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Adoption of AI in HR Practices: A Study of Talent Acquisition in North-East India

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Abstract: Artificial intelligence (AI) has revolutionised global talent-hiring processes but the impact of AI in regions that have unique socio-economic realities in North East India has remained understudied. The current study evaluates the contributions of competency, effectiveness, perceived ease of use and perceived usefulness to the adoption of AI by HR professionals in talent acquisition within the region. The questionnaire was structured, and 328 practitioners in various industries were given the questionnaire, and the results were analysed using factor analysis and multiple regressions. The results point to perceived ease of use and perceived usefulness as the main factors of AI adoption. Respondents prefer those tools that are user-friendly and bring instant benefits, especially when it comes to the simplification of the recruitment processes and candidate screening. On the contrary, competency and effectiveness do not have any significant impacts, and this could be due to the constraints in technical expertise and training. That is why the study indicates the importance of designing programs that are accessible and locally relevant AI applications in the context of uneven diffusion of technology. The research adds to the international discussions about the automation of HR and underlines the necessity of localised AI solutions. The findings provide practical recommendations to the HR practitioners who are willing to incorporate AI into talent acquisition practices and place them in the context of the overall scope of AI contribution to the recruitment process.

1. Introduction

The fast development of Artificial Intelligence (AI) is transforming talent acquisition practice worldwide, and North East India is not an exception. This study investigates the ways in which AI is having a transformative impact on talent acquisition in the area, and in particular how it is impacting competency, effectiveness, ease of use, and perceived usefulness, so as to gain insights into how these technological advancements are changing approaches to recruitment and organisational performance in this distinctive environment.

Artificial intelligence (AI) in talent acquisition is changing the way recruitment is carried out because it automates the process of screening resumes, finding candidates, and the initial interview, thus making the process more efficient, competent, and better decision-making (Chien, 2020; Binns, 2018). The candidate experience is being enhanced with recruitment systems driven by AI, which have the ability to offer personalised communication and real-time updates, which is in line with contemporary expectations of a smooth process (Nair & George, 2021). Nevertheless, AI in recruitment has a number of concerns, e.g., algorithmic bias, i.e., the fact that AI systems trained on past data may unintentionally reproduce the existing bias based on gender, ethnicity, or socio-economic background (Binns, 2018). Also, the issue of data privacy and the combination of AI and conventional HR activities pose serious risks, especially in such a region as North East India, where the legislative framework and the infrastructure to offer advanced technologies might be underdeveloped (Chien, 2020; Soni & Kumar, 2019). Moreover, the applicability of AI in the local setting, where demographic and cultural variations should be taken into account, is still an issue, and the adoption of AI systems by both HR professionals and candidates is always received with hesitation because of the perceived absence of human interaction in decision-making (Soni & Kumar, 2019; Nair & George, 2021). Finally, implementing AI may be too expensive to most organisations within North East India, which further restricts the use of AI in the region (Chien, 2020). Therefore, although AI can transform the process of talent acquisition, such tendencies, problems, and challenges must be overcome in order to integrate AI into the practice of regional talent acquisition.

The study of the influence of AI on talent acquisition in North East India is influenced by some of the established theories that investigate the issues of technology adoption, effectiveness, and user experiences. The Technology Acceptance Model (TAM), proposed by Davis (1989), has been a cornerstone in understanding how perceived ease of use and perceived usefulness influence individuals' willingness to adopt new technologies. Likewise, Unified Theory of Acceptance and Use of Technology (UTAUT) created by Venkatesh et al. (2003) further elaborated on TAM by including other constructs of performance expectancy and social influence, which also help to understand the influence of AI on talent acquisition practices. Also, the Resource-Based View (RBV) theory states that organisations can achieve competitive advantage by integrating valuable, rare, and inimitable resources such as AI technologies (Barney, 1991). Additionally, the theory of Diffusion of Innovations (DOI) by Rogers (2003) can be used to understand the diffusion of innovations, including AI within social systems and the determinants that determine the adoption rates in various geographical locations like North East India. These theoretical frameworks collectively inform the study's exploration of AI's role in enhancing competency, effectiveness, ease of use, and usefulness in talent acquisition within this specific region.

Artificial intelligence (AI) has been a quickly adopted technology in talent acquisition and has transformed the recruitment system in the world, but its influence on talent acquisition in North East India has not been explored. The purpose of the research is to assess the impact of AI on the competency, effectiveness, ease of use, and usefulness in the case of recruitment in this peculiar regional environment. Although AI could improve the efficiency and decision-making process of hiring, the limitations of the infrastructure, regional differences in the use of technology, and the issue of data privacy and bias might interfere with its efficiency. Relevance of the study can be attributed to the fact that the study is conducted in North East India which has quite different demographic, cultural and economic attributes and where AI has not been extensively used in HR practices. Through the investigation on the effect of AI on recruitment in this region, the research will provide meaningful information to organisations, policymakers, and HR professionals to optimally implement AI in this region taking into consideration the challenges in this region. The study is critical in explaining the potential of AI to be applied in talent acquisition procedures in areas that have different and changing requirements.

Artificial Intelligence (AI) can revolutionise HRM (Human Resource Management), especially regarding talent acquisition. Organisations aiming to enhance their success rate must explore how artificial intelligence can streamline repetitive tasks, deliver precise measurements, and facilitate decision-making processes. Although the global excitement around AI-driven recruitment has been immense, almost no conversations are taking place about the unique opportunities and challenges facing different regions of the world like North East India. This gap provides an opportunity for research on how AI technology can improve the accuracy, efficiency, price competitiveness and convenience of talent attraction in a uniquely set organisational ecology.

This research contributes to the understanding of how artificial intelligence deployment impacts recruitment processes in the human resources sectors of North East India, addressing a gap in existing literature and empirical evidence on this topic. While most studies have elaborated on the advantages of AI in global recruitment, more is needed to know about how they operate in regions with unique socio-economic and cultural dynamics like North East India. Studies like Pills & Sivathanu (2020) and Vedapradha et al. (2023) have elucidated the previous work. Studies for the future have already shown the positive outlook from applications of AI in recruitment and management roles; however, how such changes are perceived among HR professionals from a region like North East India is yet to be uncovered.

This study stands out by analysing four key aspects in relation to AI-driven recruitment: Competency, Effectiveness (encompassing both task and outcome), Perceived ease of use, and usefulness. It uniquely explores these attributes within the context of artificial intelligence-based hiring processes.

