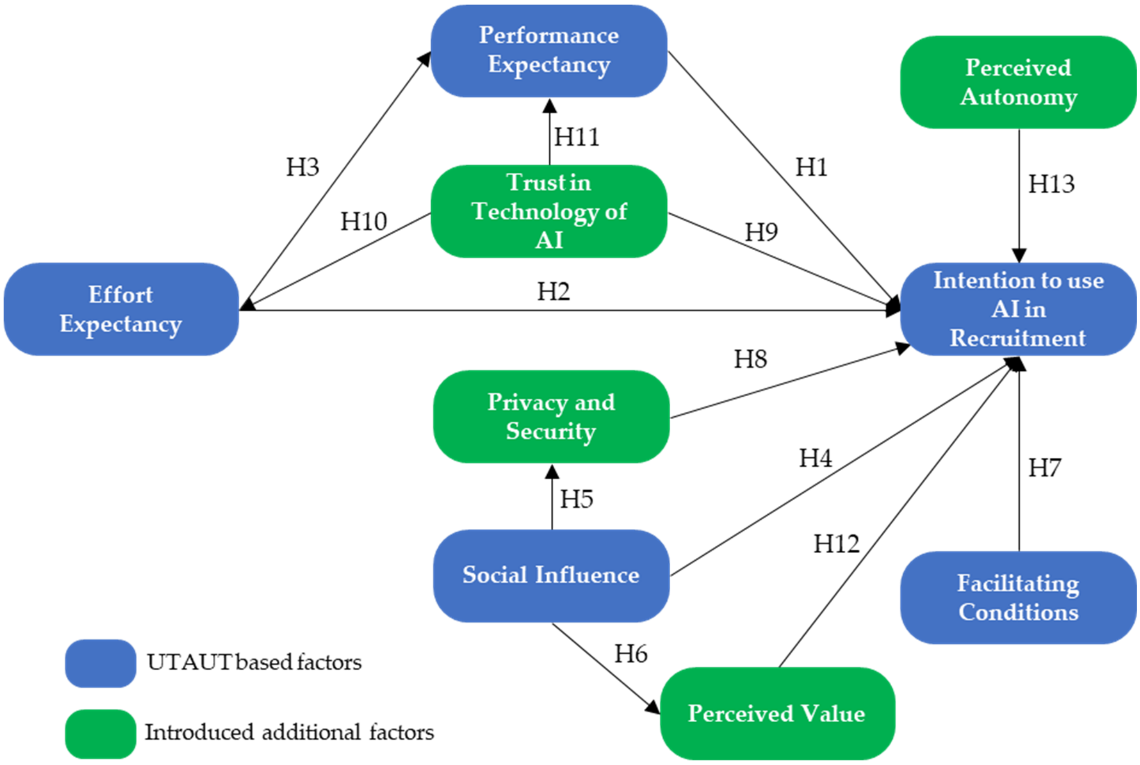

Figure 1. Proposed UTAUT-based model with additional factors of privacy and security, trust in AI technology, perceived value, and perceived autonomy.

4. Research Design and Methodology

The study utilized both quantitative and qualitative methods, as detailed in Figure 2. The study model was initially developed using information gathered from the literature review of previous research studies. Subsequently, in-depth interviews were conducted to validate the important factors in the proposed model and enhance the questionnaire framework for an upcoming survey, aiming to ensure its suitability within the context of recruitment in Thailand.

4.1. Research Design

4.1.1. Secondary Research

The information was collected from reliable sources, including e-journals, business articles, research reports, and online news. This data acquisition marked the initial phase in enhancing researchers' comprehension of AI technology's features and its application in recruitment, as well as the motivating factors and other pertinent insights.

4.1.2. In-Depth Interviews

Twenty comprehensive interviews were conducted, involving 7 jobseekers (J1–J7), 8 HR professionals (HR1–HR8), and 5 hiring managers (HM1–HM5) across different sectors, representing diverse age groups encompassing both Generation Y and Generation Z and technological experience levels. The interviews aimed to gather insights and validation for a research model that combines elements from the UTAUT with additional factors. The open-ended questions covered topics including expectations, benefits, challenges, concerns, contributing factors, and recommendations regarding AI use in recruitment. The interview findings revealed a consensus among the majority of participants, affirming the agreement of each influencing factor is represented by mark "x" in Table 1.

Table 1. Comprehensive interview outcome summary.

