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Investigating the Role of AI in Transforming Recruitment: Insights from HR and Talent Acquisition

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ABSTRACT

The method of recruitment has changed dramatically due to the integration of Artificial Intelligence (AI) into Human Resource Management (HRM), which has increased both efficacy and efficiency. This study aims to examine how AI is transforming the recruitment process and its impact on candidate sourcing, screening, and selection. Chatbots, applicant tracking systems, and predictive analytics are examples of AI-based solutions which are increasingly used to automate repetitive tasks, reduce human bias, and raise the accuracy of decisions. This quantitative study investigates the impact of AI-driven recruitment systems in Sri Lanka, focusing on four organizations. Data was collected from 50 executive employees via a structured online survey using Google Forms, comprising Likert-scale items rated on a five-point scale. Statistical analysis was conducted using IBM SPSS Statistics version 30.0.0 and SmartPLS 4 for structural equation modeling (SEM). This study aims to provide empirical evidence on executives' perceptions of AI tools in recruitment, assess the reliability and validity of the measurement model, and examine the structural impact of variables. The findings offer practical implications for HR practitioners seeking to implement or optimize AI-based hiring processes in Sri Lankan organizational settings. AI technologies can enhance HRM innovation by aligning with organizational goals and ethical standards. However, successful implementation requires careful planning, transparency, and continuous evaluation to ensure fairness and accountability. HR practitioners must adapt to AI-driven recruitment solutions in Sri Lanka to improve performance and global competitiveness. Continued research in AI-driven recruitment systems is crucial to address new opportunities and challenges, ensuring businesses stay ahead of the curve in HRM innovation and best practices.

Keywords: AI in HRM, Future Recruitment, Recruitment effect on AI

INTRODUCTION

This integration of AI into HRM recruitment practices has gained notable attention due to its potential to streamline tasks that traditionally relied on human judgment, thus addressing inefficiencies and biases inherent in conventional hiring methods (Bersin, 2019). The adoption of AI in recruitment has led to significant advancements, including automated candidate screening, interview scheduling, and the use of AI-driven chatbots for engaging with applicants (Cheng & Jiang, 2020). These innovations not only expedite the hiring process but also provide data-driven insights that support more objective evaluations of candidates, thereby potentially mitigating the effects of unconscious bias (Tambe et al., 2019).

However, concerns regarding algorithmic bias and ethical implications continue to be prominent topics of discussion, as AI systems may inadvertently replicate existing prejudices present in their training data (Duggan

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& Sherman, 2020). While the benefits of AI in HRM recruitment are substantial, such as reduced time-to-hire, enhanced candidate engagement, and cost savings, challenges remain (Bersin, 2019). Issues related to regulatory compliance, transparency, and the need for ongoing audits of AI systems necessitate careful management to ensure equitable hiring practices (Cheng & Jiang, 2020).

The future of AI in recruitment suggests a balance between harnessing technological advancements and addressing ethical considerations, emphasizing the importance of human oversight in AI-driven processes (Tambe et al., 2019). As organizations navigate this rapidly evolving landscape, the strategic role of HR professionals is also shifting (Bersin, 2019). Rather than merely executing administrative tasks, HR teams are now empowered to focus on innovation and ethical practices, fostering a more inclusive workforce while leveraging the benefits of AI technologies (Duggan & Sherman, 2020).

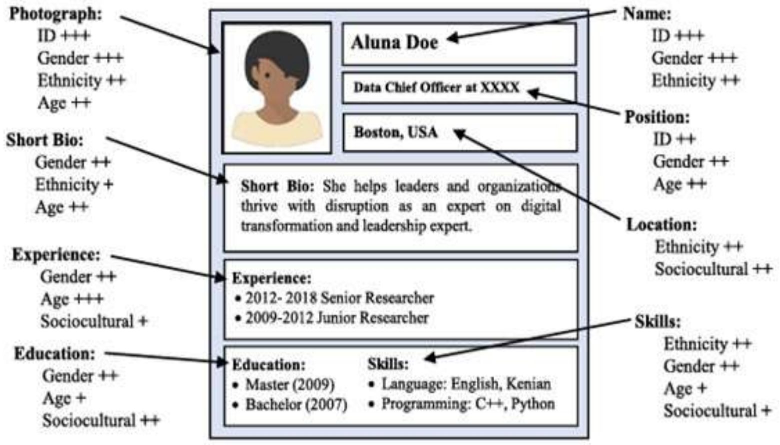

Fig. 1 Information blocks in a resume and personal attributes that can be derived from each one. The number of crosses represent the level of sensitive information (+++ = high, ++ = medium, + = low)

Figure 01: Demonstrating the sensitive information of Applicants.

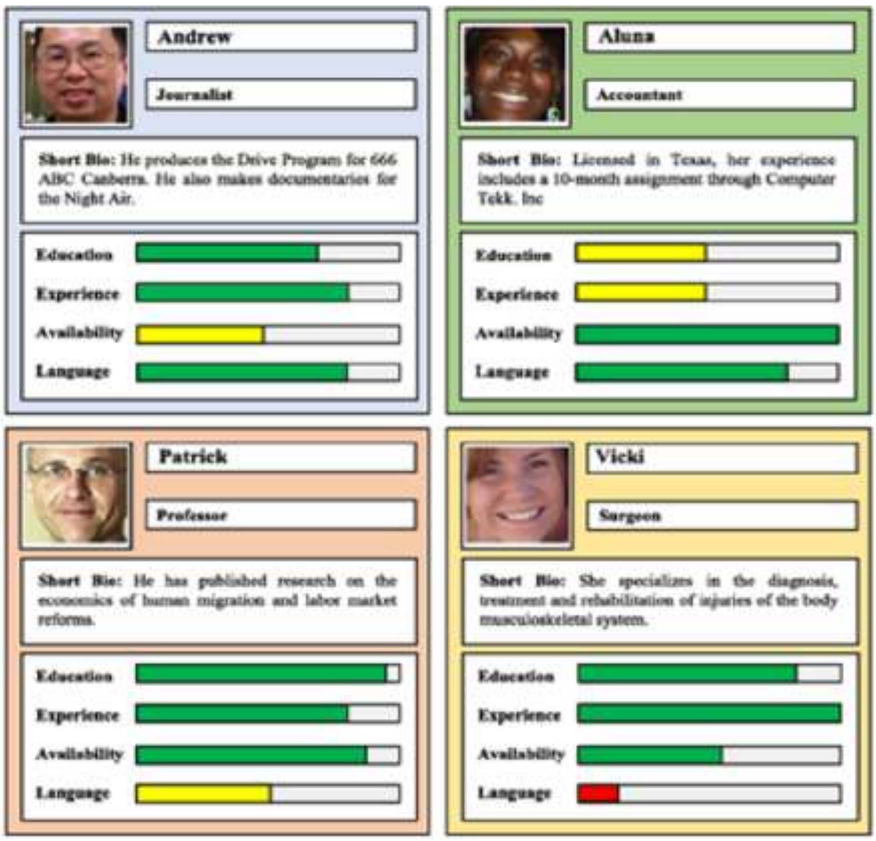

Figure 02: Visual example of the FairCVdb symthetic resume.

