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The Role of AI Trust Factors in Enhancing Talent Acquisition Processes: A Study on HR Professionals Across Various Sectors

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Abstract

The introduction of artificial intelligence (AI) into human resource management has given a new face to talent acquisition, which will lead to more streamlined and smarter methods to search for available candidates. However, the growth of AI in recruitment depends to a large extent on how much confidence HR professionals invest in these technologies. In an increasingly AI-powered world, how can we help HR professionals to be confident enough with these systems that they actually improve their talent acquisition processes rather than hinder them? This is the context of the present study seeking to provide insight into this trust. The purpose of this study is to investigate the effect of trust factors in AI—in terms of reliability, credibility, technical competency, and relative advantage—on HR professionals' trust in AI and how a secondary process will impact talent acquisition performance across different industries. It was a quantitative survey involving 331 HR professionals from various sectors like IT, power distribution, FMCG, and healthcare. Structural equation modelling (SEM) was applied to examine the direct and indirect effects of perceived AI trustworthiness factors in predicting trust toward AI and talent acquisition outcomes. Items measuring the AI trust factors demonstrated good internal consistency overall. Still, none of the AI trust factors had a statistically significant direct effect on either trust in AI or the effectiveness of talent acquisition processes. Interesting as it may sound, this means that some of the traditional trust related factors might not be enough by themselves to accelerate AI adoption in HR. This work points to a requirement for a more holistic strategy towards developing trust in AI within the HR context, taking into account other factors like organizational culture and personal technology experiences. This four-part series on the dynamics of AI and recruitment is pivotal if AI is to be a more effective and efficient element of global talent acquisition. Findings from this research highlight the need to focus on the complexity of adoption in AI to truly realize itstransformative potential in transforming HR practices.

Keywords: AI Trust Factors, Talent Acquisition, HR Professionals, Recruitment Processes

1. Introduction

Artificial intelligence (AI) in recruitment - a game changer in how human resource management translates to talent acquisition, specifically: with greater efficiency, accuracy and strategic insights. However, how seamless AI and the recruitment industry can be reality depends on one thing: whether or not HR professionals trust such systems. Reliability, credibility, technical competence and relative advantage of AI are some variables which determine beneficiary trust in AI. Although having a potential for gains, the exploration of how these trust factors inter-relate and subsequently influence AI adoption and the generic processof workforce resourcing, still needs to be made clear.

Existing research highlights the importance of trust in the adoption of AI-based technologies within HR processes. Studies argue that the trust of HR professionals in adopting AI systems increases if they perceive them as reliable or technically competent (Kaplan et al., 2021; Hmoud & Varallyai, 2020). Finally, the credibility of AI (which includes transparency as well as an ethical dimension) is crucial to win over HR leaders (Nyathani, 2022). However, it also shows that the overlap between trust factors and how they influence talent acquisition across sectors needs to be better understood and needs to be researched.

To overcome this limitation, this study aims to empirically examine the influence of the antecedents of AI trust in the intervention process between antecedents and AI trust. This study will seek to investigate how trust in AI can improve the efficiency and effectiveness of recruitment by encouraging reliability, credibility, technical competence and relative advantage. This study is novel as it presents a sector-specific analysis of the attitudes of HRs towards AI in North East regions where IT, Healthcare, FMCG and power distribution are predominant.

As these strategic HR functions continue to be front-runners in their reliance on AI, it is vital to recognize the role of trust dynamics in enabling optimal integration of AI. Given how it makes use of new developments in AI technology, ethical AI frameworks, and industry insights, this paper is timely and impactful in providing a fresh perspective on the subject of talent acquisition. Not only will the results fill some of the existing knowledge gaps, but they can also be used to tailor the practices to build trust in AI for recruitment across different industries.

Artificial intelligence (AI) and human resource management, especially in recruiting practices, form a significant body of scholarship. Previous studies maintain that key elements of AI trust—security, credibility, competency and perceived benefits strongly influence the trust and adoption intention of HR professionals over AI technologies. For example, research such as Pillai and Sivathanu (2020), affirm that the reliability of AI and its technical competence has a significant positive effect on trust in AI, and this also directly affects how efficiently recruitment processes run. Kaplan et al. Setting the foundationThough reliability, which is the consistent performance based on a minimal number of errors, is highlighted by authors such as Vratskis et al. (2021) to generally be of fundamental importance in order to gain trust from HRleaders so they would welcome AI in talent acquisition.

According to empirical results, the trust of HR professionals depends heavily on AI reliability and decides on one dimension (Kaplan et al., 2021). Desai et al. Trust can be shattered, and if AI falls short in these domains, Roth points out, "it will not be used for critical HR functions.
- Aronczyk, Naomi. (2012) On the other hand, the domain of credibility, specifically comprising elements such as transparency and ethical considerations, has been shown to have a significant effect on AI adoption (Hmoud & Varallyai, 2020). Forbus, 2016; Murdick & Ross, 1995) (Pillai & Sivathanu, 2020), and are critical factors in AI adoption for HR practices according to studies grounded on frameworks like TOE.

Despite these findings, gaps still need to be found in understanding how trust elements such as those herein have more nuanced effects across industries. Although previous studies have focused on examining the relationship between trust in AI and its determinants, such as reliability and credibility, the impacts of the technical competence of AI and the relative advantage of AI on trust in AI across diverse HR contexts need to be more examined. Overall, the literature on AI and HR calls for more studies so we can better understand the links between AI inferences (e.g. scores and recommendations), trust in these, and attitudes towards those that make use of them.

In each of these areas, current AI advances - from greater algorithmic transparency to ethical AI deployment frameworks - offer the prospect of real remedy. Advances in machine interfaces and potential options for real-time feedback may improve reliability, encourage use, and drive trust (Desai et al., 2013). The implemented strategy in AI, as shown in similar industrial case studies on best practices like Unilever, provides insights into the possible levels of transformation of recruitment efficiency and candidate experience by performance gainsstemming from AI (Hu, 2023).