No.	Age	Education Level	Occupation/Position	PE	EE	SI	FC	PS	TA	PV	PA
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			
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 Director	x	x			x	x	x	
HR8	39	Master	General manager—HR	x	x	x		x	x	x	x
HM1	34	Master	Business development	x	x	x		x	x	x	
HM2	37	Bachelor	Digital 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

4.1.3. Questionnaire

The study utilizes survey questionnaire items designed from the previous literature, and inputs from interview participants were to ensure its relevance to the recruitment process within Thai companies. The questionnaire, presented in the Thai language for accessibility, was structured into three primary sections. The initial part contains general inquiries, including a screening question to identify HR/recruiting roles and additional queries aimed at collecting demographic data from respondents, such as gender, age group, occupation, academic background, professional experience, business type, and organization size. The second part consists of 35 Likert-scale questions related to the eight factors influencing AI adoption in recruitment, employing a Likert scale for multi-item measurement. Respondents expressed their opinions on these factors using a five-point Likert scale, with 5 indicating “strongly agree”, 4 representing “agree”, 3 denoting “neutral”, 2 indicating “disagree”, and 1 signifying “strongly disagree” [101]. The English version of the questionnaire is available in Appendix A.

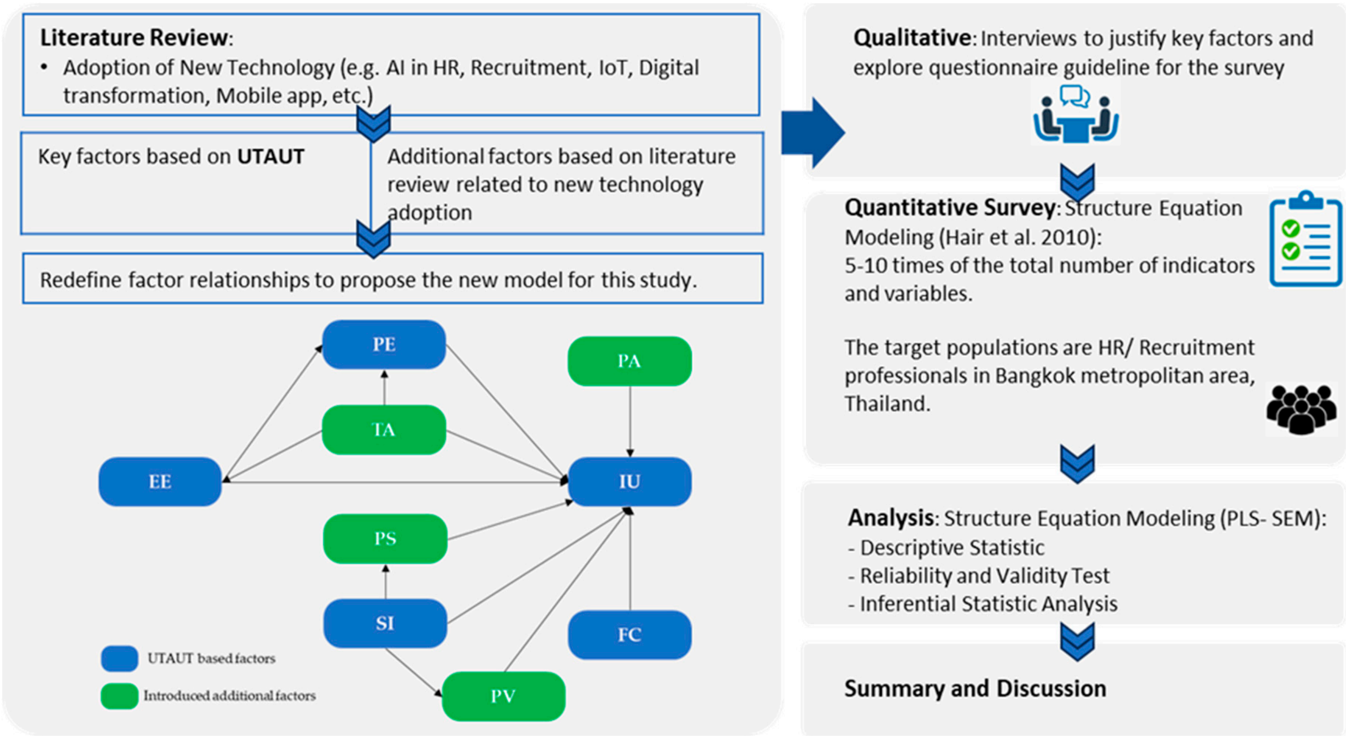

Figure 2. Outline for the study design [102].

4.2. Sampling Plan

The study focused on HR and recruiting professionals in the Bangkok metropolitan area, selected due to its importance as a prominent economic and business hub. The Bangkok metropolitan region encompasses diverse industries both nationally and internationally, making it a compelling focus for the study. Surveying HR and recruiting professionals in this area provided valuable insights across various business sectors. Sample size determination followed guidelines from Structure Equation Modeling (SEM) [102,103], suggesting a sample size ranging from 5 to 10 times the total number of indicators. It was imperative to ensure a minimum sample size of at least 100 respondents, which meant a minimum requirement of 175 respondents based on multiplying 35 indicators by 5. To enhance the study's reliability, data were collected from 364 participants as demonstrated in Table 2. The sampling method in this study was nonprobability convenience sampling [104], chosen as the preferred method given that a particular segment of the population was the focus. Additionally, the study utilized a deliberate online sampling approach, distributing the online survey questionnaire through social media channels such as LinkedIn and email.