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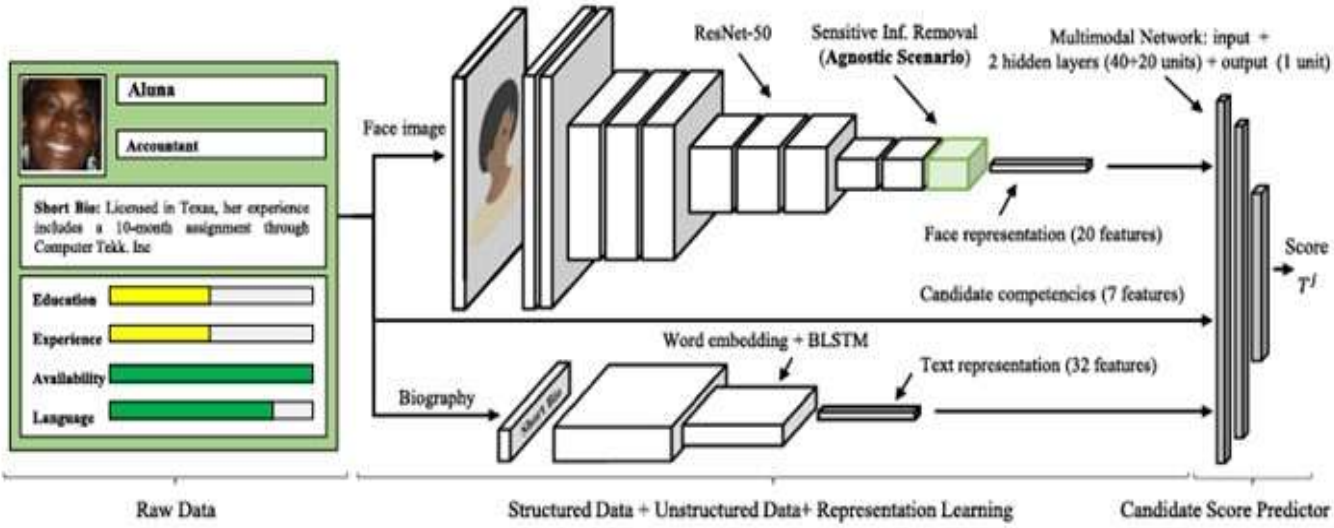

Figure 03: Multimodal deep learning architecture for candidate score prediction.

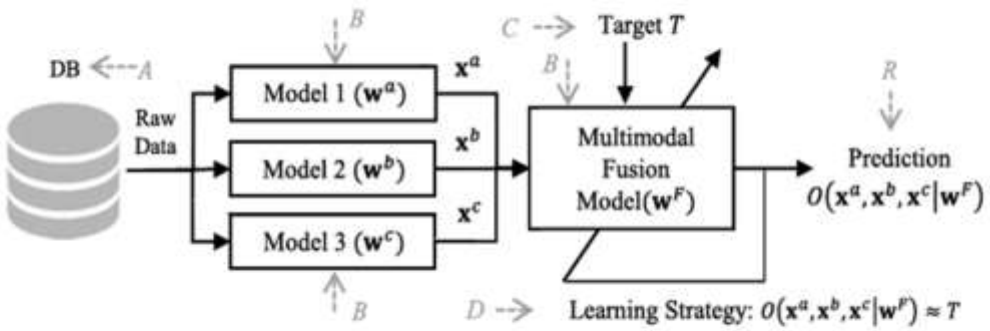

Figure 04: Block diagram of the

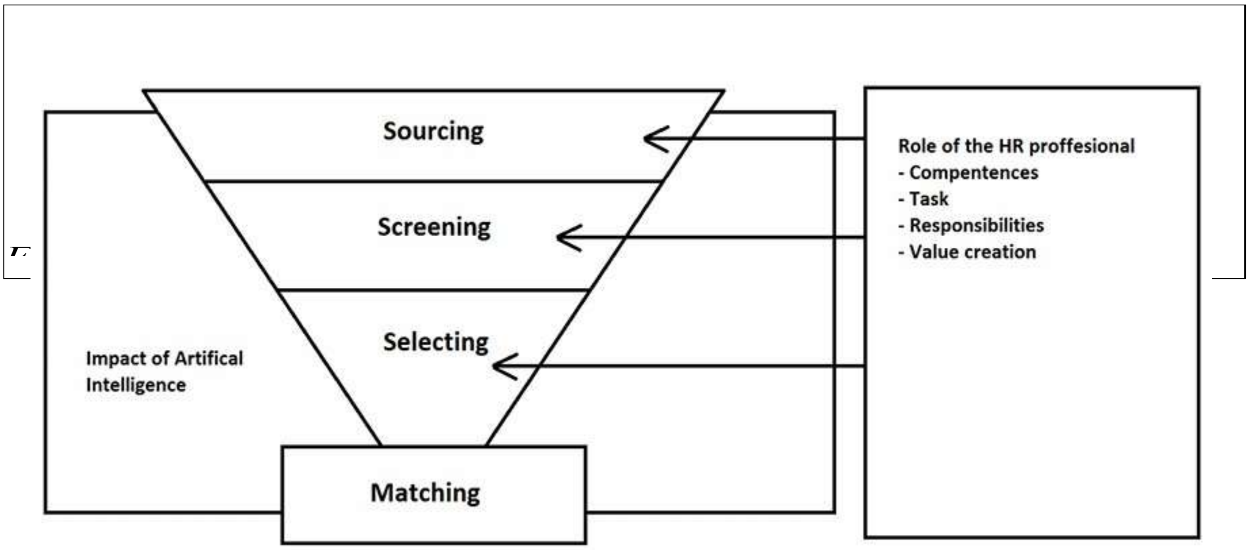

Figure 05: Impact of AI on recruitment stages

Research Questions

- How does social influence affect individuals' intention to use AI in recruitment processes?

- What impact do privacy and security concerns have on the intention to adopt AI in recruitment?
- In what ways does trust in technology shape the intention to use AI tools during recruitment?
- What is the relationship between performance expectancy and intention to use AI in recruitment activities?
- How does perceived autonomy (received autonomy) influence individuals' intention to adopt AI in recruitment?