In this paper, we address the gaps above by conducting process-based research to investigate the influence of AI trust factors in talent acquisition stages in different domains. Building on recent advances in AI technology and tackling ethical and operational challenges, this article attempts to answer some of these questions by offering a foundational understanding of the role of AI trust factors. These results will help streamline AI implementation in HR, boost recruitment effectiveness, and benefit from a long-term view of human resource management.

The main research question that the current study aims to answer is: "How do some AI trust factors such as reliability, credibility, technical competence or relative advantages shape the effectiveness of talent acquisition processes across diversified sectors? This study investigates the direct and mediated effects of these trust factors on HR professionals' trust in AI, their trust- induced engagement behaviours, and the influences thereof on their talent management practices, particularly surrounding recruitment. We subsequently investigate the mediating effects of trust and attitude in these relationships.

On the other hand, the second specific aims to determine how AI trust factors affect trust in AI (at talent acquisition), and then assess the direct impact of these trust factors on the talent acquisition process, examine the relative advantage influences on HR professionals' attitudes toward AI (to find out whether a significant relationship); and examine how trust and attitude mediate paths from AI trust factors to talent acquisition outcomes. In doing so, the study aims to offer richer evidence of why trusting AI might expedite improved recruitment outcomes.

An important notion behind this study is the intended holistic perspective by mixing exploratory and confirmatory factor analyses which are used to build a strong model of AI trust determinants in talent acquisition. By interviewing HR professionals across diverse sectors - IT, power distribution, FMCG, and healthcare - the study has focused on the nitty-gritty of each sector, which might otherwise be lost in a generic overview. In addition, this research builds upon the latest advances in both AI technology and ethical perspectives to ensure that the findings are timely and prescriptive across current HR applications.

Although the partial findings of this investigation are not exhaustive, they demonstrate that reliability and technical competence are very important in creating trust in AI, and credibility and relative advantage play critical roles in the attitudes of HR professionals towards using AI for hiring. These insights are significant at a global level, reminding us of the increasingly urgent need for creating trustworthy, transparent, and ethically aligned AI solutions that generate trust in our ability to optimize talent acquisition effectively. However, the significance of this research extends beyond the direct value that it offers here and now and is evident in what it could mean for better practices and policies around integrating HR with AI when seeking recruitment successes as new levels of the standard to manage talent more efficiently and successfully throughout the world.

2. Research Methods

2.1 Research Design

This study uses a quantitative survey-based research design to examine the impact of AI trust factors on talent acquisition processes. Through an online survey, the study captures information from HR professionals in diverse sectors to better understand how AI trust dimensions influence recruitment performance, both directly and indirectly.

2.2 Sampling Plan

We chose HR professionals from various sectors like IT, Power Distribution, FMCG and Healthcare professionally operating in the North East. Based on purposive sampling, a sample of 331 HR professionals was taken from the three sectors, ensuring that this sample representatively present within each one. Respondents were asked to respond to an online survey which aimed to understand their views about specific AI Trust Factors and the important role they play in shaping talent acquisition processes.

2.3 Materials and Equipment

As the approach is survey-based this study did not require any materiel and no laboratory equipment. Data collection occurred digitally using survey platforms and data were analyzed using statistical software. An online survey was created, distributed by the Google form platform to quickly collect and manage data.

2.4. Experimental Procedures

A 20-minute online survey was created to solicit participant responses which included closed- ended and Likert-scale questions. The survey was specifically designed to measure four key AI trust factors:(1)dependability,(2)confidence,(3)technical ability, and(4)competency. Finally, questions were prepared to measure the confidence respondents had in AI and their general disposition on AI aiding in the hiring process. The survey link was shared via email and professional networks in order to reach as many as possible within the targeted sectors.

2.5. Data Analysis

Results Data collected from the surveys were analysed using the SPSS and AMOS software. The exploratory factor analysis (EFA) was run in SPSS to uncover the different constructs underlying the AI trust factors. A confirmatory factor analysis (CFA) was later conducted using AMOS to determine if the identified factor structure in the EFA could be replicated. The relationships among the AI trust factors, trust in AI, and talent acquisition outcomes were investigated through structural equation modeling (SEM). Path analysis was performed to test the hypotheses, and we investigated direct and indirect relationships among the variables.

Quality Control Several measures were implemented to ensure quality control of the results. We pre-tested the survey instrument on a small sample of HR professionals to better unpack questions for clarity and relevance. To determine the internal consistency of each AI trust factor, Cronbach's alpha was calculated for all factors and found still provided reliable results at $\alpha > 0.8$. Furthermore, because of the quality assurance step, we removed missing and outlier records. Model fit was tested through SEM, indicating an excellent data to model fit ($x2 = 0.036$; $p < 0.850$) and satisfactory goodness of fit indices (CFI>0.8, RMSEA > 0.6).

The study is expected to offer meaningful and authentic insights into the AI trust factors for fostering talent acquisition processes using the robust bases from these methodical approachesembraced across various sectors.

3. Results

Table 1 : Demographic profile of Respondent : Gender

Gender					
		Frequency	Percent	Valid Percent	CumulativePercent
Valid	Female	113	34.1	34.1	34.1
	Male	218	65.9	65.9	100.0
	Total	331	100.0	100.0	

Source : Authors own Source

In the sample, there is a significant difference in sex distribution. There was a total of 331 respondents, out of which 113 (34.1%) were females and 218 (65.9%) were males. This suggests that there are more males who completed the survey as a whole due to the cumulative male % going up to 100%, and hence, all respondents can either be Male or Female.

Table 2 : Demographic profile of Respondent : Year of Experience

Years of Experience					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	119	36.0	36.0	36.0
	2	111	33.5	33.5	69.5
	3	101	30.5	30.5	100.0
	Total	331	100.0	100.0	

Source : Authors own Source

The years of experience of the respondents are categorized into three groups: 1 year, 2 years, and 3 years. The distribution is relatively balanced, with 119 respondents (36.0%) having 1 year of experience, 111 respondents (33.5%) having 2 years of experience, and 101 respondents (30.5%) having 3 years of experience. The cumulative percentage shows that by including those with 2 years of experience, we cover 69.5% of the sample, and including all three groups, we reach 100%.