The sample size was calculated using the method proposed by [102,103], 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. Among the 364 valid 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.

Table 2. Analysis of the demographic characteristics.

Categories	Dimensions	N	%
Gender	Male	153	42%
	Female	211	58%
Age	Younger than 25 years	25	7%
	25–34 years	165	45%
	35–44 years	121	33%
	45–54 years	45	12%
	55 years or older	8	2%
Education Level	Doctorate	4	1%
	Master's	148	41%
	Bachelor's	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%
	15 years or more	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%
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. Data Analysis

To assess the framework model and quantify the concurrent influences among its factors, the gathered data were subjected to analysis using the Structural Equation Modeling (SEM) technique, performed with SmartPLS 4 software [105]. Regression analysis was employed to examine the association between the independent and dependent variables. The incorporation of Partial Least Squares (PLS) algorithms facilitated the evaluation of the structural relationships among the model's elements and the verification of the research hypotheses.

In the specific context of conducting Structural Equation Modeling (SEM) research on AI in recruitment in Thailand with a sample size of 364 respondents, choosing Partial

Least Squares (PLS)-SEM can be justified for several reasons. PLS-SEM is particularly advantageous when dealing with smaller sample sizes, providing robust results even in non-normally distributed data, which is common in social sciences research [106].

Partial Least Squares-Structural Equation Modeling (PLS-SEM) stands as a frequently employed method in Structural Equation Modeling, and it continues to find applications in studies encompassing the adoption of diverse technologies with similar sample sizes, including AI applications [107], AI integration in accounting information [108], chatbot adoption [68,109], and the incorporation of digital technology at the corporate level [54,77,110]. Leveraging insights from the existing literature, PLS-SEM has been utilized to confirm the influence and effects of emerging technologies. Thus, given the predictive focus often associated with the practical applications of AI in recruitment, PLS-SEM's emphasis on prediction makes it a suitable choice for studies aiming to understand and predict relationships in real-world scenarios [106].

5. Results and Discussion

The results of employing PLS-SEM, a statistical method used for scrutinizing relationships between variables in research, are depicted in Figure 3. This visual presentation enhances the understanding of insights and discoveries from PLS-SEM, contributing to a more profound comprehension of the study's outcomes.