Research Objectives

- To examine the effect of social influence on individuals' intention to adopt AI-driven recruitment systems.
- To evaluate how privacy and security perceptions impact the propensity to use AI in recruitment processes.
- To investigate the role of trust in technology in shaping intentions to employ AI tools during recruitment.
- To assess the extent to which performance expectancy drives the adoption intention of AI recruitment solutions.
- To determine how perceived autonomy influences individuals' intention to utilize AI-enabled recruitment platforms.

LITERATURE REVIEW

Talent Acquisition Framework

Both internal and external methods are included in recruitment (Armstrong, 2006). Due to the fact that it understands the candidate profile, internal recruitment is cost-effective and concentrates on talent development (Barber, 1998). In order to fill skills gaps, external recruitment looks outside the company, particularly when internal candidates change roles (Cascio, 2018). It also highlights the significance of cultural fit in lowering turnover (Taylor & Collins, 2000). Job analysis, profile creation, scheduling, interviews, testing, shortlisting, contracts, and onboarding are all standard steps in the hiring process (Heneman & Judge, 2009).

According to this approach, traditional recruitment consists of four main duties (Breaugh, 2008). Identifying candidates is the first step, after which job descriptions and requirements are created to determine the necessary abilities and duties (Levesque & Whitaker, 2013). Attracting applications is the second phase, which is typically accomplished by engaging potential prospects through advertising in various media (Stone et al., 2015). The third responsibility is processing incoming applicants, which includes interacting with the hiring staff and sorting and screening applicants (Chapman & Mayers, 2015). Communicating with applicants to inform them of their rejection or next actions is the last stage (Breaugh & Starke, 2000).

In a similar vein, recruitment strategy, strategic development, sourcing and attraction, screening, evaluation, and tracking are all considered standard recruitment procedures (Taylor & Collins, 2000). These procedures entail finding job openings, crafting job descriptions that include soft skill requirements, locating and vetting applicants, selecting a shortlist for interviews, and making the ultimate decision (Heneman & Judge, 2009). Nonetheless, traditional hiring is often referred to as in-person and paperbased, and the main strategies for drawing applicants are newspapers, manual job boards, and in-person meetings in particular places (Levesque & Whitaker, 2013)

AI-Driven Recruitment in the Digital Era: A Strategic Perspective

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 (Stone et al., 2015). The use of an online assessment is on the rise for appraising candidates, ensuring a selection process that takes into account both technical and interpersonal skills (Chapman & Mayers, 2015). The digital era has brought about significant transformations in the recruitment domain, and the evolving digital technologies of the past few decades have played an increasingly prominent role for both employees and Human Resource Management (Cascio, 2018).

Artificial intelligence (AI) is present in numerous facets of our lives, including robots, online banking, social networks, voice assistants like Siri and Alexa, and the processing of credit cards and loans (Davenport & Dyché, 2013). AI has the potential to increase productivity and convenience while also improving human well-being (Bersin, 2018). AI has become widely used in the recruiting industry as a result of the fierce competition in talent acquisition brought on by the expansion of the global economy in recent years (Breaugh, 2008).

The selection of applicants from an extensive pool has significantly improved as a result of this integration (Taylor & Collins, 2000). Initial resume screening, recognizing promising individuals, and pairing them with appropriate roles are among AI's skills (Davenport & Dyché, 2013). Candidates are contacted by virtual assistants via a variety of communication venues (Stone et al., 2015). AI reduces the need for human intervention by automating the entire hiring process, from conception to onboarding, and ensuring accurate, bias-free job descriptions (Bersin, 2018).

The most effective AI hiring platforms are essential at various phases of the hiring process (Chapman & Mayers, 2015). Textio, whose software is used by companies like Atos and McDonald's, uses Natural Language Processing (NLP) to improve job posting language, lowering bias and increasing response rates (Textio, n.d.). A Canadian firm called Knockri has created bias-free hiring software that uses AI and NLP technology to increase diversity (Knockri, n.d.). GoBe, a recruiting chatbot, handles the preliminary evaluations of candidates, and Mya Systems uses conversational AI to expedite the hiring process for companies such as Deloitte and L'Oréal (Mya Systems, n.d.).

Theoretical Background

The intention to engage in a behavior is molded by one's attitude and subjective norms, according to the Theory of Reasoned Action (TRA), which was first proposed by Icek Ajzen and Martin Fischbein in 1975 (Ajzen & Fishbein, 1975). The Technology Acceptance Model (TAM), a framework for comprehending technology acceptance behavior, was created in 1989 (Davis, 1989). It expands on the TRA by emphasizing attitude, intention to use, perceived usefulness (PU), and perceived ease of use (PEOU). The Theory of Planned Conduct (TPB), which Icek Ajzen developed in 1991 as an extension of TRA, emphasizes that behavioral intention which is impacted by attitude, subjective standards, and perceived behavioral control directs actual conduct (Ajzen, 1991).

In order to predict personal computer usage based on attitudes, social conventions, habits, and expected consequences, Thompson and colleagues modified an existing behavior model to present the Model of Personal Computer Utilization (MPCU) in 1991 (Thompson et al., 1991). The Motivational Model (MM), which was first presented in 1992, emphasizes the significance of perceived advantages and enjoyment of computers while concentrating on both inner and extrinsic incentives as drivers of technology adoption (Deci & Ryan, 1992). Introduced in 1995, the Innovation Diffusion Theory (IDT) focuses on how innovations spread within a social system, taking into account elements such as the innovation-decision process, the innovation's qualities, and adopters' characteristics (Rogers, 1995).

The Unified Theory for Acceptance and Use of Technology (UTAUT) is one of several technology adoption models that are integrated into a single framework. These models include the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), PC Utilization Model (MPCU), Motivational Model (MM), Social Cognitive Theory (SCT), and Innovation Diffusion Theory (IDT) (Venkatesh et al., 2003). In addition to addressing TAM's shortcomings, UTAUT offers information on consumers' technology adoption aspirations.

Social Influence

The moment industry concerns technology adoption, the idea of social influence refers to the ways in which consumer views are impacted by their social surroundings, which include peers, superiors, and management. The degree to which people perceive that important people in their lives, such family and friends, consider people should use a certain technology is known as social influence. It has been observed that social influence plays a critical role in the use of modern technology in a variety of fields, including business ERP adoption, AI-based talent acquisition for job seekers, and mobile technology in healthcare. The first hypothesis is evaluated as, according to previous research, HR and recruiting professionals can obtain direction, representation, and beneficial knowledge about AI software in hiring, resulting in increases their confidence when deciding whether to employ the system. Social influence has been found to have a direct impact on security in addition to its direct influence on user intention. Therefore, it is possible to develop the first hypothesis, which holds that social influence directly affects privacy and security. Additionally, previous studies in the field of mobile payment uptake indicated that perceived value was directly impacted by social influence. It is crucial to keep in mind that perceived worth is greatly impacted by social influence.