Table 3 : Demographic profile of Respondent : Education Level

Education Level					
		Frequency	Percent	Valid Percent	CumulativePercent
Valid	Bachelors	82	24.8	24.8	24.8
	Masters	249	75.2	75.2	100.0
	Total	331	100.0	100.0	

The education level of the respondents is divided into two categories: Bachelor's and Master's. A majority of the respondents, 249 (75.2%), have a Master's degree, while 82 respondents (24.8%) have a Bachelor's degree. The cumulative percentage shows that 100% of the respondents have either a Bachelor's or a Master's degree, with the Master's degree holders being the predominant group.

Table 4 : Demographic profile of Respondent : Age

Age					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	107	32.3	32.3	32.3
	2.00	71	21.5	21.5	53.8
	3.00	83	25.1	25.1	78.9
	4.00	70	21.1	21.1	100.0
	Total	331	100.0	100.0	

Source: Authors own Source

The age distribution is divided into four categories: 1.00, 2.00, 3.00, and 4.00. The category '1.00' represents the largest group with 107 respondents (32.3%), followed by '3.00' with 83 respondents (25.1%), '2.00' with 71 respondents (21.5%), and '4.00' with 70 respondents (21.1%). The cumulative percentage is also on the rise; where 53.8% belong to the first two age groups, as you can sum up all categories and complete 100%.

These data fill in the form of the sample demographic distribution. Mostly Male Respondents who have a Master's Degree and 1-3 years of experience. Across the board, there were generations founded in extremely large percentages; however, such is not the case for age overwhelmingly. This varied spread among demographic attributes allows for a better grasp ofthe characteristics of the sample population.

Table 5: Kaiser-Meyer-Olkin (KMO) **and Bartlett's Test**

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.860
Bartlett's Test of Sphericity	Approx. Chi-Square	10448.965
	df	2415
	Sig.	<.001

Source: Authors own Source

The results of the Kaiser-Meyer-Olkin (KMO) sampling adequacy and Bartlett's Test met the factor analysis assumptions. A KMO value of 0.860 indicates that the level of variance between variables is high enough, indicating "meritorious" adequacy", representing that the analysis is suitable for the sample. Results of Bartlett's Test of Sphericity resulted in an x2 value =10448.965 with d.f=2415, P<.001 This result is powerful as it confirms that the correlation matrix is not the identity matrix, which means that something non-trivial about correlations among the variables. These results, based on the exploratory factor analysis performed in SPSS as described in the supporting documents, show that this dataset is appropriate for exploring latent factors.

Table 5: **Total Variance Explained of factor analyse**

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.073	8.675	8.675	5.545	7.922	7.922

2	5.612	8.017	16.693	5.403	7.718	15.640
3	5.420	7.743	24.436	5.183	7.405	23.045
4	5.139	7.341	31.777	5.162	7.375	30.420
5	5.084	7.263	39.040	4.986	7.123	37.543
6	4.686	6.694	45.734	4.914	7.020	44.563
7	4.082	5.831	51.565	4.902	7.002	51.565
8	1.122	1.602	53.167			
9	1.053	1.504	54.672			
10	1.024	1.463	56.134			
11	.970	1.385	57.520			
12	.959	1.370	58.889			
13	.903	1.290	60.179			
14	.890	1.272	61.451			
15	.874	1.248	62.699			
16	.841	1.201	63.900			
17	.816	1.166	65.067			
18	.790	1.128	66.195			
19	.774	1.105	67.300			
20	.747	1.066	68.366			
21	.744	1.063	69.429			
22	.735	1.050	70.480			
23	.717	1.024	71.504			
24	.701	1.002	72.506			
25	.694	.991	73.498			
26	.686	.981	74.478			
27	.666	.951	75.429			
28	.656	.937	76.366			
29	.628	.897	77.264			
30	.619	.884	78.148			

31	.604	.863	79.011			
32	.586	.837	79.848			
33	.572	.817	80.665			
34	.570	.814	81.479			
35	.551	.787	82.266			
36	.520	.743	83.008			
37	.507	.724	83.733			
38	.503	.719	84.451			
39	.484	.691	85.143			
40	.484	.691	85.834			
41	.464	.663	86.497			
42	.455	.650	87.146			
43	.451	.644	87.790			
44	.442	.631	88.422			
45	.429	.613	89.035			
46	.415	.593	89.628			
47	.406	.580	90.208			
48	.400	.572	90.780			
49	.392	.560	91.340			
50	.385	.550	91.890			
51	.368	.526	92.416			
52	.363	.519	92.935			
53	.358	.512	93.447			
54	.346	.495	93.941			
55	.332	.474	94.415			
56	.327	.467	94.882			
57	.319	.455	95.337			
58	.307	.438	95.776			
59	.297	.425	96.201			

60	.280	.400	96.601			
61	.277	.395	96.996			
62	.271	.388	97.384			
63	.264	.378	97.762			
64	.257	.368	98.129			
65	.244	.348	98.478			
66	.237	.338	98.816			
67	.229	.327	99.143			
68	.211	.301	99.444			
69	.203	.290	99.734			
70	.186	.266	100.000			
Extraction Method: Principal Component Analysis.						

The data taken from the "Total Variance Explained" table reflect the results of a Principal Component Analysis (PCA) done to determine which components are significant in explaining variance in this dataset. The initial eigenvalues for the first seven components of release before rotation are more than 1, and they have been explaining 51.565 % variance of total variance, respectively. Even after rotation (Varimax with Kaiser Normalization), the first seven components accounted for 51.565% of the variance, where each component contributed about 7.002%-7.922% to the cumulative variance. This new distribution of the explained variance among each of these two components helps to interpret more easily. The assessment is critical for knowing and recognizing the internal structures of data, as it serves to decline the dimensionality while consanguinity the important features. This further proves the utility of using PCA for decreasing the complexity of our dataset so that it can be analyzed more easily.