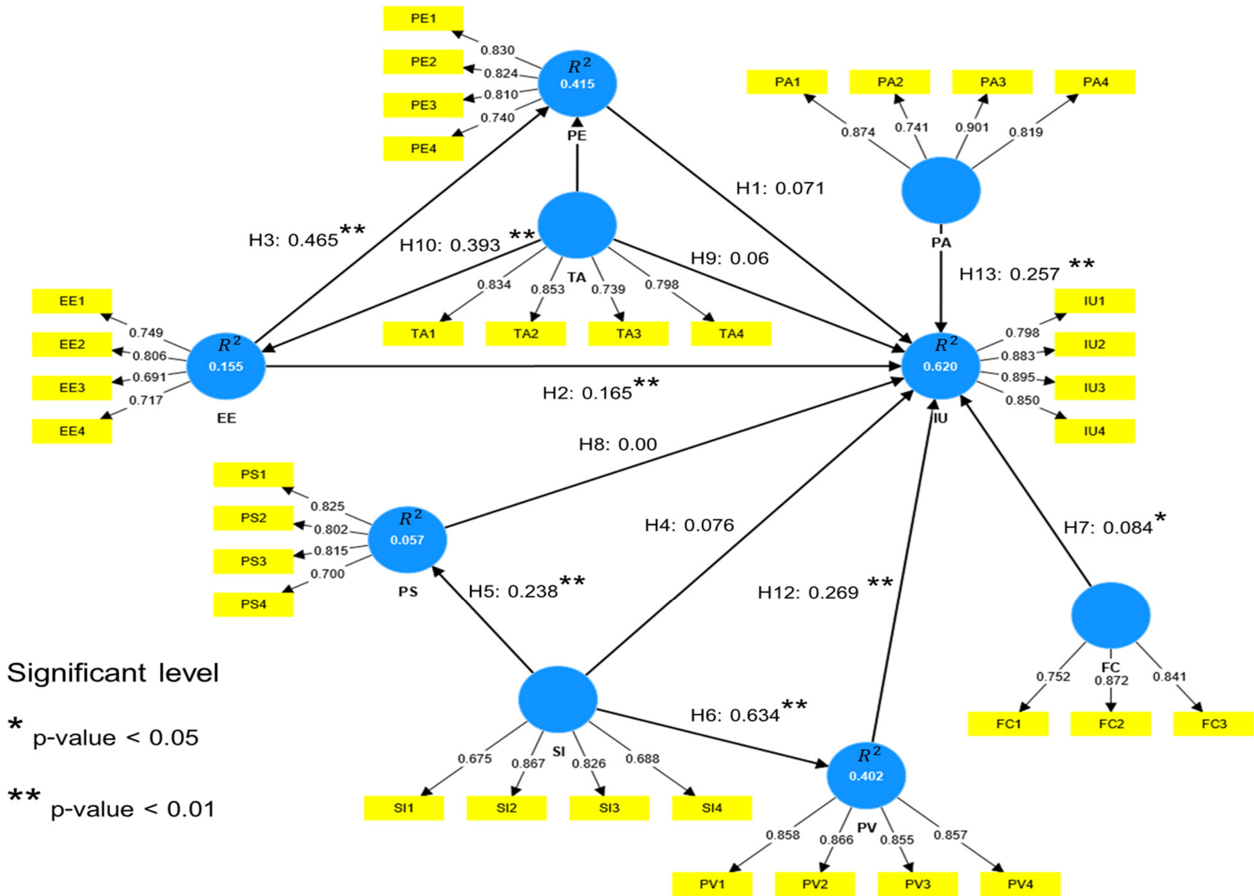

Figure 3. PLS-SEM results with the path coefficients.

5.1. Reliability and Validity

Based on the outcomes presented in Table 3, it can be inferred that the measurement 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 surpassed 0.7, indicating good reliability for the constructs validated in this study [111]. The composite reliability values of each factor are greater than 0.80, which is very high for the proposed construct [112,113]. Therefore, the suggested model meets the requirement for construct reliability. Additionally, Average Variance Extracted (AVE) remains the preferred metric for evaluating convergent validity. AVE values exceeding the recommended minimum threshold of 0.5 confirm the existence of convergent validity. As all AVE values surpassed the 0.5 threshold, it can be concluded that the structural model meets the requirements for convergent validity [114].

Table 3. Reliability and validity construction.

Factors	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
EE	0.726	0.83	0.551
FC	0.76	0.863	0.678
IU	0.879	0.917	0.735
PA	0.854	0.902	0.699
PE	0.814	0.878	0.643
PS	0.793	0.866	0.619
PV	0.881	0.918	0.738
SI	0.764	0.851	0.591
TA	0.821	0.882	0.651

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, with a range of 0.7 or higher typically considered good [111]. All factors, namely the EE (0.726), FC (0.76), IU (0.879), PA (0.854), PE (0.814), PS (0.793), PV (0.881), SI (0.764), and TA (0.821), were assessed at a good level, as all the values were above 0.7 (see Figure 4). Consequently, the suggested model meets the requirement for good reliability.

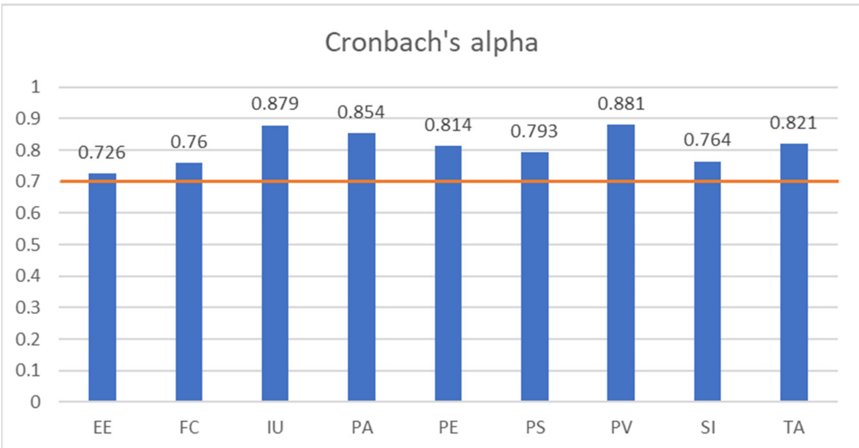

Figure 4. Cronbach's alpha for all variables, with the minimum threshold exceeding 0.7.

In the context of the construct model under consideration, the assessment of convergent validity was conducted using the composite reliability indicator (CR), with a threshold of CR > 0.8, which was very high for the proposed construct [112,113]. In the research findings, the composite reliability indicator (CR) demonstrated a range of values spanning from 0.83 to 0.918, as illustrated in Figure 5.