Hypothesis 1 (H1): Social influence (SI) significantly influences the user's intention to use AI in recruitment (IU).

Privacy and Security

The confidentiality of information is the main focus of this investigation. Certain individuals decide to restrict "privacy" to particular types of personal data. It is obvious that there are issues about protecting "private" data; these are known as "security concerns." In essence, this acknowledges the need of protecting personal data and categorizes it as a security concern. Organizations have to develop workable rules to address the security and privacy issues associated with implementing modern technologies. In order to prevent impeding the adoption of technology in the name of security and privacy, senior management ought to find a balance between these concerns. Technology adoption in a variety of fields, including as mobile payment, mobile self-checkout, and AI use in Customer Relationship Management (CRM) applications, is positively impacted by secure systems with privacy safeguards.

On March 19, 2022, the Personal Data Protection Act of Sri Lanka, which outlines guidelines for "personal data processing," went into full effect with the goal of protecting the personal information of both individuals and organizations (Parliament of Sri Lanka, 2022). Microsoft Sri Lanka suggested strengthening the security and privacy infrastructure and incorporating AI laws into the PDPA in order to get ready for AI integration. The PDPA, which requires consumers' and data owners' approval before data is stored, shared, or used, has the potential to revolutionize personal data protection in Sri Lanka. The six hypotheses can be evaluated by considering the privacy and security. aspect as having a favorable influence on HR and hiring professionals' intentions to adopt AI-driven hiring solutions.

Hypothesis 2 (H2): Privacy and security (PS) significantly influence the user's intention to use AI in recruitment (IU).

Trust in AI Technology

The confidentiality of information is the main focus of this investigation. Certain individuals decide to restrict "privacy" to particular types of personal data. It is obvious that there are issues about protecting "private" data; these are known as "security concerns." In essence, this acknowledges the need of protecting personal data and categorizes it as a security concern. Organizations have to develop workable rules to address the security and privacy issues associated with implementing modern technologies. In order to prevent impeding the adoption of technology in the name of security and privacy, senior management ought to find a balance between these concerns. Technology adoption in a variety of fields, including as mobile payment, mobile self-checkout, and AI use in Customer Relationship Management (CRM) applications, is positively impacted by secure systems with privacy safeguards.

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It is acknowledged that trust is an effective strategy for negotiating the increasing complexity of organizations, technology, and interpersonal interactions individuals confront. Businesses, governments, and the general public are becoming more conscious of AI's potential impact as trust becomes more crucial in determining the adoption of new technologies. This makes developing reliable AI systems a top priority. Government agencies, industry behemoths like Google and Microsoft, and trade groups like the IEEE have all issued guidelines in recent years that stress the importance of designing AI systems with reliability as a fundamental tenet. According to a study on the adoption of technology, trust is essential for promoting the usage of information technologies. Research suggests that users' readiness to adopt a new system is strongly influenced by how much faith they have in the information system and the technology provider. User behavior is greatly influenced by trust, which has been incorporated into models for embracing technology in order to predict future behavior. Trust was found to be the most significant predictor of the intention to utilize an AI system in a study on biometric acceptance. Furthermore, customers' willingness to adopt new technologies such as AI-driven CRM, AI-integrated HR systems, sustainable mobile banking app adoption, or AI chatbot-powered transportation services is greatly influenced by their level of trust.

Furthermore, studies on the adoption of emerging technologies in a variety of sectors, such as e-document authority and mobile payment information systems, have shown that trust has a direct impact on both performance expectancy and effort expectancy (Venkatesh et al., 2003). According to a study on the enlarged Technology Acceptance Model (TAM), perceived usefulness and trust are positively correlated (Pavlou, 2003). The tenth and eleventh hypotheses are thus developed in accordance with the relevance of evaluating these linkages. Therefore, a user's desire to utilize a new system, such as AI in recruitment, can be directly impacted by their level of faith in the technology. The following is one way to examine the third hypothesis.

Hypothesis 3 (H3): Trust in AI technology (TA) significantly influences the user’s intention to use AI in recruitment (IU).

Performance Expectancy

Performance Expectancy is a measure of the way users believe a specific system is going to impact their ability to do their jobs. It shares a close relationship with the Technology Acceptance Model's (TAM) notion of perceived utility (Davis, 1989). Previous studies found a significant influence of performance expectancy on behavioral intention in a variety of domains, which involve a developing nation's uptake of portable health services. Therefore, people's desire to embrace new technology is influenced by their perception of performance expectations along with how useful it can be, such as AI in talent recruitment. The following is how the fourth hypothesis was created:

Hypothesis 4 (H4): Performance expectancy (PE) significantly influences the user’s intention to use AI in recruitment (IU).

Perceived Autonomy

Human progress and well-being depend on autonomy, defined as the capacity to make decisions for one and exercise self-government. Autonomy, as defined by the Self-Determination Theory, is the ability to make conscious judgments after weighing one's options (Deci & Ryan, 1985). Restoring confidence in human-machine interactions requires a more comprehensive view of autonomy. The ability of AI technology to carry out tasks that are inspired by human behavior without requiring direct human intervention is known as AI autonomy.
According to studies on intelligent personal assistants, AI autonomy is defined as perceptions, ideas, and behaviors that directly affect how intelligent personal assistants are perceived and how they are intended to be used.

Perceived autonomy has also been proven to have a significant impact on the use of online courses and the adoption of the Internet of Things in another research. Therefore, the intention to apply AI in the hiring process is positively impacted by perceived autonomy. The following is how the fifth hypothesis can be tested:

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Hypothesis 5 (H5): Perceived autonomy (PA) significantly influences the user's intention to use AI in recruitment (IU).

RESEARCH METHODOLOGY

Population and Sampling

This study adopted a quantitative research strategy. The conceptual model was first crafted using insights from an extensive literature review (secondary data). Next, a detailed questionnaire was designed to validate key factors and refine the survey instrument, ensuring its alignment with Sri Lanka's recruitment context. The research targeted executive employees of Formix (Pvt) Ltd, Atz Solution (Pvt) Ltd, Experienz (Pvt) Ltd, and EPR Groupers (Pvt) Ltd in Sri Lanka. The study population included all executives actively employed at the company. From this population, a sample of 50 executives was drawn using a non-probability convenience sampling technique, stratified proportionally across operational divisions. The survey was administered on a basis proportional to departmental representation, ensuring meaningful coverage despite the non-random sampling approach. Convenience sampling allows efficient access to participants when randomized sampling isn't practical in corporate settings. Proportional stratification ensures diverse executive roles are represented, mitigating biases from purely ad-hoc selection.