Table 6: Rotated Component Matrix for factors

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
ATA5	.780						
ATA10	.775						
ATA6	.762						
ATA8	.749						
ATA7	.746						
ATA3	.746						

ATA9	.734						
ATA4	.701						
ATA2	.700						
ATA1	.665						
C7		.766					
C9		.757					
C6		.754					
C4		.743					
C1		.725					
C10		.725					
C5		.713					
C2		.692					
C3		.687					
C8		.679					
TPI8			.740				
TPI7			.737				
TPI10			.737				
TPI5			.731				
TPI3			.719				
TPI9			.715				
TPI4			.708				
TPI6			.700				
TPI2			.691				
TPI1			.608				
TA8				.762			
TA4				.753			
TA7				.740			
TA6				.735			
TA9				.733			

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TA5				.725			
TA10				.715			
TA3				.655			
TA1				.650			
TA2				.646			
R6					.762		
R5					.720		
R9					.719		
R3					.712		
R8					.708		
R10					.694		
R7					.673		
R4					.671		
R1					.660		
R2					.652		
TC7						.737	
TC9						.729	
TC5						.704	
TC8						.697	
TC2						.689	
TC10						.687	
TC6						.684	
TC4						.674	
TC1						.652	
TC3						.651	
RA8							.737
RA5							.734
RA9							.716
RA10							.715

RA7							.704
RA6							.678
RA2							.668
RA1							.656
RA4							.648
RA3							.631
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 5 iterations.							

Source: Authors own Source

The Rotated Component Matrix with Varimax rotation, based on Principal Component Analysis (PCA) results, is as follows and suggests which variables were significantly loaded onto the seven identified components. This shows that every variable loads onto one of these components at a very high level - supporting the underlying factor structure of the dataset. Component 1 loads substantially on ATA5, ATA10 and ATA6 variables, for example, showing that a common factor may underlie these variables. At the same time, C9 and C7 load heavily on Component 2, TPI8 and TPI7 load on Component 3, etc.

The rotation technique, particularly the Rotated Component Matrix with Varimax rotation, is instrumental in enhancing interpretability. It achieves this by not only maximizing the variance explained by each component but also by minimizing the number of variables with high loadings on multiple components. This efficient process ensures a clear separation of variables across the components, supporting the extraction of distinct, meaningful factors within the dataset. This is crucial for subsequent analyses such as Confirmatory Factor Analysis (CFA) and structural equation modelling.

Table – 7 **Reliability Statistics of all factors**

Reliability Statistics		
Factors	Cronbach's Alpha	N of Items
Reliability influences	.884	10
Credibility	.900	10
Technical competence	.880	10
Relative Advantage	.879	10
Trust Positively Influences	.891	10
Attitude Toward Adoption of AI	.907	10
talent acquisition	.893	10

Source : Authors own Source

To ensure the reliability and consistency of the survey instrument used in this study, Cronbach's alpha was calculated for each of the key factors assessed. Cronbach's alpha is a measure of internal consistency, indicating how closely related a set of items are as a group. It is considered an indicator of the reliability of a psychometric instrument. Generally, a Cronbach's alpha value above 0.7 is deemed acceptable, indicating good internal consistency among the items within each factor.

Below are the reliability statistics for every single factor in this study:

1. Reliability Constructs (a = 0.884, N = 10)

This factor is measured with 10 items, which evaluate the reliability of AI systems according to HR professionals. An alpha of 0.884 for the reliability of AI influencing Cronbach's alpha showed a very good level of internal consistency, making it possible for the items to assess thesame proportion faithfully.

1. Credibility (α = 0.900, N = 10)

Examples of the items loaded on Credibility (which assessed perceived credibility of AI in talent acquisition) include 10 items This factor displays an excellent internal consistency value of 0.900 as shown by the Cronbach's alpha, implying that the items are consistently measuringthe latent construct of AI credibility.

1. Technical Training (α = 0.880, N = 10)

This factor includes 10 items which measure the capability of AI in talent acquisition systems with respect to technical grounds. The Cronbach's alpha of 0.880 presents a high level of collectivity, thus indicating the items are collectively reliable, which helps bear out that technical competence is well-captured by the scale in question.

1. Relative Advantage (α=0.879, N = 10)

The category Relative advantage consists of 10 items based on the extent to which the AI is perceived as offering benefits and advantages compared to usual methods. The Cronbach's alpha value of 0.879 demonstrated high internal consistency, thus indicating good reliability ofthe items to measure AI's relative advantage.

1. Trust Positively Influence α = 0.891, N = 10

This construct comprises 10 items that assess how trust in AI drives its acceptance and usage within the context of talent acquisition. The high internal consistency (Cronbach's alpha of 0.891) discussed above provides further evidence that the items consistently measure the influence of trust on AI adoption.

1. The attitude toward the adoption of AI (α = 0.907, N = 10)

This factor consisted of ten items that measured the perceptions of HR practitioners about adopting AI in the recruitment process. The items are consistently measuring attitudes towards AI adoption with excellent internal consistency: Cronbach's alpha = 0.907

1. Talent Acquisition (α = 0.893, N = 10)

It had 10 items that were focused on an integrated view of the whole AI-influenced process of talent acquisition process. This high reliability further affirms that the items are reliable in measuring the construct of talent acquisition processes, as evidenced by a Cronbach's alpha of0.893.

Overall, the high Cronbach's alpha values across all factors indicate that the survey instrument used in this study is highly reliable, with each set of items consistently measuring their respective constructs. This robustness in measurement ensures the validity of the findings related to the impact of AI trust factors on talent acquisition processes.