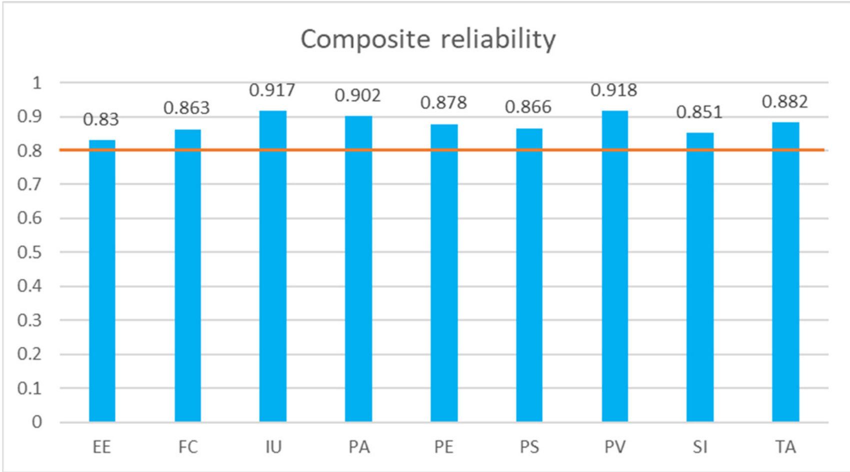

Figure 5. Composite reliability of all the variables, with the minimum threshold exceeding 0.8.

In the realm of convergent validity, it is worth noting that the Average Variance Extracted (AVE) is the recommended measure for evaluating convergent validity. When dealing with structural models, confirming the convergent validity is achieved if the AVE values for the factors surpass the recommended minimum threshold of 0.5 [114]. In the structural model, the AVE fell within the range of 0.551 to 0.738, all surpassing the 0.5 threshold (as depicted in Figure 6). Thus, the confirmation of convergent validity for the proposed construct model is affirmed.

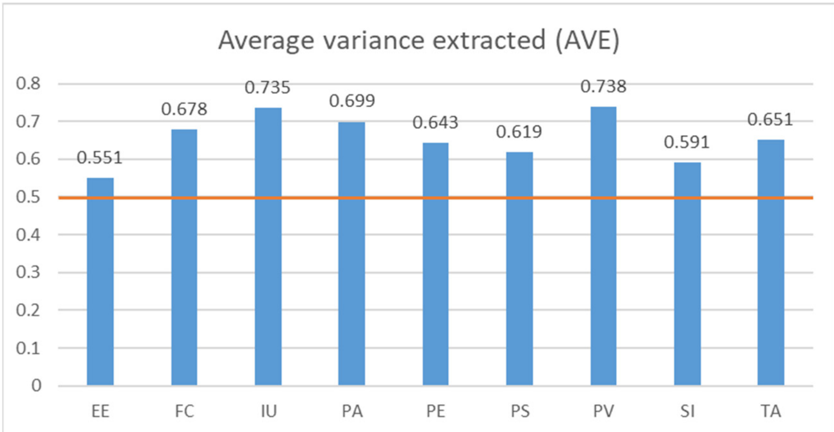

Figure 6. Average Variance Extracted of all the variables, with the minimum threshold exceeding 0.5.

5.2. Discriminant Validity Test

By examining Table 4, it is evident that, regarding Fornell and Larcker's criteria [115], the constructs demonstrated discriminant validity, as the square root of the AVE values on the diagonal for the constructs exceeded the correlations between constructs [115,116]. The square root of the AVE for IU, measuring 0.857, surpassed both the vertical (0.694, 0.626, 0.319, 0.714, 0.598, and 0.532) and horizontal (0.581 and 0.372) correlation values. As a result, the construct model fulfills the condition of discriminant validity.

Table 4. 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	0.670	0.802				
PS	0.286	0.426	0.319	0.300	0.300	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 anticipated correlation matrix is under 0.08 [117], it demonstrates the model's appropriateness. In this study, the average difference (SRMR) was 0.075, which was below 0.08, so the proposed model was both effective and pertinent.

Another approach for assessing discriminant validity is by applying the Heterotrait–Monotrait Ratio (HTMT) criterion, which implies that the variations between correlations among different constructs should not exceed 0.85 [118]. The variances between these correlations for the variables in the model were found to be below the 0.85 threshold, as described in Figure 7.

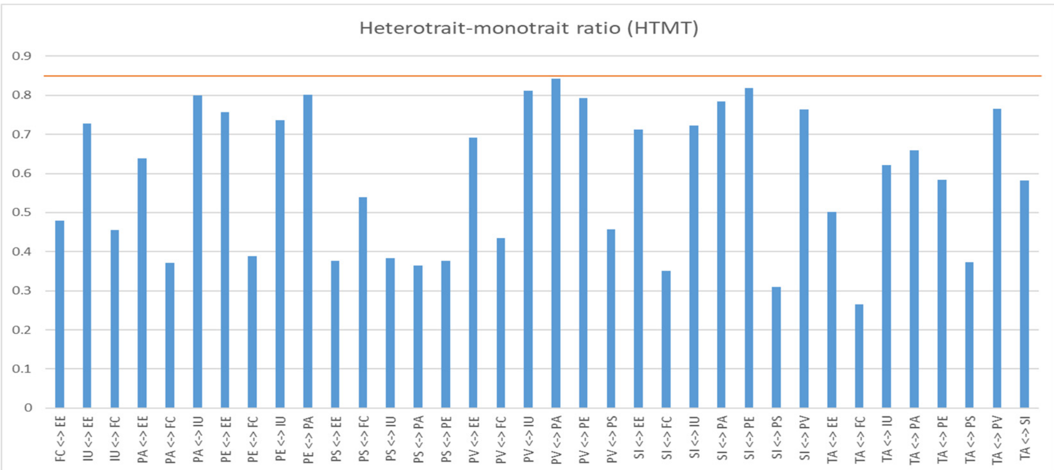

Figure 7. Heterotrait–Monotrait Ratio with a baseline below 0.85.