These findings are specific to the local context of North East India and can be extrapolated in other similar settings. This research not only addresses a crucial gap in the literature but also provides recommendations for human resources practitioners in an alternative geographical area.

With northeast India developing its own economic and technological landscape, AI can help North East India attract talent and be competitive. As such, the current study aims to theoretically broaden academic discussions on AI in HRM and practically by providing valuable insights for HR practitioners.

With the context and importance of the given study determined, it is essential to analyse the available body of literature to comprehend the current situation with regards to AI in talent acquisition, especially in such a region as North East India. The literature review will analyse the past research on the use of AI in recruitment with emphasis on competency, effectiveness, ease of use and usefulness. The challenges and barriers to the adoption of AI will also be covered in this part, and so will the implications of the same in the regional context. The literature review will also synthesise the existing literature to identify the gaps and establish the theoretical framework of the current research and also provide a basis to comprehend how AI could be used to define the future of talent acquisition in North East India.

2. Review of Literature

The use of Artificial Intelligence (AI) in executing the talent acquisition process has drastically changed how enterprises look for and employ talent. As expected, recruitment has also been renovated with machines taking on the role of human recruiter and performing their job faster, efficiently and cost-effectively thanks to technologies such as AI. AI can automatically handle routine activities like resume filtering, scheduling interviews, and even conducting initial candidate evaluations, enabling HR specialists to take care of additional strategic facets of talent acquisition (Yadav et al., 2023).

It reduced time-to-hire, improved the accuracy of candidate matching and left recruiters with better talent. This, for example, was the case with Unilever: Using AI in their recruitment processes, automated interview analysis, and gamified assessments saves time and money to hire while providing a better candidate experience (Hu, 2023). In addition, AI-based tools can help organisations develop novel and more inclusive workforces by reducing the biases often associated with human recruiters (Liu & Murphy, 2022).

Studies have also shown that using AI allows organisations to handle many job applications more efficiently and provide more individualised and timely service for the candidate throughout the hiring process. This helps strengthen their employer brand, which is key to attracting top talents (Baratelli & Colleoni, 2022). Moreover, AI aids HR teams with the sourcing of candidates in a more accurate and faster manner by using machine algorithms to detect which candidates better match each role through data-based insights (Pillai & Sivathanu, 2020).

Competency is an important criterion for adopting AI. In other words, it is about the competence of your AI system and all HR professionals working towards optimising their talent acquisition process. Chen et al. (2021) apply AI tools to predict job candidates' competency levels, which helps make more optimised recruitment decisions by analysing factors like knowledge, motivation and job fit. Negatively, such AI systems' effective rollout and management (Vedapradha et al., 2023) is critical to their successful adoption. Organisations are more likely to adopt AI technologies that they believe are effective in improving recruitment processes. Potential benefits AI has produced in the talent acquisition process are presented below (Yadav et al., 2023). Perceived ease of use is the second major factor influencing its adoption. However, it is very hard for the user to decide how easily a system should use artificial intelligence. The Technology Acceptance Model, TAM, states that if a particular technology looks easy, it will likely be adopted by the users. User-friendly and light-loaded

AI tools that impose practically no effort on HR professionals are more commonly employed in talent acquisition (Damerji & Salimi, 2021). The perceived usefulness of AI technologies is another important factor affecting its adoption. HR practitioners value AI tools that deliver clear benefits, such as augmenting candidate similarity and intelligence, building a diverse team, and eliminating bias from the hiring process by providing them with what they seek in the AI community (Pillai & Sivathanu, 2020). Suppose AI systems are shown to be useful in meeting recruitment goals. In that case, organisations will implement those technologies more readily than if they believe human labor is the only way.

Competence is one of the key factors in implementing artificial intelligence in recruiting and making it functional. Organisations must validate the efficacy of their AI systems and HR professionals to ensure that they are competent in taking on more complicated recruitment functions. This data helps to predict what later competencies the candidates could possess: knowledge, motivation or scientific or professional behavior that may be necessary for organisational objectives. AI has been one of the key technological disruptions in HR because it helps gauge candidate competency and streamlines talent acquisition (Vedapradha et al., 2023) . AI augments talent acquisition by making processes like shortlisting resumes, scheduling interviews and conducting them more effective. While HR professionals are flagged for anything out of the ordinary and can go in directly to review a small number of candidates for full-time positions, this frees them up to spend more time on strategic work overall. Studies have found that using AI (Yadav et al., 2023) has been shown to increase efficiency in hiring by reducing the time taken to hire appropriate people and improving the candidate-job fit.The Technology Acceptance Model (TAM) posits that when AI tools are user-friendly and ease of use , it will foster HR teams to willingly use them. Further, increased ease of use is possible by enhancing the user experience and making AI tools more adaptable by talent acquisition (Venkatesh & Davis, 1996). Perceived usefulness also forms the list of essential factors in AI being adopted in recruitment processes. Candidates match and speed up the recruitment process, which are expected outcomes that AI tools deliver better, and the higher the chance they have to be integrated with talent acquisition workflows. Thus, the perceived usefulness of AI tools has an elaborative influence on HR professionals' intention to use these technologies, as one determinant is believed might lead to another and finally achieve a broader adoption of AI (Damerji & Salimi, 2021).

Competency is important in adopting and using AI for Talent Management. AI adoption significantly depends on the capabilities of HR professionals and AI systems to evaluate candidate competencies. For example, AI-powered tools that assess candidate competencies using multiple lenses (knowledge, skills, and job fit) allow smarter talent management decisions. We can see in the IT industry that AI systems adoption gets higher as long we are using competency (Vedapradha et al., 2023).AI streamlines numerous time-consuming talent management processes, like screening, interviewing, and candidate matching. How it Works The perceived effectiveness of these AI systems positively influences their adoption and usage, which are expected. Companies witness a more efficient and accurate method of hiring when they have better recruitment outcomes due to effective AI systems that ultimately promote talent management (Yadav et al.,2023). The ease with which AI systems can be used mediates the adoption of AI in talent management. Whether AI tools are intuitive and easy to implement makes a significant difference in whether HR professionals will find them accessible during recruitment. The Technology Acceptance Model (TAM) supports the proposition that easier-to-use systems will more likely be integrated into organisational routines (Gefen & Straub, 2000). Support for this easy usage allows Companies to automate huge parts of the tasks and, therefore, is a crucial ingredient in making AI work on the HR side. The more the perceived usefulness, the greater the chance of adoption and using AI in talent management. HR professionals are more inclined to adopt AI when they appreciate how it is a useful tool that enhances recruitment outcomes. The systems that organisations learned to use AI, if found useful or advantageous, would also help make more strategic talent management decisions by becoming more efficient and correcting biases in selecting candidates (Damerji & Salimi, 2021).