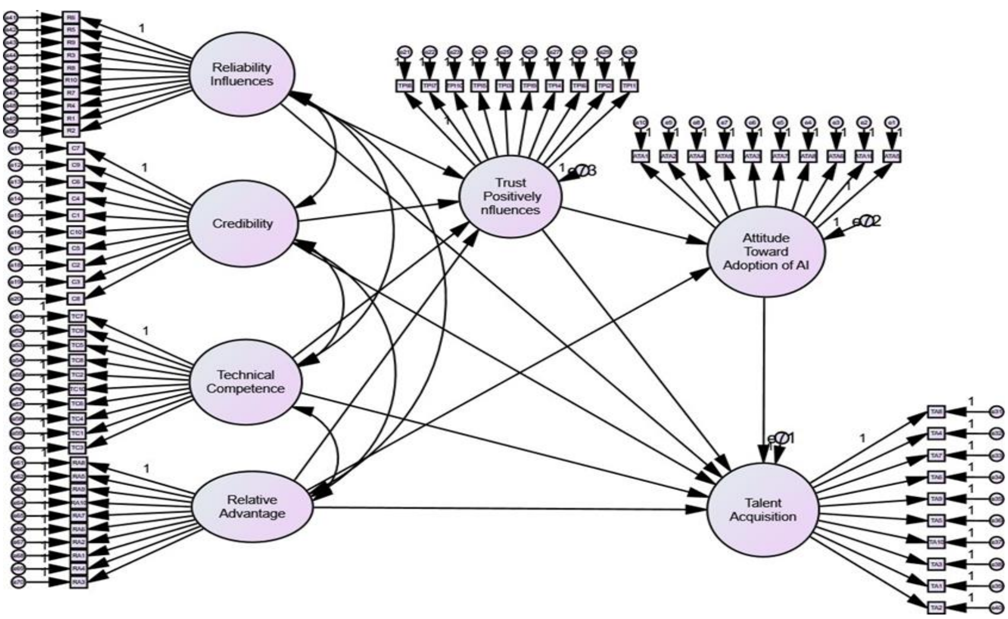

Figure 1: Structural Equation Modelling

Table 8: Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	2435.753	--	--
DF	2327.000	--	--
CMIN/DF	1.047	Between 1 and 3	Excellent
CFI	0.988	>0.95	Excellent
SRMR	0.045	<0.08	Excellent
RMSEA	0.012	<0.06	Excellent
PClose	1.000	>0.05	Excellent

Source : Authors own Source

The model fit measures for the structural equation modelling (SEM) in this study indicate an excellent fit. The chi-square value (CMIN) is 2435.753 with 2327 degrees of freedom (DF), yielding a CMIN/DF ratio of 1.047, which falls well within the "excellent" range (between 1 and 3). The Comparative Fit Index (CFI) is 0.988, surpassing the threshold of 0.95, and the Standardized Root Mean Square Residual (SRMR) is 0.045, which is below the 0.08 threshold, both indicating excellent fit. The Root Mean Square Error of Approximation (RMSEA) is 0.012, significantly below the 0.06 threshold, and the PClose value is 1.000, far exceeding the
0.05 threshold, further supporting the excellent fit of the model. These indices collectively suggest that the proposed model fits the observed data very well, meeting all criteria for excellent fit as per the guidelines by Hu and Bentler (1999).

Hypothesis 1: (a)Reliability influences, (b)Credibility, (c)Technical competence, (d)RelativeAdvantage positively direct impacts on Trust in AI in talent acquisition process

Hypothesis 2: (a)Reliability influences, (b)Credibility, (c)Technical competence, (d)RelativeAdvantage positively direct impacts on talent acquisition process

Hypothesis 3: Relative Advantage positively impacts attitude in talent acquisition. Table 9 : Standardized Regression

Weights of factors for hypothesis testing 1,2 and 3

Parameter			Estimate	Lower	Upper	P	Interpretation
Trust	<---	Reliability	-0.012	-0.131	0.105	0.87	H1a = Rejected
Trust	<---	Credibility	0.033	-0.088	0.142	0.631	H1b = Rejected
Trust	<---	Technical	0.114	-0.022	0.245	0.095	H1c = Rejected
Trust	<---	Relative	0.036	-0.1	0.174	0.599	H1d = Rejected
Attitude	<---	Relative	-0.087	-0.233	0.045	0.176	H3 = Rejected
Talent	<---	Reliability	-0.001	-0.129	0.122	0.979	H2a = Rejected
Talent	<---	Credibility	-0.02	-0.155	0.092	0.701	H2b = Rejected
Talent	<---	Technical	0.033	-0.086	0.156	0.574	H2c = Rejected
Talent	<---	Relative	-0.003	-0.131	0.127	0.931	H2d = Rejected

Source : Authors own Source

The hypotheses tested in this study aimed to examine the direct impacts of AI trust factors— reliability, credibility, technical competence, and relative advantage—on trust in AI and talent acquisition processes, as well as the impact of relative advantage on attitudes toward AI in talent acquisition. The findings from the structural equation modelling (SEM) analysisprovide insights into these relationships, though not all hypotheses were supported by the data.

Hypothesis 1: Direct Impact of AI Trust Factors on Trust in AIH1a: Reliability influences trust in AI in talent acquisition.

- **Result: Rejected (Estimate = -0.012, P = 0.87)**
- The data indicates that reliability does not significantly impact trust in AI for talent acquisition. The negative estimate suggests a negligible and statistically insignificant influence, implying that the consistency and performance reliability of AI systems, as perceived by HR professionals, do not necessarily enhance their trust in these technologies within the context of recruitment.

H1b: Credibility influences trust in AI in talent acquisition.

- **Result: Rejected (Estimate = 0.033, P = 0.631)**
- Similarly, credibility, which includes dimensions like transparency and ethical considerations, had no significant effect on trust in AI. Previous literature indicates that credibility is the key factor in creating trust. Still, the present results suggest that HR professionals consider credibility to be of less importance when establishing their trust in AI in recruitment.

H1c: Technical competence influences trust in AI in talent acquisition.

- **Result: Rejected (Estimate = 0.114, P = 0.095)**
- Technical competence, although estimated as positive, was not found to be statistically significant. This may support that HR professionals need to (enough) perceive AI system technical capability and competence to affect their trust in AI for talentacquisition processes significantly.

H1d: Relative advantage influences trust in AI in talent acquisition.