5.3. Multicollinearity Test

Multicollinearity is a situation where independent variables in a statistical model display strong correlations, potentially resulting in unreliable and unstable estimates in a 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 VIF surpasses 4.0. In the structural model, there was no concern about multicollinearity, as the VIF values for all 35 items were below the 4.0 threshold, as denoted in Figure 8 [112]. This indicates that the variables in the model were not excessively interrelated, rendering the data suitable for further structural analysis. In Figure 8, 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), and TA2 (2.439), which were all below 4.0.

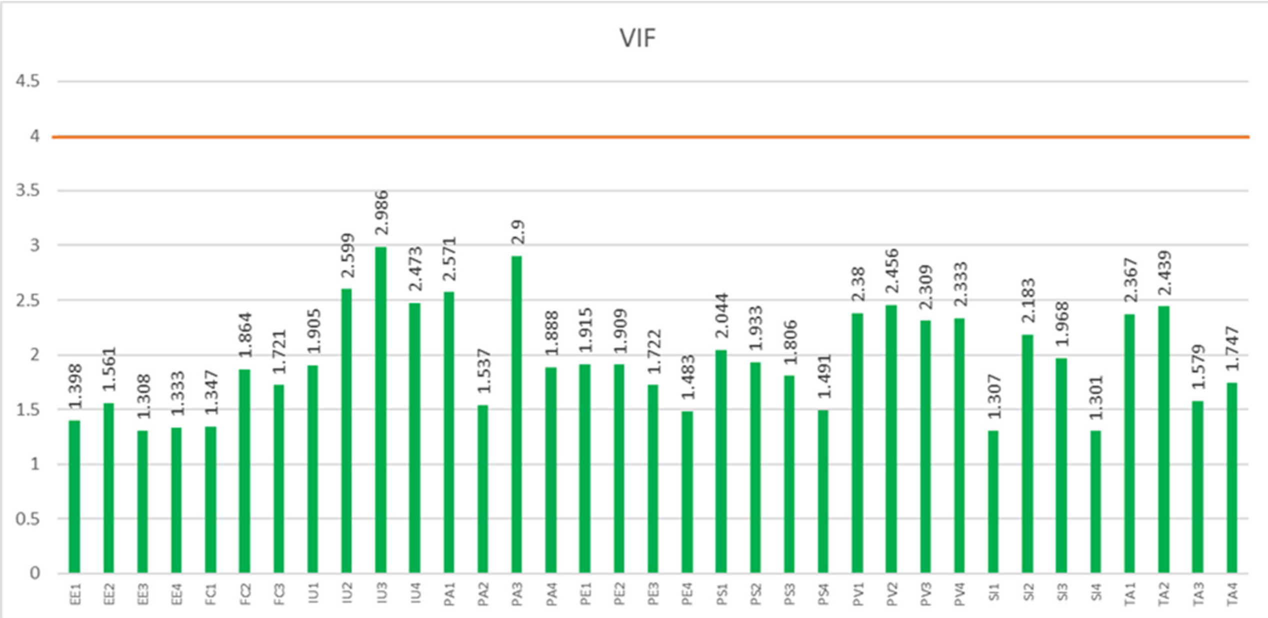

Figure 8. Variance Inflation Factor with a baseline under 4.

5.4. Structural Model Analysis

Table 5 displays the outcomes of the correlations among the construct variables, path coefficients (β), T-Statistics, and associated *p*-values. These results were obtained through the use of PLS algorithms, which enabled the evaluation of the structural relationships between model constructs and the testing of the research hypotheses. The analysis also included the Bootstrapping and Blindfolding procedures performed within SmartPLS4 with 1000 iterations.

Table 5. Summary of the path coefficients and testing results.

Hypothesis	Correlation	Path Coefficients (β)	T-Statistics	*p*-Values	Decision
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 5 presents the outcomes of the 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 the 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) as denoted in Figure 9, reveal relationships within a structural model organization. Significantly, perceived value (PV) positively affected the intention to use AI-based recruitment software with a coefficient of 0.269. Additionally, perceived autonomy (PA) directly impacted the intention to use with a coefficient of 0.257. Positive contributions to the intention to use AI in recruitment were made by the effort expectancy (EE), which had a path coefficient of 0.165, and facilitating conditions (FCs) also directly affected users' intent to accept AI-based recruitment software, with a path coefficient of 0.084.