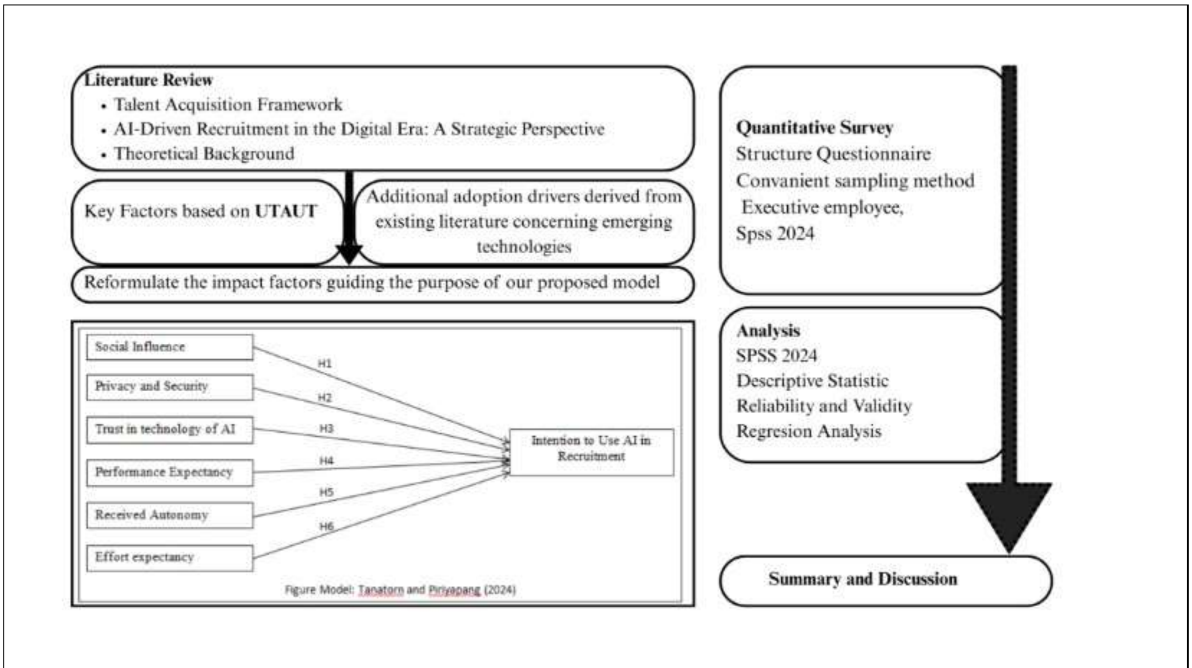
Data collection

Collection of data has been Distributed structured questionnaires to the selected executives. Participants provided demographic details and answered items measuring the model's factors. Feedback from this pilot phase validated and enhanced the survey instrument prior to the full-scale administration. The initial questionnaire was piloted among executives, with responses used to confirm important model variables and refine the instrument's clarity and relevance. The final version was then distributed to the full sample of 50 executives for data collection.

Questionnaire

A structured English-language questionnaire was developed from established literature and organized into three parts—initial screening and demographic items to identify HR/recruitment professionals and capture background information, a core section of eight multi-item constructs measured using 5-point Likert scales (1 = strongly disagree to 5 = strongly agree) assessing AI adoption factors, and full instrument details provided in

Appendix A—designed following best practices in clarity, logical flow, and balanced response anchors



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Categories	Dimensions	N	%
Gender	Male	33	66%
	Female	17	34%
Age	25–34 years	09	18%
	35–44 years	18	36%
	45–54 years	23	46%
Position Level	Officer/Staff	26	52%
	Supervisor/Team Leader	13	26%
	Manager/Department Head	11	22%
Work Experience	0–5 years	23	46%
	5–10 years	16	32%
	10–15 years	11	22%
Do you know AI based recruitment	Yes	40	80%
Software before?	No	10	20%
Have you ever used AI based	Yes	8	16%
recruitment software before?	No	42	84%
Do you think AI based recruitment can	Yes	12	24%
replace human?	No	38	76%
	Total	50	100%

RESULT AND DISCUSSION

The findings from utilizing PLS-SEM, a statistical technique for analyzing relationships among variables in research, are illustrated in Figure 3. This graphical representation aids in grasping the insights and findings derived from PLS-SEM, leading to a deeper understanding of the study's results.