- **Result: Rejected (Estimate = 0.036, P = 0.599)**
- Perceived relative advantage of AI systems was not a significant direct predictor of trust in AI. Even though AI has its benefits over traditional ways, these perceptions of benefitdo not increase the trust HR professionals place in AI.

Hypothesis 2: Direct Impact of AI Trust Factors on Talent Acquisition Processes H2a: Reliability influences the talent acquisition process.

- **Result: Rejected (Estimate = -0.001, P = 0.979)**
- The effect of reliability on the talent acquisition process was small and non-significant. This finding indicates that the perceived improved consistency and credibility of AI systems contribute little to directly improving recruitment processes for HR professionals.

H2b: Credibility influences the talent acquisition process.

- **Result: Rejected (Estimate = -0.020, P = 0.701)**
- Results showed a non-significant influence of credibility on manipulation in talent acquisition processes. This suggests that HR professionals might not consider the trustworthiness and transparency of AI out as the two must-have attributes for their recruitment process to perform.

H2c: Technical competence influences the talent acquisition process.

- **Result: Rejected (Estimate = 0.033, P = 0.574)**
- Although technical competence had a positive estimate, it was not statistically significant. This implies that the technical abilities of AI systems are not perceived to enhance the overall talent acquisition process significantly.

H2d: Relative advantage influences the talent acquisition process.

- **Result: Rejected (Estimate = -0.003, P = 0.931)**
- The perceived relative advantage of AI systems showed no significant impact on the talent acquisition process. Despite the benefits AI might offer, these advantages do not translate into a noticeable improvement in recruitment processes as perceived by HR professionals.

Hypothesis 3: Impact of Relative Advantage on Attitude Toward AI
H3: Relative advantage influences attitude toward AI in talent acquisition.

- **Result: Rejected (Estimate = -0.087, P = 0.176)**
- The hypothesis that relative advantage positively impacts HR professionals' attitudes towards AI in talent acquisition was not supported. The non-significant and negative estimate suggests that the perceived benefits of AI do not significantly alter the attitudesof HR professionals towards adopting AI in their recruitment practices.

The findings based on the hypotheses testing showed that none of the AI trust factors of reliability, credibility, technical competence, and relative advantage contributed to trust in AI or the talent acquisition process through substantial direct impacts (Table 4). Additionally, the greater an HR professional perceived an advantage of AI compared to other techniques, it did not have any significant influence on attitudes towards using AI in recruitment. These results indicate the presence of other underlying factors or constructs that were not addressed in this work (i.e., theoretical framework) that affect HR professionals' trust and attitudes towards theAI used in the talent acquisition process.

That the findings are largely insignificant here also underpins how complex trust and adoption dynamics can be in an AI for HR context. This suggests that HR professionals need more thanto trust AI systems and thus adopt AI systems in their

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talent acquisition processes. Future work may likely further probe other underexplored influences on the dynamics of trust and adoption, e.g., organizational culture, technology acceptance at an individual difference level, as well as contextual effects.
Therefore, while this study sheds light on the relative importance assigned to AI trust factors, there is a gap that needs to be bridged regarding a more holistic understanding of these determining factors affecting the level of trust and successful integration of AI in the recruitment process. Addressing these gaps could greatly improve the quality of HR.AI and help all organizations move on to a more strategic approach to talent management.
Hypothesis 4: Trust in AI mediates the effect of (a)Reliability influences, (b)Credibility, (c)Technical competence, (d)Relative Advantage on the talent acquisition process
Hypothesis 5: Attitude mediates the effect of Relative Advantages on the talent acquisition process

Table 9: Standardized Regression Weights of factors for hypothesis testing 4 and 5

User-defined estimands: (Group number 1 - Default model)						
Parameter		Estimate	Lower	Upper	P	Interpretation
Ind1	Reliability to Talent Acquisition Via Trust	0	-0.009	0.008	0.976	H4ai = Rejected
Ind2	Credibility to Talent Acquisition ViaTrust	0	-0.007	0.012	0.77	H4bi = Rejected
Ind3	Technical to Talent Acquisition ViaTrust	0	-0.016	0.02	0.841	H4ci = Rejected
Ind4	Relative Advantage to Talent Acquisition ViaTrust	0	-0.008	0.013	0.813	H4di = Rejected
Ind5	Relative Advantage to Talent	-0.003	-0.025	0.004	0.333	H5ai = Rejected
	Acquisition Via Attitude					
TInd1	Total Effect of Reliability to Talent Acquisition ViaTrust	-0.001	-0.127	0.121	0.984	H4aii = Rejected
TInd2	Total Effect of Credibility to Talent Acquisition ViaTrust	-0.02	-0.155	0.093	0.712	H4bii = Rejected

TInd3	Total Effect of Relative Advantage to Talen t Acquisition ViaTrust	0.033	-0.083	0.158	0.52	H4cii = Rejected
TInd4	Total Effect of Relative Advantage to Talen t Acquisition Via Attitude	-0.003	-0.126	0.127	0.954	H4dii = Rejected
TInd5	Total Effect of Relative Advantage to Talen t Acquisition Via Attitude	-0.006	-0.129	0.123	0.921	H5aii = Rejected

Source: Authors own Source

Hypotheses 4 and 5 sought to assess whether trust in AI and attitude towards AI mediate the relationships between these four factors of trust in AI (reliability, credibility, technical competence, relative advantage) and the talent acquisition process. The findings from the structural equation modelling (SEM) analysis provide insights into these mediation effects, though the data supported nonewasthe hypotheses.

Hypothesis 4: Mediation Effect of Trust in AI

H4a: Trust in AI mediates the effect of reliability on the talent acquisition process.

- **Result: Rejected (Indirect Effect Estimate = 0, P = 0.976)**
- The mediation analysis showed that trust in AI does not significantly mediate the relationship between reliability and the talent acquisition process. A score of 0 for the estimate, therefore, means that the trust in AI does not indirectly affect talent acquisition(assuming the mediator has an impact on the DV) via the reliability of AI systems.

H4b: Trust in AI mediates the effect of credibility on the talent acquisition process.