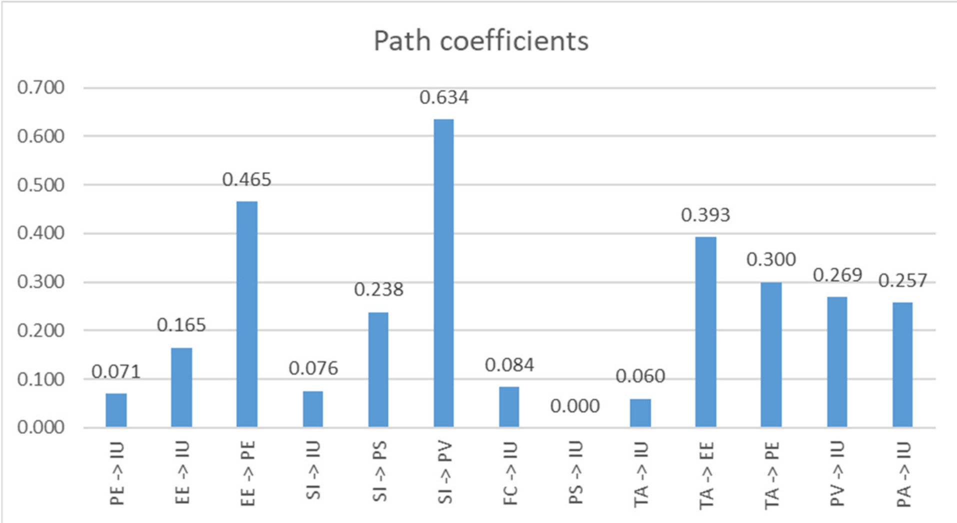

Figure 9. Path coefficients for all the variables.

In the case of the other indirect factors, social influence (SI) significantly affected the perceived value (path coefficient of 0.634), which, in turn, directly influenced the intention to use AI-based recruitment systems. Trust in AI technology (TA) had 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) did not significantly impact users' 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 users' perceptions of AI adoption. However, privacy and security (PS) did not have a direct effect on IU, as indicated by a coefficient of 0.00.

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" ($R^2 > 0.1$) [114]. As detailed in Table 6, the R-squared (R^2) value for intention to use AI-based recruitment software (IU) was impressively high at 0.620, indicating that approximately 62% of the variance was 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 technology of AI (TA) collectively contributed to around 41.5% of the variability in performance expectancy (PE). In the case of perceived value (PV), social influence (SI) alone significantly accounted for 40.2% of the variance in PV. The adjusted R-squared, being nearly identical to the R-squared, indicated that the added predictors had an insignificant contribution to the additional explanatory values [54].

Table 6. Magnitude of the 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

.

5.5. Discussion

This study delved 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, this study utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) model, creating a new conceptual framework that included eight independent variables. These variables comprised performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FCs) 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. In line with the research findings, the intention towards the adoption of AI in recruitment was positively affected by variables that demonstrated statistical significance, including:

(1) Perceived value, which has a direct impact on the intention to adopt AI in recruitment, aligns with findings from the acceptance of mobile payment solutions [82] and the adoption of assistance products such as smart speakers, voice assistance, and home appliances [71]. This means that HR and recruitment professionals are more likely to adopt AI when they perceive the benefits of AI in the recruitment process.
(2) Perceived autonomy positively affects the intention to embrace AI in the hiring process, in alignment with other technology adoption studies, including intelligent personal assistants [99], IoT adoption [54], and online course utilization [100]. Perceived autonomy directly impacts the intent to adopt AI in recruitment. This underscores the significance of granting HR and recruitment professionals the autonomy to make choices regarding AI integration.
(3) Effort expectancy positively contributes to shaping the inclination to embrace AI in recruitment, coinciding with ERP adoption in HR [77], AI acceptance among HR professionals in Indian IT industries [78,79], e-banking adoption [119], and chatbot adoption [120].
(4) Facilitating conditions also directly influence the users' intent in accepting AI-based recruitment software, which is also aligned with autonomous car adoption research [121] and a ChatGPT adoption study [122]. The facilitating conditions are essential, and this finding highlights the importance of creating a supportive environment for AI integration.
(5) For the indirect variables, it is worth highlighting the influence of social influence (SI) on perceived value (PV). This suggests that social influence has a clear and positive impact on perceived value, which, in turn, plays a direct role in shaping individuals' intention to adopt AI-based recruitment systems. This relationship is consistent with a mobile payment acceptance study [82]. Similarly, trust in AI technology (TA) was found to have a positive effect on effort expectancy (EE). This implies that individuals' trust in AI technology directly influences their expectations regarding the ease of using AI systems. This link was substantiated by a study on mobile payment adoption [65].
(6) Privacy and security may not directly impact the intention to use AI in the hiring process. However, the respondents exhibited strong expectations regarding safety and data privacy in AI-based recruitment. They were somewhat uncertain about 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 [37].