While there is a burgeoning body of literature on the impact of AI on talent acquisition globally, a large gap still exists in our understanding of how AI influences talent acquisition, specifically in regional contexts, especially within North East India. While much of the existing literature is limited to large technology-driven urban centres, with a focus on tribal societies like North East India, where HR practices would differ due to largely small-level industries and less technologically sound infrastructure and a diverse workforce further highlights an area that should have merited attention and requires unique Policy Initiatives.

2.1 Competency

AI is also relevant in the improvement of the competency of HR professionals in the management of talent acquisition tasks. Rukadikar et al. (2023) note that AI helps match skills, profile candidates, and simplify recruitment processes, so that the HR professionals will be able to handle more candidates with greater efficiency. With AI-assisted applications such as resume screening and predictive analytics, the competency of the talent acquisition team can be enhanced because they automate repetitive tasks and deliver data-driven insights (Reddy et al., 2025). However, the competency of AI systems themselves depends on the algorithms' quality, requiring HR professionals to continually adapt to new AI technologies to effectively utilise them (Kadirov et al., 2024).

2.2 Effectiveness

The success of AI in talent acquisition is realised in a number of ways. Research indicates that AI is an effective way of improving recruitment results because it lowers time-to-hire and increases the quality of the hires. The sourcing of candidates and initial screenings by using AI can be more objective and reduce human biases (Vedapradha et al., 2023). In addition, the use of AI, such as chatbots and machine learning algorithms, results in a more proficient and accurate match of candidates (Yadav et al., 2023). The efficiency of operations is enhanced by the capability of AI to automate the time consuming activities, and this frees up the HR professionals to concentrate on strategic decisions, thereby enhancing the effectiveness of the entire recruitment process.

2.3 Usability

The user-friendliness of the AI tools is vital towards the successful implementation of AI tools in talent acquisition. User-friendly AI systems that have an intuitive interface can be more easily integrated into HR's working processes. According to Rukadikar et al. (2023), the ease of use is the primary factor that encourages the use of AI in India and especially in IT firms, because the systems do not need much technical knowledge on the part of HRs. Ease of use also correlates with the technology acceptance model, where HR professionals' positive attitudes towards AI are shaped by their perceived ease of interaction with the tools (Fatin, 2025). The simpler the technology can be implemented and utilised, the more chances that it will be accepted and adopted into the HR practices (Alnsour et al., 2024).

2.4 Usefulness

The perceived usefulness of AI in talent acquisition is one of the main factors that determine its adoption. As it was shown by Reddy et al. (2025), AI has also increased the perceived usefulness of talent acquisition by largely improving the candidate experience, a major determinant of the success in the recruitment process. Moreover, the capability of AI to provide predictive analysis of candidate performance, workforce trends, and attrition rates will be of great use to the HR decision-makers (Kadirov et al., 2024). AI enhances hiring process effectiveness as well, because it offers data-driven insights, proving the HR to be more valuable to the organisations as a strategic asset. In North East India, where HR functions may still be evolving, AI's usefulness is becoming increasingly evident as it offers solutions to challenges like talent shortages and biases in traditional recruitment practices (Ibrahim & Hassan, 2019).

Further, existing research on AI adoption in recruitment has mainly discussed competency, effectiveness, perceived ease of use and perceived usefulness separately without understanding how these determinants influence or mediate the entire process and usage of such innovation, specifically in the context of HR sectors in North-East India. Even less is known about how these dimensions affect the role of AI in addressing regional challenges, such as skill shortages, industrial demands, and HR operational skills.

Therefore, there is an imperative requirement for a study in the local context to understand the competency, effectiveness, ease of use and usefulness of AI as technology volatile talent acquisition processes within North East India's HR sectors. Fulfilling this gap can provide a holistic view for academia and practitioners to design region-specific AI-driven solutions.

This paper underscores the crucial role of AI users in maximising the potential of AI. It concludes that specific adaptation of training programs is necessary to ensure that users are equipped with the skills needed to effectively leverage AI. The research will also contribute to the global discourse on AI in HR by highlighting the conditions that influence AI adoption in emerging economies. Rooted in health systems, sectors, and broader contextual complexities, this research could serve as a model for other regions facing similar challenges and provide valuable insights for international entities seeking to tailor their AI strategies to specific regional contexts. In this context, the study has the following objectives:

- To assess the skills needed for integrating AI into HR practices, especially managing employee lifecycles.
- To examine the gap between AI's perceived and actual impact on recruitment outcomes.
- To explore the usability and effectiveness of AI tools for HR professionals in talent acquisition.
- To offer recommendations for improving AI-driven talent acquisition in organisations in North East India.

The study has set the following hypotheses for testing:

Hypothesis 1: The application of AI positively impacts Talent Acquisition process.

Hypothesis 2: Competency, Effectiveness, Perceived Ease of Use, and Perceived Usefulness impact the adoption and actual usage of AI in Talent Acquisition.

Hypothesis 2a: Competency impacts the adoption and actual usage of AI in Talent Acquisition.
Hypothesis 2b: Effectiveness influences the adoption and actual usage of AI in Talent Acquisition.
Hypothesis 2c: Perceived Ease of Use affects the adoption and actual usage of AI in Talent Acquisition.
Hypothesis 2d: Perceived Usefulness impacts the adoption and actual usage of AI in Talent Acquisition.
Hypothesis 3: Competency, Effectiveness, Perceived Ease of Use, and Perceived Usefulness impact Talent Acquisition process.
Hypothesis 3a: Competency impacts in Talent Acquisition process.
Hypothesis 3b: Effectiveness influences in Talent Acquisition process.
Hypothesis 3c: Perceived Ease of Use affects in Talent Acquisition process.
Hypothesis 3d: Perceived Usefulness impacts in Talent Acquisition process.
Hypothesis 4: The adoption & actual usage mediate the effect of Competency, Effectiveness, Perceived Ease of Use and Perceived Usefulness on Talent Management.