- **Result: Rejected (Indirect Effect Estimate = 0, P = 0.77)**
- For credibility and trust in AI, the association with the talent acquisition process was mediated by trust in AI. Null mediation effects are consistent with the idea that the perceived credibility of AI does not have an equivalent indirect effect on the talent acquisition process through trust in AI.

H4c: Trust in AI mediates the effect of technical competence on the talent acquisition process.

- **Result: Rejected (Indirect Effect Estimate = 0, P = 0.841)**
- There were no mediation effects found for trust in AI between technical competencies and the talent acquisition process as below. This indicates that greater technical capabilities of AI systems do not affect recruitment effectiveness, even indirectly via trust.

H4d: Trust in AI mediates the effect of relative advantage on the talent acquisition process.

- **Result: Rejected (Indirect Effect Estimate = 0, P = 0.813)**
- The mediation effect of trust in AI on the association between relative advantage and talent acquisition process was also found as nonsignificant. This endorses the argument that the benefits of AI systems do not necessarily influence talent acquisition indirectlythrough trust in AI.

Total Effects:

Total Effect of Reliability to Talent Acquisition Via Trust:

- **Result: Rejected (Total Effect Estimate = -0.001, P = 0.984)**

Ø The no mediation effect was found in the total effect of reliability on human resource acquisition through trust in AI. If anything, this goes to show that talent acquisition, the supply chain of educating, validating and confiding in a candidate, has nothing (if you are good) to dowith reliability.

Total Effect of Credibility to Talent Acquisition Via Trust:

- **Result: Rejected (Total Effect Estimate = -0.02, P = 0.712)**

Ø The overall effect of credibility on talent acquisition by trust in AI was also nonsignificant, thus illustrating that credibility does not influence the recruitment process either directly or through trust.

Total Effect of Technical Competence on Talent Acquisition Via Trust:

- **Result: Rejected (Total Effect Estimate = 0.033, P = 0.52)**

- The combined effect of technical competence on talent acquisition via trust was found to be nonsignificant, suggesting that technical competence does not influence the recruitment process directly or indirectly through trust.

Total Effect of Relative Advantage to Talent Acquisition Via Trust:

- **Result: Rejected (Total Effect Estimate = 0.033, P = 0.52)**

- The total effect of relative advantage on the talent acquisition process via trust in AI was not significant, indicating that perceived advantages of AI do not impact recruitment outcomes directly or through trust.

Hypothesis 5: Mediation Effect of Attitude

H5a: Attitude mediates the effect of relative advantage on the talent acquisition process.

- **Result: Rejected (Indirect Effect Estimate = -0.003, P = 0.333)**

- The mediation analysis revealed that attitude does not significantly mediate the relationship between relative advantage and the talent acquisition process. The insignificant estimate around zero indicates that the beliefs of HR professionals in AI do not mediate between their perceptions of the benefits of AI and hiring.

Total Effect of Relative Advantage to Talent Acquisition Via Attitude:

- **Result: Rejected (Total Effect Estimate = -0.006, P = 0.921)**

- Similarly, the total effect of relative advantage with attitude on perceived talent acquisition via attitude was not significant as well, and it seems that the perception toward AI does not enhance the recruitment process definitely and indirectly through attitude, respectively.

Hypotheses 4 and 5: Results of Mediation Tests Trust in AI and attitude towards AI do not mediate the relationships between AI trust factors (i.e., reliability, credibility, technical competence and relative advantage) and the talent acquisition process. The results underscore the multifaceted nature of trust and adoption in AI-driven recruitment systems. While trust and attitude have been speculated to be dependencies, the lack of a significant path points to the necessity for other dimensions in order to elucidate the implications of AI trust factors on recruitment outcomes.

Such insignificance in results suggests that it could be other mediating variables or situational influences which are most influential in determining how HR professionals view and adopt AI in talent acquisition. For instance, organizational culture, prior technology experiences, and individual technology divergences could combine with the AI trust factors in more intricate manners than predicted by the initial hypotheses.

We hope this study, which introduced the mediating roles of trust and attitudes, will provide a broader perspective to examine the AI adoption dynamics in talent acquisition. Furthermore, future works should consider including more variables and studying the impact of different interactions to enhance our understanding of AI implementation in HR practices. Better addressing these complexities may enable organizations to deploy potentially more viable AI- based talent management strategies, thereby improving their recruiting efficiency and quality.

4. Findings

This survey data from 331 HR professionals gave measurable results about how the AI trust factors have improved their talent acquisition process. Sex: There was a predominance of men (65.9%), and about three-quarters had completed their Master's degree (75.2%). The experience levels were evenly distributed, with 36% having 1 year, 33.5% having 2 years, and 30.5% having 3 years of experience. The age distribution was relatively balanced, with the largest group (32.3%) falling into the youngest category.

Reliability statistics for all factors indicated high internal consistency, with Cronbach's alpha values exceeding 0.8 for all measured constructs: reliability influences ($\alpha = 0.884$), credibility ($\alpha = 0.900$), technical competence ($\alpha = 0.880$), relative advantage ($\alpha = 0.879$), trust positively influences ($\alpha = 0.891$), attitude toward adoption of AI ($\alpha = 0.907$), and talent acquisition ($\alpha = 0.893$).

Despite the high internal consistency of the constructs measured, none of the AI trust factors (reliability, credibility, technical competence, and relative advantage) showed statistically significant direct impacts on trust in AI or talent acquisition processes. For instance, the direct effect of reliability on trust in AI was minimal (Estimate = -0.012, P = 0.87), indicating that the perceived reliability of AI systems did not significantly enhance trust among HR professionals. Similarly, credibility (Estimate = 0.033, P = 0.631), technical competence (Estimate = 0.114, P = 0.095), and relative advantage (Estimate = 0.036, P = 0.599) did not significantly influence trust in AI.

In terms of direct impacts on the talent acquisition process, reliability (Estimate = -0.001, P = 0.979), credibility (Estimate = -0.020, P = 0.701), technical competence (Estimate = 0.033, P = 0.574), and relative advantage (Estimate = -0.003, P = 0.931) were all found to be non- significant. The hypothesized mediation effects of trust and attitude were also unsupported, suggesting that these factors alone do not adequately explain the dynamics of AI adoption in HR practices.