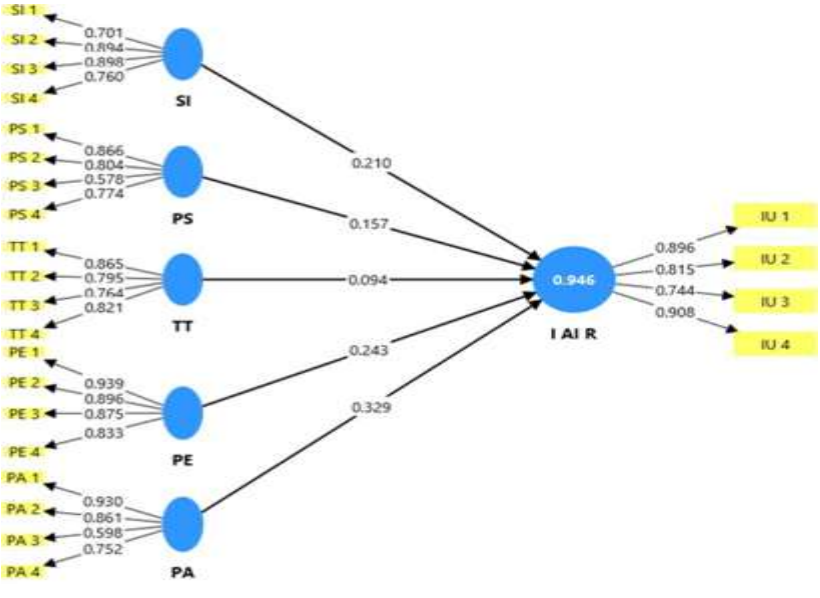


Figure 3: PLS-SEM results with the path coefficients

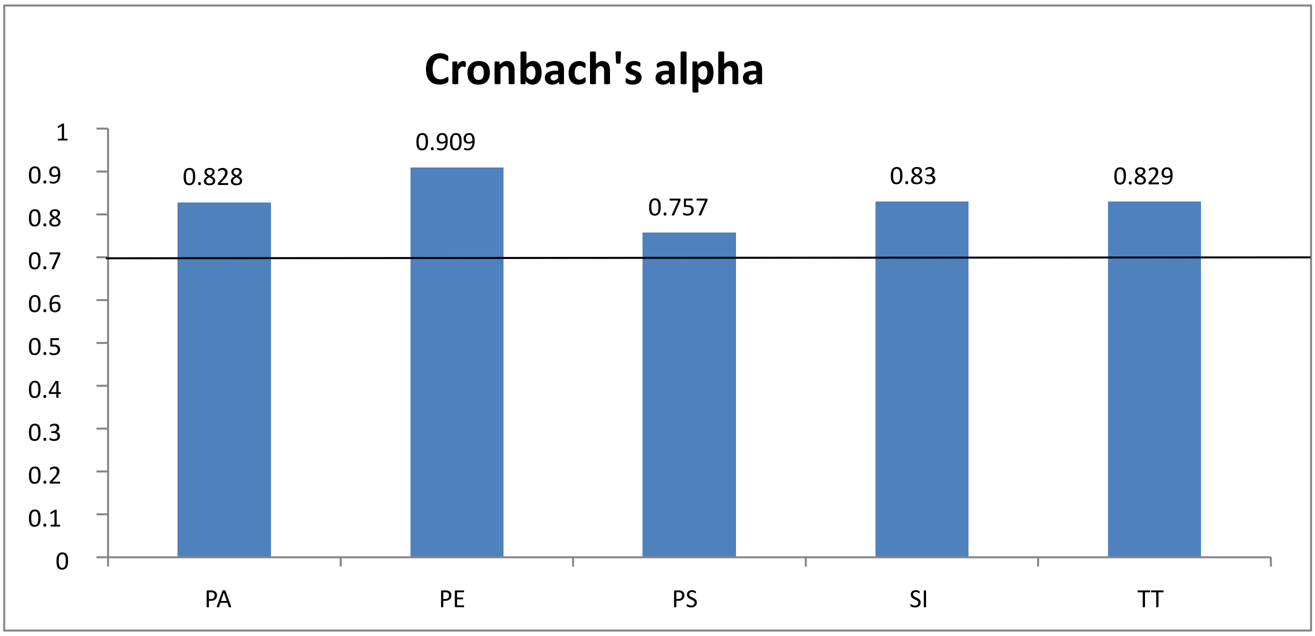
Reliability and Validity

Reliability is demonstrated by the SI, PS, TT, PE, and PA measurements, according to the results shown in Table 3. This conclusion is derived from the results shown in Table 3. The fact that each variable's Cronbach's alpha value exceeded 0.7 suggests that the constructs verified in this study had excellent validity. For the suggested construct, each factor's composite reliability values are more than 0.80, considered extremely high. As a result, the proposed model fits constructor responsibility requirements. Furthermore, the recommended metric for convergent validity is still Average Variance Extracted (AVE).

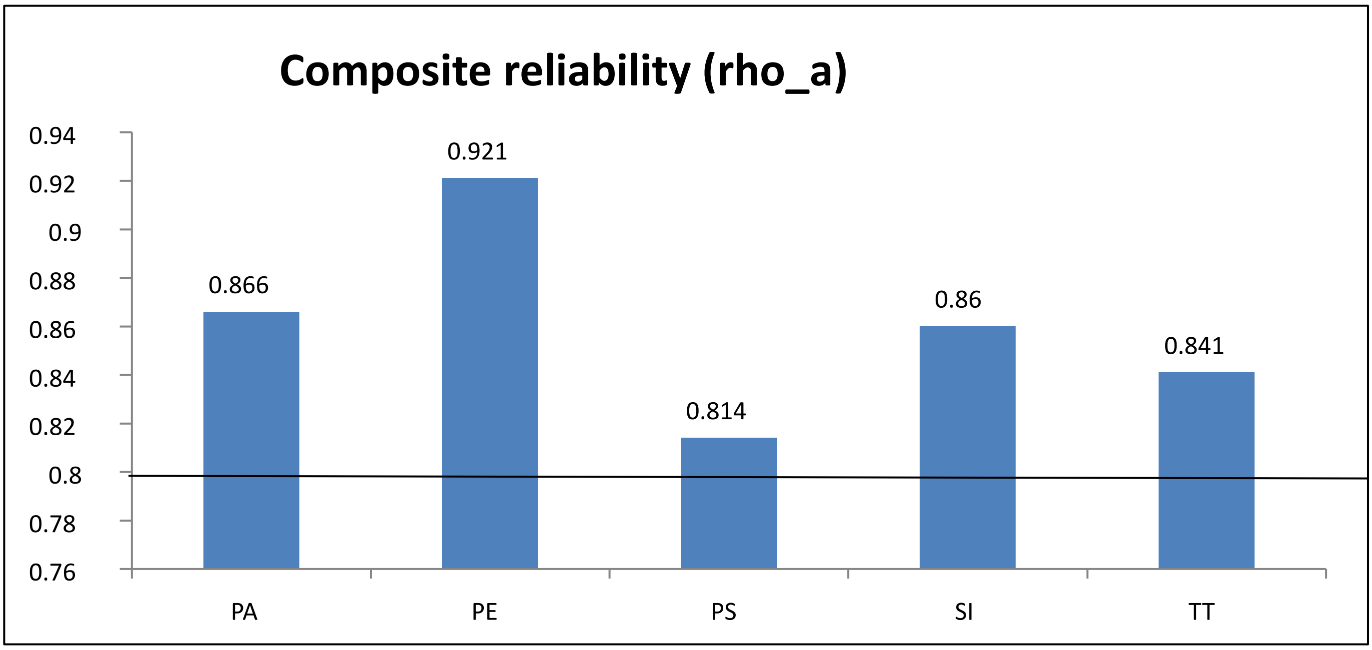
Table 3: Reliability and validity construction.

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average varianc extracted (AVE)**
I AI R	0.863	0.873	0.907	0.711
PA	0.797	0.841	0.87	0.633
PE	0.909	0.921	0.936	0.786
PS	0.757	0.814	0.845	0.783
SI	0.83	0.86	0.889	0.668
TT	0.829	0.841	0.885	0.659

Higher reliability is indicated by an increase in Cronbach's alpha, which ranges from 0 to 1. It is suggested that the variables' indicators be equal to or more than 0.6 in order to evaluate convergent validity in a construct model; a range of 0.7 or higher is generally regarded as desirable. Since all of the values were above 0.7, all of the factors the PA (0.79), PE (0.90), PS (0.75), SI (0.83), and TT (0.82) were evaluated at a satisfactory level (see Figure 4). Precisely consequence, the recommended model satisfies the satisfactory reliability criteria.



Cronbach's alpha for each factor is illustrated in Figure 4, with a minimum threshold of more than 0.7 With a threshold of (CR) 0.8, which was extremely significant for the indicated construct, the composite reliability indicator (CR) was used to evaluate convergent validity in the context of the construct model under discussion.



indicated by Figure 5, the composite reliability indicator (CR) in the study findings demonstrated a range of values from 0.81 to 0.92. Variance Extracted (AVE) is the suggested metric for assessing convergent validity in the context of convergent validity. If the AVE values for the factors above what is suggested minimum threshold of 0.5, convergent validity is confirmed whenever utilizing structural models. As demonstrated in Figure 6, the AVE in the structural model ranged from 0.551 to 0.738, all of which were above the 0.5 criterion. Therefore, the suggested construct model's convergent validity is verified.