3. Research Methodology

3.1 Research Design

This study employs a quantitative research approach, utilising a survey methodology to examine the impact of AI on personnel recruitment. We opted for a survey to gather comprehensive feedback regarding HR professionals' views and encounters with AI in their hiring processes. This method facilitates the collection of substantial data, which is essential for conducting a statistically robust analysis.

3.2 Sampling Plan

A study has been undertaken in North-Eastern India, focusing on HR professionals engaged in talent acquisition across various industries, including IT, Power Distribution, FMCG, and Healthcare. The survey collected responses using random sampling and Google Form from more than 328 HR professionals, aiming to provide a comprehensive and varied sample that demonstrates the impact of AI on talent acquisition within this geographical region.

3.3 Materials and Equipment

The data analysis and examination of research hypotheses are conducted using SPSS 29 and AMOS 24 software packages.

3.4 Experimental Procedures

Data is usually collected by following several important steps:
Development of the Survey: A comprehensive questionnaire containing validated scales to assess competency, effectiveness, perceived ease of use and usefulness of AI in recruiting is established. It also includes demographic questions so the surveyor understands who is completing this form better.

Pilot Testing: A small group of HR professionals is asked to complete the questionnaire to assess the clarity of survey questions and reliability. The pilot study was done to ascertain the clarity and reliability of the survey that was applied in this research. The survey was done on a small sample of 30 HR professionals in North-East India who gave their feedback on wording, structure, and time it takes to complete the survey. On this basis, the survey was revised to make it better. Reliability analysis using Cronbach's alpha showed excellent internal consistency across all factors (0.967 to 0.972), and factor analysis confirmed the suitability of the data for further analysis, with a KMO value of 0.937 and significant Bartlett's Test of Sphericity ($p < 0.001$). This pilot study made the final survey to be reliable and valid in the data collection.

Administration of survey: An email with a link to the finalised questionary is sent out to the chosen sample, and participants are given around two weeks to respond.

Data Collection: The online platform ensures that responses are collected in a manner that protects data integrity while maintaining confidentiality.

3.5 Data Analysis

The data is analysed by SPSS (Statistical Package for Social Science) version 29. Descriptive statistics calculate the demographic characteristics of the sample. With multiple regression and correlation, hypothesis testing is carried out to test the impact of competency, effectiveness, perceived ease of use and usefulness on AI adoption and talent acquisition process. In the second section, Mediation analysis is administered to measure the mediating effect of AI adoption and usage on independent factors with talent management outcomes. This is performed with AMOS 24 software.

3.6 Quality Controls and Assurances

Each of the following measures has been implemented to ensure the validity and reliability of the results:

Pilot Testing: Pilot testing of the survey instrument is conducted to help address problems with question wording or structure.

Reliability analysis: Cronbach's alpha is computed to test the internal consistency of each scale.

Validity: Content validity is guaranteed by expert reviews of the survey questions. Factor analysis is used for construct validity.

Cleaning data: Raw data is reviewed to remove incomplete or irrelevant answers.

3.7 Statistical Assumptions

To ensure the appropriateness of statistical techniques, it is essential to verify assumptions such as normality, linearity and homoscedasticity when conducting regression analysis. We used histograms to verify the distribution of the residuals in order to test the normality. Scatter plots were used to investigate the correlation between independent and dependent variables, which is linearity. Lastly, the test by White was used to test the homoscedasticity in that the residual variance was to be constant across all the levels of the independent variables. Our regression models were validated with the help of these diagnostic procedures.

4. Data Analysis

The research encompassed 328 human resources professionals from various industries in North East India, offering a comprehensive view of the sample's demographic profile. This information is crucial when considered alongside the study itself, as it illustrates the potential impact of artificial intelligence on talent acquisition.

Table 1: Demographic profile of respondents

Age					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	20-30	81	24.7	24.7	24.7
	31-40	91	27.7	27.7	52.4
	41-50	68	20.7	20.7	73.2
	51-60	88	26.8	26.8	100.0
	Total	328	100.0	100.0	
Gender					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Male	229	69.8	69.8	69.8
	Female	99	30.2	30.2	100.0
	Total	328	100.0	100.0	
Experience					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	1-10 Years	82	25.0	25.0	25.0
	11-20 Years	94	28.7	28.7	53.7
	21-30 Years	107	32.6	32.6	86.3
	31-40 Years	45	13.7	13.7	100.0
	Total	328	100.0	100.0	
Education Level					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	MBA	243	74.1	74.1	74.1
	MCom	78	23.8	23.8	97.9
	PhD	7	2.1	2.1	100.0
	Total	328	100.0	100.0	

Source: Author's collection.

The survey respondents' ages were distributed as follows: 24.7% were 20-30 years old, 27.7% were 31-40 years old, 20.7% were 41-50 years old, and 26.8% were between 51 and 60 years old. Table 1 illustrates a wide range of ages from under 30 to 60, suggesting a diversity of experiences and perspectives among HR professionals. The second-largest group, comprising 26.8% of the sample, was the 51-60 age bracket. This well-balanced distribution offers a comprehensive insight into how AI impacts individuals at various stages of their careers.

One of the most notable aspects of this survey is the gender distribution in Table 1, which includes 69.8% male and only 30.2% female respondents. This signifies that this is a male-majority sample, resonant with the locality's overarching HR professional demographic. As a profession that employs more men than any other white-collar field, a higher percentage of male HR practitioners could be shaping the views around AI adoption and utilisation, which may shed light on some of the gender-specific obstacles and advantages in talent acquisition.

For Professional experience in table-1, the total count was as follows: 25.0% experienced 1–10 years, 28.7% experienced 11–20 years,32.6% experienced 21–30 years, and13.8% experienced 31–40 years. Cumulatively, more than three-fifths of the respondents (61.3%) have 11–30 years of HR experience, suggesting a sample with considerable professional heritage and capability in their chosen discipline. This wealth of experience is essential for making accurate judgments about AI's relative value and feasibility in talent acquisition.

The educational background in table -1 of the respondents reveals that 74.1% are MBAs, 23.8% MComs, and only 2.1% hold a PhD. The large number of MBA holders implies a good level of overall managerial and business training among the HR professionals, which is important to consider when evaluating these masterminds' competence and readiness for deploying AI technologies. This small proportion of PhD holders is consistent with the emphasis on practical experience in this study and professional rather than more academic degrees held by most respondents.