6. Conclusions

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

6.1. Theoretical Implications

This study investigates the factors impacting the inclination of HR and recruiting professionals to adopt AI in recruitment. The results unveil both new and established factors influencing AI adoption in the recruitment process.

Firstly, perceived value significantly influences the intention to embrace AI in recruitment. While previous studies stressed the importance of perceived value in adopting various technologies, such as sustainable e-learning systems [123], AI smart product acceptance [71], and technological interface and digital payment enablers [124], this study provides a new perspective within the context of AI adoption in recruitment in Thailand. Secondly, the discovery of perceived autonomy highlights its role in directly influencing users' intent to use AI-based recruitment in Thailand, aligning with insights from technology adoption studies in other areas [54] about the IoT adoption and the work of [100] regarding online learning. Thirdly, social influence positively affects perceived value, which directly influences the intention to use AI-based recruitment systems, introducing a new aspect to AI-based recruitment adoption in Thailand. This is also highlighted by [82] concerning mobile payment. Fourthly, trust in AI technology has a direct impact on effort expectancy, which, in turn, directly influences users' intent to use AI in recruitment. This is similar to a study of mobile payment adoption [65]. Additionally, a positive association is identified between effort expectancy and the openness to adopt AI, reinforcing the existing research on AI acceptance in recruitment [39,74]. Lastly, the facilitating conditions emerge as a determinant directly influencing users' willingness to adopt AI-based recruitment software, supporting prior studies on AI acceptance in recruitment [39,73].

6.2. Managerial Implications

AI-powered recruitment plays a crucial role in propelling Thailand's economic progress in alignment with the Thailand 4.0 initiative. Government efforts highlight AI's transformative potential, projecting a possible economic gain of 2.6 trillion THB by 2030. Investing in digital skills could yield 1.0 trillion THB by 2030, promoting job creation and productivity [125]. In the competitive recruitment landscape, AI-based recruitment emerges as a strategic tool, contributing significantly to economic growth. This study offers valuable insights for stakeholders:

Organizations: For companies and organizations looking to stay competitive and efficient in the recruitment process, this study provides practical guidance. The study highlights the importance of user-friendliness (effort expectancy), the influence of colleagues (social influence), and the perceived value of AI integration. Organizations can use these findings to design and implement AI-based recruitment solutions that are more likely to be accepted and accepted by HR and recruiting teams. By addressing the concerns related to AI, organizations can foster trust among their employees.

AI Developers: Developers and technology providers specializing in AI-based recruitment tools can gain valuable insights from this study. They can use the information to enhance the user-friendliness of their products, address privacy and security concerns in accordance with Thailand's PDPA law, and build trust with HR and recruiting professionals. By aligning their products with the factors identified as significant in this study, AI developers can better meet the needs and expectations of their target audience.

HR and Recruiting Professionals: This report serves as a valuable resource for HR and recruiting professionals in Thailand and beyond. It provides them with a deeper understanding of the factors influencing their peers' intentions to embrace AI in recruitment. By leveraging the insights from this study, HR practitioners can make informed decisions about integrating AI technology into their recruitment processes. They can focus on enhancing user-friendliness, providing necessary support. This knowledge empowers them to optimize their recruitment procedures, expedite processes, and increase efficiency while maintaining the quality of their candidate selection.

6.3. Limitations and Recommendation

This study, while providing valuable insights, is not exempt from 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 the HR and recruiting professionals did not possess extensive expertise in the domain of AI or sophisticated IT. Future research 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. This 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 the UTAUT has its own set of limitations, like other theories. The 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 research 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.

Author Contributions: Framework design, T.T. and P.W.; methodology, T.T. and P.W.; formal analysis, T.T. and P.W.; writing—original draft preparation, T.T.; writing—review and editing, T.T. and P.W.; supervision, T.T. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Author Piriyapong Wongras is employed by the company Harmless Harvest Ltd. All authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Table A1. Constructs and measurement items.

Construct	Measurement Item	Source
Performance Expectancy	PE1: I think AI is useful in recruitment PE2: I think that AI will make recruitment process faster PE3: I think AI can increase efficiency of recruitment work PE4: I think using AI can help analyze candidates more accurately	[38,73]
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.	[38,73]
Social Influence	SI1: My decision to use AI in recruitment would be based on proportion of coworkers who use the software or system 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	[38,69,73]

Table A1. *Cont.*

Construct	Measurement Item	Source
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 FC3: I think guidance would be available in AI based recruitment system	[38,69,73]
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 users' personal data.	[54]
Trust in Technology of AI	TA1: I trust that AI algorithm is reliable in screening candidates to match organization's requirement 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	[89]
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 PV4: I feel that using AI in recruitment will make impression on candidates	[97]
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	[54]
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	[38]

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