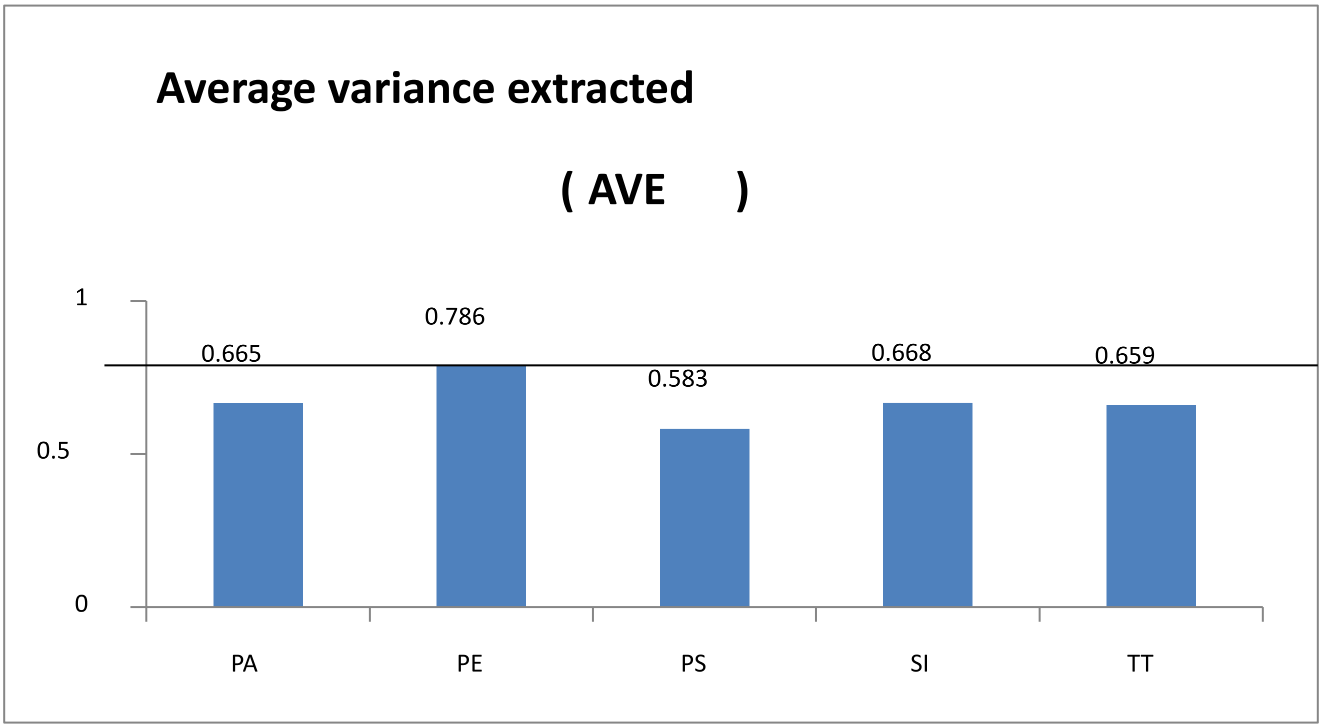


Figure 6. Average Variance Extracted of all the variables, with the minimum threshold exceeding 0.5.

Discriminant Validity Test

Table 4 makes it apparent that the constructs satisfied According to Fornell and Larcker's requirements for discriminant validity given the square root of the AVE values on the diagonal for the constructs significantly

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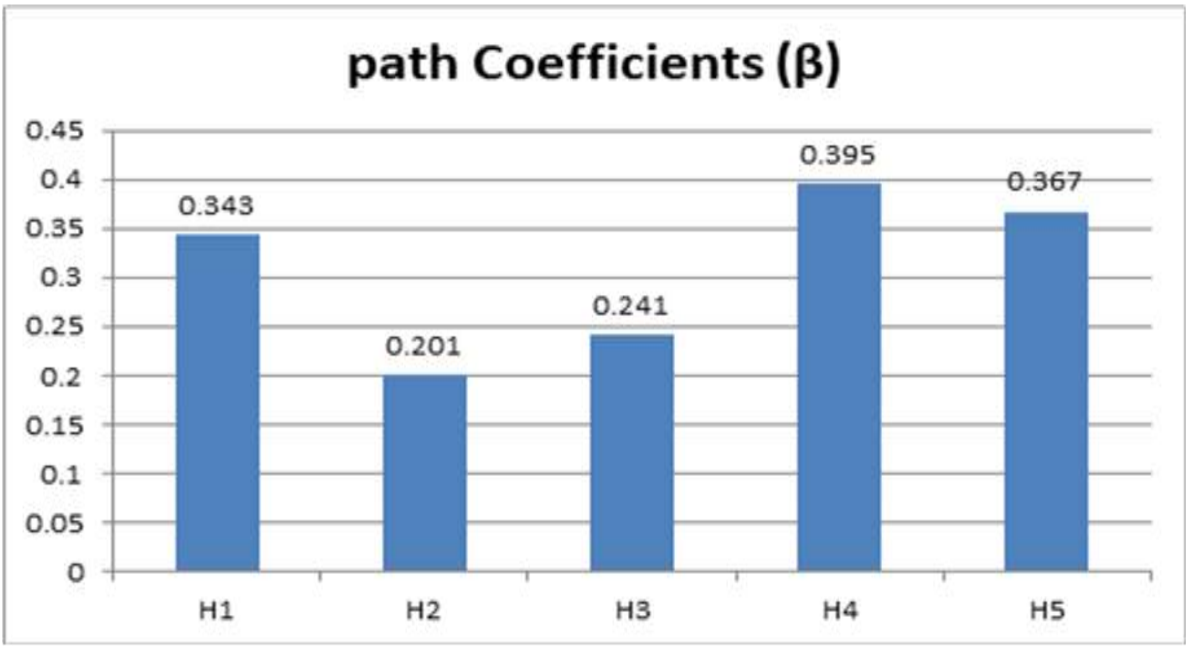
greater than the correlations between components. The AVE for IU outperformed the horizontal and vertical (0.665, 0.786, 0.583, 0.668, and 0.659) correlation values. Consequently, the construct model satisfies the discriminant validity requirement.