Table 2: KMO and Bartlett's Test

Test Statistics		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.937
Bartlett's Test of Sphericity	Approx. Chi-Square	25651.589
	df	2415
	Sig.	<.001

Source: Author's collection.

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity in Table 2 provide important information based on data collected from HR professionals in North East India, specifically regarding the impact of AI on talent acquisition. The KMO value is 0.937, which means the sample was adequately large. Values near 1.0 indicate that the data is appropriate for factor analysis. Bartlett's Test of Sphericity also supports this appropriateness with an approx. Chi-square value of 25,651.589, degrees of freedom (df) = 2,415 and Sig. of less than 0.001. This result is meaningful as it indicates strong enough correlations among the items to conduct a factor analysis.

Table 3: Rotated Component Matrix

Component Matrix[a]	**1**	**2**	**3**	**4**	**5**	**6**	**7**
TA10	.907						
TA5	.906						
TA8	.897						
TA7	.896						
TA3	.887						
TA6	.883						
TA4	.882						
TA9	.881						
TA1	.877						
TA2	.876						
EU9		.901					
EU7		.901					
EU2		.897					
EU1		.896					
EU6		.892					
EU8		.891					
EU3		.889					
EU4		.876					
EU5		.870					
EU10		.869					

Component Matrix[a]	**1**	**2**	**3**	**4**	**5**	**6**	**7**
AAU3			.899				
AAU1			.897				
AAU5			.897				
AAU6			.895				
AAU10			.890				
AAU9			.889				
AAU7			.883				
AAU2			.880				
AAU4			.872				
AAU8			.869				
U7				.901			
U2				.901			
U6				.891			
U4				.891			
U1				.890			
U10				.887			
U3				.882			
U9				.882			
U8				.874			
U5				.867			
C5					.902		
C4					.899		
C10					.896		
C6					.885		
C2					.884		
C7					.884		
C9					.881		
C1					.881		
C8					.880		
C3					.876		
AAA5						.898	
AAA10						.896	
AAA3						.889	
AAA9						.887	
AAA7						.884	
AAA8						.881	
AAA6						.876	
AAA1						.872	
AAA2						.868	
AAA4						.860	
E2							.899
E8							.887
E6							.884
E4							.882
E5							.881
E10							.874
E1							.873
E3							.864
E7							.860
E9							.855

Note: Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization, and a. Rotation converged in 6 iterations.

Source: Author's calculation.

Results show seven components based on the Rotated Component Matrix, which was obtained by applying Principal Component Analysis with Varimax rotation to explain the variance in data. Different factors within survey data are represented as components, and items load strongly on certain components.

Table 4: Total Variance Explained

	Rotation Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**
1	8.016	11.452	11.452
2	8.007	11.439	22.890
3	7.953	11.362	34.252
4	7.945	11.350	45.601
5	7.941	11.344	56.946
6	7.863	11.233	68.178
7	7.734	11.048	79.227

Extraction Method: Principal Component Analysis.

Source: Author's calculation.

The combined variance in table-4 accounted for by the seventh component is substantial. The first component tells you 11.452% of the variance, whereas the second component will have something like 11.439%. For instance, for the third, fourth, fifth, sixth and seventh components, they explain 11.362%, 11.350%, 11.344%, 11.233% and 11.048% of variance accordingly. Together, these components explain 79.227% of the total variance, which suggests a stable factor structure and accounts for high common covariance.

Table 5: Reliability Statistics of different factors

Reliability Statistics		
Factors	**Cronbach's Alpha**	**No. of Items**
AI Application Awareness	0.969	10
Competency	0.970	10
Effectiveness	0.967	10
Ease of Use	0.971	10
Usefulness	0.971	10
Adoption	0.972	10
Talent Acquisition	0.971	10

Source: Author's calculation.

The survey tools in this study were evaluated for their reliability by Cronbach's Alpha, which tests the consistency of the survey items. A high Cronbach's Alpha value indicates that the questions inside a factor are related to one another and that these answer the same question, proving that the survey items measure what they intended to provide.

AI Application Awareness: This factor has a Cronbach's Alpha of 0.969, suggesting an optimal consistency.
Competency: "Competency" is also highly reliable (Cronbach's Alpha = 0.970). This indicates that the 10 questions used to survey respondents' AI talent acquisition competence are reliable.
Effectiveness: The Cronbach's Alpha is 0.967, suggesting high reliability of the measure on a scale from 1 to 10 for both "Effectiveness" factors.
Ease of Use: The Cronbach's Alpha of the "Ease of Use" factor gets 0.971, which also shows excellent reliability.
Usefulness: Also, the "Usefulness" factor has high reliability (Cronbach's Alpha: 0.971). The 10 questions that gauge the utility of AI in hiring are therefore reliable- they provide an accurate measure consistently.
Adoption: The most consistent section in the questions of AI tool usage and adoption with Cronbach's Alpha 0.972:

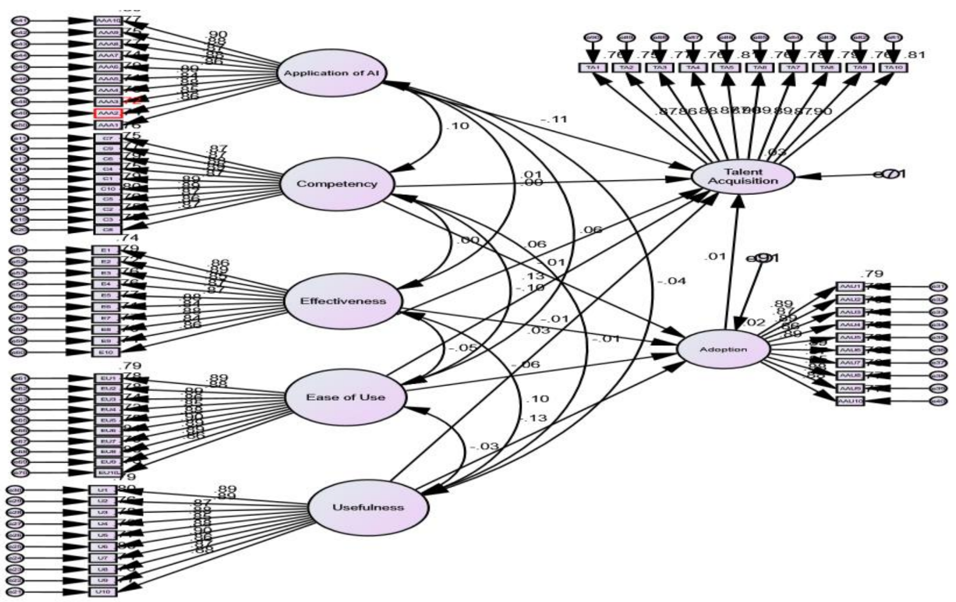

Figure 1: Structural Equation Model

Table 6: Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	2452.273	--	--
DF	2325.000	--	--
CMIN/DF	1.055	Between 1 and 3	Excellent
CFI	0.995	>0.95	Excellent
SRMR	0.033	<0.08	Excellent
RMSEA	0.013	<0.06	Excellent
PClose	1.000	>0.05	Excellent

Source: Authors' calculation.

The CMIN value (Chi-Square) is 2452.273, with a DF of 2325 corresponding to the model. The value of DF (degrees of freedom) 2325.000 indicates the number of independent values or parameters which can vary in the statistical model. It is applied in computing chi-square statistic (CMIN) that determines model fit. The larger the DF, the more complex the model and the more variables or data points, which implies that the model can account variance in the data. The DF of 2325 in this study shows the complexity of the model to be utilised in analysing data of North East Indian HR professionals. Although Chi-Square alone can sometimes be sensitive to sample size and may not always provide the best indication, the CMIN/DF, where CMIN is the goodness of fit statistics term compared to DF, helps with this.

The CMIN/DF Ratio (1.055 is very good, with the ideal range being between 1 and 3). It indicates that the model complexity and data are well-defined; hence, it does a great job representing the relationships in the study.

According to the CFI value of 0.995, This is also more than the minimum threshold of 0.95 recommended in the literature37 38. This corresponds to a model doing a very good job fitting the data, significantly better than the baseline (or starting) model.

The SRMR value is 0.033, well below the recommended maximum of 0. That is a good fit since SRMR measures the discrepancy of real vs. expected values; thus, smaller denotes a better fit.

The RMSEA is 0.013, comfortably below the accepted cut-off value of 0.06. This means that the model fits the underlying data structure extremely well.

The PClose, as evidenced by 1.000, is much higher than the suggested minimum value of 0,05. This is a test to see if RMSEA is small enough, and PClose is higher, which means a better fit of the model.

The model fit measures indicate that the proposed evaluation framework to measure the Impact of AI in Talent Acquisition is excellent. Results are in recommended ranges, suggesting a well-fitting model that accurately represents the data and relationships being investigated. It is critical to note that these analyses were conducted within a single strong model fit construct, confirming the validity and reliability of our findings on AI event (1) influencing competence, effectiveness, ease-of-use and utility in talent acquisition.

The goodness of fit statistics shows that the model fits well with the data; the model fit indices, including CMIN/DF (1.055), CFI (0.995), SRMR (0.033), and RMSEA (0.013), indicate that the model is an excellent fit. This large fit shows that the constructs that are being measured (e.g., competency, effectiveness, ease of use, and usefulness) have good representations in the model and therefore construct validity. The model shows that variables are related as the hypothesised and the indices are validating the constructs. While the provided table-6 doesn't directly provide information to assess discriminant validity (such as cross-loadings in factor analysis or Average Variance Extracted (AVE) comparisons), the high CFI and low RMSEA values imply that the model differentiates between constructs effectively. An adequate model will be less likely to overlap constructs, which indirectly supports discriminant validity, because it implies that constructs are not too similar.

Hypothesis 1: The application of AI positively impacts Talent Acquisition process
Hypothesis 2: (a) Competency, (b) Effectiveness, (c) Perceived Ease of Use and (d) Perceived Usefulness impact the adoption & actual usage of AI in Talent Acquisition
Hypothesis 3: (a) Competency, (b) Effectiveness, (c)Perceived Ease of Use and (d) Perceived Usefulness impact Talent Acquisition process.

Table 7: Standardised Regression Weights of Model

Standardised Regression Weights: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P	Interpretation
Adoption and Actual Usage	<---	Competency	-0.009	-0.123	0.106	0.869	H2a = Rejected
Adoption and Actual Usage	<---	Ease of Use	-0.06	-0.172	0.048	0.259	H2c = Rejected
Adoption and Actual Usage	<---	Usefulness	-0.132	-0.243	-0.015	0.027	H2d = Accepted
Adoption and Actual Usage	<---	Effectiveness	-0.008	-0.121	0.102	0.881	H2b = Rejected
Talent Acquisition	<---	Application AI	-0.109	-0.223	0.008	0.067	H1 = Rejected
Talent Acquisition	<---	Competency	0.006	-0.11	0.121	0.922	H3a = Rejected
Talent Acquisition	<---	Effectiveness	0.056	-0.044	0.167	0.27	H3b = Rejected
Talent Acquisition	<---	Ease of Use	0.132	0.021	0.244	0.026	H3c = Accepted
Talent Acquisition	<---	Usefulness	0.027	-0.075	0.142	0.598	H3d = Rejected

Source: Authors' calculation.

Table 8: Squared Multiple Correlations of Model

Parameter	Estimate	Lower	Upper	P
Adoption	.021	.001	.044	.038
Talent Acquisition	.031		.055	.094

Source: Authors' calculation.

Hypothesis 1: The use of AI impacts talent acquisition efficiency positively.

The data presented in this table indicates that the standardised regression coefficient for the impact of AI on talent acquisition is -0.109, with a corresponding p-value of 0.067. Given that this p-value exceeds the conventional significance threshold of 0.05, we are compelled to dismiss hypothesis H_1.

Consequently, within this particular sample, the findings suggest that AI does not exert a statistically significant positive influence on the process of talent acquisition.

Hypothesis 2: (a) Competency, (b) Effectiveness, (c)Perceived Ease of Use, and (d) Perceived Usefulness impact the adoption & actual usage of AI in Talent Acquisition

The effect of competency on AI adoption has a regression weight of -0.009 (p = 0.869); thus, Hypothesis 2a is also rejected.

The regression weight for the impact of Ease of Use on AI adoption is -0.060 (p = 0.259); therefore, Hypothesis 2c was also rejected.