	VIF
IU 1	3.381
IU 2	2.214
IU 3	1.831
IU 4	3.714
PA 1	3.431
PA 2	2.534
PA 3	1.311
PA 4	1.606
PE 1	3.382
PE 2	3.19
PE 3	2.644
PE 4	2.178
PS 1	1.735
PS 2	1.849
PS 3	1.288
PS 4	1.759
SI 1	2.095
SI 2	2.933
SI 3	2.534
SI 4	2.467
TT 1	2.205

	Saturated model	Estimated model
SRMR	0.026	0.026
d_ULS	0.355	0.355
d_G	0.424	0.424
Chi-square	632.622	632.622
NFI	0.886	0.886

Hypothesis	Correlation	path Coefficients (β)	T statistics (|O/STDEV|)	P values	Decisions
H1	PA -> I AI R	0.343	3.193	0.000	Supported
H2	PE -> I AI R	0.201	4.213	0.000	Supported
H3	PS -> I AI R	0.241	4.071	0.000	Supported
H4	SI -> I AI R	0.395	3.517	0.000	Supported
H5	TT -> I AI R	0.367	4.656	0.000	Supported



METHODOLOGY

This research adopts a **qualitative and literature-based analysis** approach:

1. **Secondary data** was collected from existing academic papers, industry reports, and case studies involving organizations like Amazon, Hired, and GapJumpers.
2. Technologies such as ML, NLP, chatbots, and generative AI were reviewed in terms of their implementation and impact.
3. Ethical and regulatory frameworks like GDPR and CCPA were examined to understand compliance challenges.

Key Findings

1. **Efficiency Gains**: AI significantly reduces time-to-hire and administrative burdens through automation in resume screening, scheduling, and communication.
2. **Bias Reduction**: Properly designed AI systems can help minimize unconscious bias, though flawed algorithms may reinforce existing prejudices.
3. **Enhanced Candidate Experience**: Chabot's and real-time AI tools improve engagement and transparency for applicants.
4. **Cost Reduction**: Automation leads to lower recruitment costs while improving hire quality.
5. **Scalability**: AI tools can scale recruitment efforts to handle large volumes of applications effectively.
6. **Operational Challenges**: Integration issues, skill gaps in HR, and data management present barriers to adoption.

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7. **Ethical Concerns**: Algorithmic bias, lack of transparency, and privacy concerns are major limitations of AI adoption in HR.

Theoretical Framework

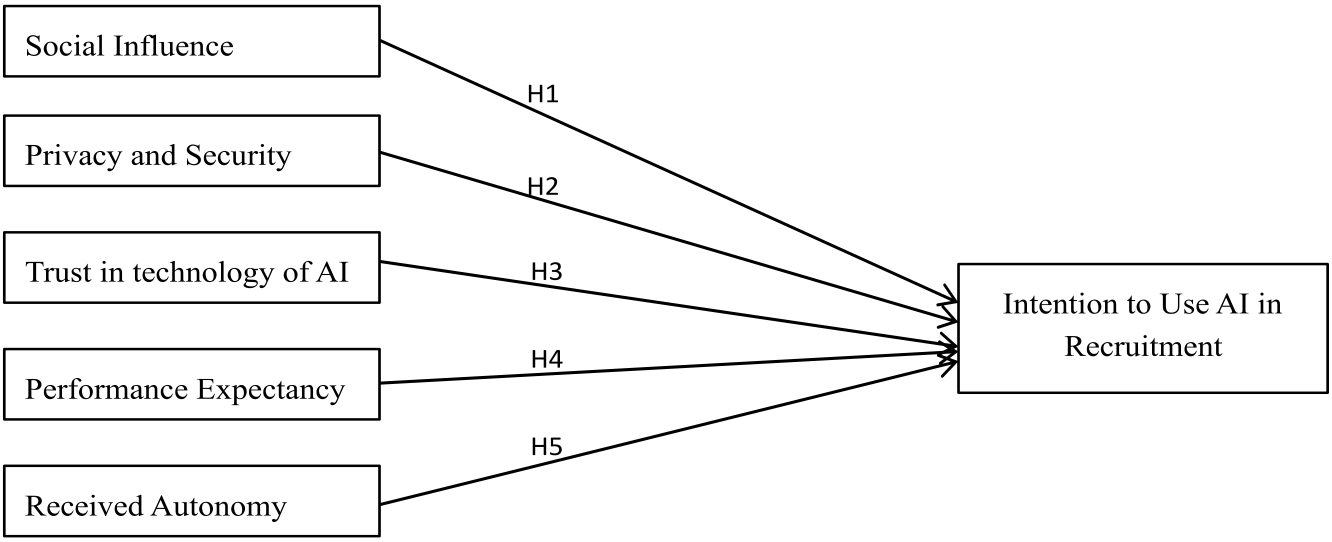

Figure Model: Tanatorn and Piriyapang (2024)

CONCLUSION

AI has emerged as a powerful tool in HRM recruitment, offering benefits like efficiency, objectivity, and enhanced candidate interaction. However, it is not without challenges. Ethical concerns, regulatory compliance, and operational hurdles must be carefully managed. The future of AI in recruitment lies in a hybrid model where human oversight complements automated processes. As AI evolves, HR professionals must adopt strategic roles, balancing innovation with equity and fairness.

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STATEMENTS OF THE QUESTIONNAIRE.

1. My decision to use AI in recruitment would be based on proportion of coworkers who use the software or system
2. Those who use AI in recruitment would have more advantages than those who do not
3. With the rapid technology trend, AI integrated in recruitment is necessary for my company
4. I think the introduction of AI in recruitment into our company will be trendy in my industry
5. I expect that AI based recruitment software will be safe and secure
6. I expect AI based recruitment software will strictly comply data privacy policy regarding Personal Data Protection Act
7. I feel safe and protected by the use of encryption
8. I think AI software developer will protect and ensure safety of users' personal data
9. I trust that AI algorithm is reliable in screening candidates to match organization's requirement
10. I trust that AI based recruitment software has reliable database to complete recruitment
11. I think there will be a government organization to ensure AI based recruitment software is secured

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12. I trust that AI software developer is honest and will not take advantage over user's information 13) I think AI is useful in recruitment
13. I think using AI can help analyze candidates more accurately
14. I think AI can increase efficiency of recruitment work
15. I think that AI will make recruitment process faster
16. I think AI in recruitment will reduce the number of decisions to get the
17. Using AI in recruitment will allow recruiters/HR officers to have more freedom to develop preferred skills and tasks
18. Using AI will give recruiters/HR officers the opportunity to better coordinate with candidates
19. Utilizing AI will provide recruiters and HR officers with more flexibility to manage other essential responsibilities more effectively
20. I Using AI based recruitment software is a good and modern idea
21. I like the idea of using AI in recruitment
22. The AI based recruitment software makes me more interested
23. I have a high wiliness to use AI in recruitment