Its usefulness greatly affects adoption, and the regression weight is -0.132 (p = 0.027). As such, Hypothesis 2d (based on the Perceived Usefulness of AI) is supported, demonstrating that the more useful AI solutions are perceived to be in recruitment processes, the more liable companies will opt to adopt these within a chosen talent acquisition function.

Contrary to the hypothesised positive relationship between AI adoption and effectiveness, the regression weight for effectiveness on AI adoption was -0.008 (p = 0.881), which led to a rejection of Hypothesis 2b.

Hypothesis 3 : Competency, Effectiveness, Perceived Ease of Use and Perceived Usefulness directly affect the talent acquisition process.

Hypothesis 3a, relating to competency influence on talent acquisition, is not supported as the weight of its regression coefficient is 0.006 (p = 0.922).

No support was found for Hypothesis 3b with the non-significant regression weight of Effectiveness on talent acquisition (0.056, p = 0.270).

In the case of Talent acquisition, ease of use also has a positive and significant effect with the regression weight 0.132 (p = 0.026). Thus, Hypothesis 3c is supported, suggesting that perceptual ease of use supremely affects the talent acquisition process.

Hypothesis 3d is also rejected because the regression weight of usefulness for talent acquisition is insignificant (0.027, p = 0,598).

R-Square values indicate the proportion of variations in outcomes that are explained by factors included in the model

The R-Square value for AI adoption is 0.021, indicating that only 2.1% of the variance in AI adoption behaviour can be explained by competency, effectiveness, perceived ease of use, and perceived usefulness. This could mean that others can have a larger impact on AI adoption.

We find a low value of the R-Square for talent acquisition (0.031), suggesting that AI and adoption factors explain only 3.1% of the variation in talent acquisition. This indicates that further variables need to be taken into account to get a thorough understanding of the effect on Talent Acquisition.

Hypothesis 4: The adoption & actual usage mediate the effect of Competency, Effectiveness, Perceived Ease of Use and Perceived Usefulness on Talent Management.

Table 9: Impact of Competency, Effectiveness, Perceived Ease of Use, and Perceived Usefulness on Talent Management Outcomes

Parameter		**Estimate**	**Lower**	**Upper**	**P**	**Interpretation**
Indirect Effect						
Ind1	Competency to Talent Acquisition Via Adoption	0	-0.01	0.007	0.841	H4ai=Rejected
Ind2	Effectiveness to Talent Acquisition Via Adoption	0	-0.011	0.007	0.774	H4bi=Rejected
Ind3	Perceived Ease of Use to Talent Acquisition Via	-0.001	-0.017	0.006	0.577	H4ci=Rejected

Parameter		Estimate	Lower	Upper	P	Interpretation
Ind4	Adoption Perceived Usefulness to Talent Acquisition Via Adoption	-0.002	-0.024	0.013	0.706	H4di=Rejected
Total Effect						
TInd1	Total Effect of Competency to Talent Acquisition Via Adoption	0.006	-0.119	0.13	0.916	H4aii=Rejected
TInd2	Total Effect of Effectiveness to Talent Acquisition Via Adoption	0.063	-0.051	0.184	0.279	H4bii=Rejected
TInd3	Total Effect of Perceived Ease of Use to Talent Acquisition Via Adoption	0.136	0.022	0.251	0.025	H4cii=Accepted
TInd4	Total Effect of Perceived Usefulness to Talent Acquisition Via Adoption	0.026	-0.08	0.145	0.63	H4dii=Rejected

Source: Authors' calculation.

The results revealed a non-significant indirect effect of 0, with a p-value of .841, indicating no substantial impact. Consequently, Hypothesis 4ai was not supported and thus dismissed. The results showed an indirect effect of 0 ($p=0.774$), suggesting no significant mediation. Consequently, Hypothesis 4bi is not supported. The indirect effect, with a value of -0.001 and a p-value of 0.577, was found to be statistically insignificant as a mediation effect. Consequently, the evidence does not support Hypothesis 4ci. The mediation effect lacks statistical significance, as evidenced by the indirect effect of -0.002 ($p = 0.706$). Consequently, we do not find support for Hypothesis 4di.

The overall effect is 0.006 ($p = 0.916$) of Competency to Talent Acquisition Via Adoption, indicating no statistically significant. Consequently, we do not accept Hypothesis 4aii.The total effect of Effectiveness to Talent Acquisition Via Adoption is 0.063, which yields $p = 0.279$, indicating that the total effect is not significant. Therefore, we fail to support Hypothesis 4bii. The Total Indirect Effect of Ease of Use on Talent Acquisition through Adoption is 0.136, with a p-value of 0.025, leading to the acceptance of hypothesis H4cii. The overall effect is 0.026 (p-value = 0.63), suggesting no substantial total impact. Consequently, Hypothesis 4dii is not supported.

5. Results and Discussion

The research findings indicated that neither AI systems' competency nor HR professionals' expertise had a statistically significant direct impact on the adoption of AI in talent acquisition. The standardised regression coefficient for competency exhibited the statistically lowest values of any (-0.009, $p = 0.869$), suggesting that whilst AI-driven recruitment did not demonstrate competence as crucial, it did not influence the adoption behaviour pattern in this study. This outcome can be attributed to a deficiency in technical training amongst HR professionals, highlighting the necessity for enhanced skill development prior to widespread implementation of AI systems.

The notion of perceived AI system efficacy did not significantly influence AI adoption rates. This rendered the hypothesis inconsequential, as we were unable to incorporate effectiveness as a direct predictor of AI utilisation in recruitment (regression weight -0.008, $p = 0.881$). It is conceivable that even if AI were to substantially enhance recruitment outcomes—which it has the capacity to do far more effectively than other software, as we have repeatedly emphasised over the years—this alone was insufficient to prompt a shift in usage at present.

The adoption of AI in talent acquisition was not primarily driven by its ease of use. The positive coefficient ($\beta = +0.132$; $p=0.026$) suggests that AI tools, which are more intuitive and simpler to implement are better integrated into HR practices. The willingness of HR professionals to utilise AI systems was significantly influenced by the user-friendliness of the AI technology during the period when adoption and usage were of interest. As anticipated, AI solutions that were more human-friendly and straightforward to deploy were more readily incorporated into HR processes.

The study also revealed that perceived usefulness significantly impacted AI adoption (regression weight = -0.132; p=0.027). This finding suggests that HR professionals were largely supportive of purpose-driven AI or AI for positive outcomes — implementing technology in areas where it could offer practical advantages, such as reducing bias, improving the match between candidates and jobs, or streamlining the recruitment process.

The analysis of mediation showed that the adoption and utilisation of AI acted as a mediator in the connection between ease of use and outcomes in talent acquisition. Specifically, the overall unreported mediation effect on talent acquisition was found to be 0.136 (p = 0.025). This finding suggests that as AI tools become more complex to use, human resources professionals face greater challenges in implementing effective talent acquisition strategies.

The R-squared values for AI adoption (0.021) and talent acquisition (0.031) indicate that, whilst ease of use and perceived usefulness impact these constructs, additional undiscovered or unexplored factors may also play a role. This finding suggests that additional research would be valuable to identify other factors influencing AI adoption, particularly within the North East Indian context.

In this study, the Hypothesis 2d (Perceived Usefulness) and Hypothesis 3c (Perceived Ease of Use) were accepted. Hypothesis 2d was validated with a significant negative regression coefficient (p = 0.027), and it was shown that the perceived usefulness has a positive effect on AI adoption. Equally, the Hypothesis 3c was accepted and the regression weight (beta = 0.132, p = 0.026) was significant indicating that ease of use is an important factor in improving the talent acquisition process.

These results emphasise the importance of ease of use and perceived benefits in relation to AI adoption and its eventual effect on talent acquisition. More generally, HR professionals preferred to use AI if the tools were simple or intuitive to ease in getting used to. This is indicative of a high hurdle caused by the sophistication of AI systems, hence, reducing these features could spark widespread adoption in HR practices. Second, the practical application AI has as a tool in areas of HR—such as its capacity to make sourcing more efficient without bias or improve matching between candidate and role—also determined whether these technologies were being implemented by different types of HR practitioners.

On the flip side, competency and effectiveness expected to have a major impact did not yield statistically significant effects on AI adoption or recruiting talent. While this points to the future potential of AI in HR, it also implies that possibly HR professionals in North East India are not yet technically equipped or trained in various aspects of AI thereby lowering the effectiveness of the technology. Also, AI tools might not yet be tuned to solve the unique problems of the HR sector in the region.

For AI to be effectively integrated into successful recruitment processes, HR professionals need solutions that are both efficient and user-friendly. This study reveals a significant gap between AI's potential and its practical implementation in business. Whilst global trends suggest AI has transformed HR practices, evidence from North East India presents a contrasting perspective. Moreover, although ease of use emerges as the primary factor driving AI adoption among this demographic, its apparent simplicity masks underwhelming results in terms of competency and effectiveness. This underscores a marked disparity between HR professionals' expectations of AI and the current capabilities available in the market.

The findings suggest that artificial intelligence can significantly enhance human resources practices when it aligns closely with the expertise of decision-makers and addresses local requirements. This research challenges the widespread belief that AI should be implemented uniformly across all contexts. Such a standardised approach may not be entirely appropriate, particularly in areas like North East India where technological infrastructure is limited.

The findings lend credence to the Technology Acceptance Model (TAM), which posits that perceived ease of use and perceived usefulness positively affect technology adoption. As initially noted by Venkatesh and Davis (1996) and recently corroborated by Damerji & Salimi (2021), systems that are inherently user-friendly are more likely to be integrated into routine organisational activities, a notion this study strongly confirms. Moreover, in line with Pillai & Sivathanu (2020) and earlier research, perceived usefulness emerges as a crucial factor in AI adoption for HR; organisations are more inclined to implement these tools when they recognise their utility!

Unlike previous research conducted in more developed and technologically advanced areas, this investigation suggests that competence and efficacy, despite being frequently emphasised in academic literature, may not be as crucial in regions with less mature technological infrastructure. Vedapradha et al. (2023) found that effectiveness is contingent upon the level of HR readiness and technological sophistication in a given area. The findings of this study corroborate this notion, emphasising that the impact of AI can be limited when there is insufficient skill or training to fully harness its capabilities.

6. Conclusion

The results of this research study underline the significance of contextualised knowledge and localisation of the implementation of Artificial Intelligence (AI) in talent acquisition especially in such a region as North East India. Although AI may provide considerable benefits in the efficiency of recruitment, the ease of use and the perceived usefulness of the AI tools are more valued by HR professionals in this region than technical competencies. This implies that organisations should emphasise on the simplification of AI systems and training programs to the HR professionals that will make them more competent in using the tools. To HR managers, embracing an AI that is easy to navigate, user-friendly and able to show tangible, immediate returns will be central to unlocking the full potential of AI-driven recruitment.

The significance of the study in context of literature is that it fills the knowledge gap about the adoption of AI in the context of North East India, which forms a socio-economic and cultural background. The analysis questions the wider, global view in which competency and effectiveness are the main forces behind the use of AI. Rather, it demonstrates that ease of use and perceived usefulness is more important. The future study is to explore further regional impacts that can influence the AI adoption, including access to infrastructure, social-cultural acceptance of AI in the HR process, and the changing nature of AI technologies across various industrial sectors. Furthermore, the investigation of the indirect effects of AI on the results of the talent acquisition, especially those covering diversity and inclusion, should be conducted.

The AI revolution in talent acquisition can lead to wide-ranging implications on society, especially to increase the inclusivity and minimise bias during the hiring process. With the increased use of AI tools in the region, they can change the traditional ways of recruitment which could have been based on gender, ethnic or socio-economic background biases. This may lead to the more diverse and equitable hiring. Nevertheless, the social adoption of AI will need to overcome the objections related to the issue of data privacy, the prospects of algorithmic bias, and the consequences of automation on employment. Policies ought to be made to make sure that AI technologies are applied in a responsible way especially in areas that lack advanced technological infrastructure.

The factors that contribute to the successful outcomes of AI in various industries and geographical areas and the transformation of the adoption behaviour of HR professionals over time, should be the areas of future studies. The paper indicates that the use of AI is low in North East India, but the increased attention to the perceived ease of use and utility could result in its increased implementation in the future. In this regard, there is a need to do longitudinal studies to understand the long-term effect of AI on recruitment practices, and talent management. In addition, the creation of region-specific AI tools to meet the needs of a particular region and sufficient training of HR professionals can improve the efficiency of AI implementation and help develop sustainable talent acquisition practices.

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