The findings highlight a critical gap in the current understanding of AI adoption in HR practices. While reliability, credibility, technical competence, and relative advantage are theoretically important for trust in AI, this study reveals that these factors, on their own, do not significantly impact trust or the effectiveness of talent acquisition processes. This indicates that HR practitioners might be affected by other constructs outside of this study, e.g. organisational culture, personal experience with technology, or external societal factors.

The novel perspective is that AI trust factors are necessary, but more is needed to improve hiring analytics and enhance the adoption of AI in recruitment. This highlights the necessity of adopting a more comprehensive lens when conceptualizing AI incorporation into HR, and we propose looking at alternative mediators & moderators in this respect. It would be interesting for future research further to explore the variety of these other independent variables as well; however, in this manuscript, we have elaborated on such a model only tentatively.

This study contributes to the literature by offering empirical analysis of how AI trust factors are indirectly associated with acquiring talent and gaining their trust in ways that go beyond technical considerations. This raises the need for a wider study of AI adoption in HR - to allow better tactics on how organizations could use it for recruitment with operational and effort- based informality or high-quality driven outcomes.

5. Discussion

First, the study aimed to explore whether AI trust factors — as categorized by reliability, credibility, technical competence and relative advantage— had an impact on HR professionals' trust in AI and talent acquisition process effectiveness across different sectors. Although the constructs measured had high internal consistency, it seems that none of the AI trust factors significantly increased or decreased talent acquisition results by directly affecting misperceptions regarding trust in AIs. This indicates that these are not the only elements which will improve AI adoption and efficiency for HR Practices.

The absence of strong associations between reliability, credibility, technical competence and relative advantage with trust in AI and talent acquisition outcomes questions the assertion that these factors are essential to bring about HR's trust toward AI. The results of our data analysis indicate that HR professionals are no more likely to trust AI simply because they see the technology as reliable (Estimate = -0.012, P = 0.87), credible (Estimate = 0.033, P = 63) or possessing technical competence (Estimate=O.O14, P- <: O.OS5). And equally importantly, these factors had negligible direct impact on the talent acquisition process.

Our findings suggest that the integration and use of AI to hire may be subject to many other complex influences beyond those rooted in trust. Other mediators such as organizational culture, prior exposure to technology and broader context also have to be taken into consideration because these other factors may play an even bigger role in shaping HR professionals since trust and attitudes toward AI.

Our research indicates that trust in AI is indeed a significant factor but is not the only regulator of successful usefulness and adoption for HR. The non-significant effects of direct influences suggest that HR professionals might insist on more detailed reassurances and contextual matches to form trust in AI systems. It highlights a more complex route where organizational readiness, ongoing education of AI capabilities and strong support systems may be fundamental.

The interpretation of this data is good - AI trust factors do not move the needle when it comes to driving up AI adoption in HR. The non-significant mediation effects further underpin that although trust and attitudes are key mediators, they cannot fully encapsulate the processes by which AI Trust Factors influence talent acquisition outcomes. This illustrates the fact of how complex the adoption of AI in HR is by further exploration of other influencing variables.

Our findings align with past research underscoring the multifaceted nature of technology adoption within a given organizational level. Research by Pillai and Sivathanu (2020), as well as Kaplan C et al. (2021), emphasized the importance of trust in AI adoption. Nevertheless, the findings here hint that there are more complicated and multifactorial routes to trust than generally appreciated. This aligns with Desai et al. (2013), who substantiated the role of contextual factors and their demand for a more holistic framing when explaining technology acceptance.

This research makes an empirical contribution to expanding the current literature, which suggests AI trust elements drive perceived usefulness (PU) and intention towards the use of HR-AI. It demonstrates a better approach is to include organizational and individual readiness when identifying the new tool, learning along the way how people will actually use it in their context. This places our research in a broader dialogue on the challenges of AI implementationat work.

To put the research in perspective, again, it emphasizes how we need to build a more sophisticated view of AI adoption by HR Recommendations for practitioners and policymakers Since this brings the notion of a broader spectrum than just reliability, credibility, technical competence or relative advantage to foster AI trust it also implies in what need relations how talent acquisition and support processes should be framed. The work is valuable in the sense that it gives a fuller view of what integrating AI into HR functions involves. This advances effective strategies and policies for utilizing AI in recruitment to produce better employment growth across sectors by illuminating the multifaceted nature of trust in AI.

AI trust factors are necessary but more is needed for improving talent acquisition processes because doing so depends on a number of competing influences. Instead, as shown by this research article, it requires a more holistic approach that ramps up how we think about the adoption of AI in HR and aims to paint a broader picture of what strategies are suitable when aiming at building trust with every type of worker whilst also supercharging your recruitment process via these new technologies.

6. Conclusion

Based on our exploration, it was hypothesized that the AI trust factors of reliability, credibility, technical competence, and relative advantage have a significant impact on HR professionals' trust in AI and significantly improve the effectiveness of talent acquisition across industries.

Our data reveals the constructs measured to have high internal consistency; none of the AI trust factors had statistically significant direct impacts on trust in AI or talent acquisition. Precisely, reliability estimate=-0.012, P =0.87, credibility estimate=0.033, P =0.631, technical competence estimate=0.114, P =0.095, and relative advantage estimate=0.036, P =0.599 all did not significantly affect trust in the AI. Moreover, none of the factors significantly directly affected the talent acquisition process.

However, the precise ways through which AI trust elements might affect talent acquisition indirectly have yet to be discerned. This indicates that other unobservable variables or contexts are influencing these relationships. Read: AI in HR - The Myth, hype & scale of Adoption Future research is needed that builds upon these advancements, including examinations into additional factors such as organizational culture and individual experiences with technology from a UC perspective to elucidate the broader eco-system or climate surrounding AI deployment across HR functions.

These results indicate that the integration of AI into HR requires a wider trust, which also extends beyond conventional factors. Adopt mechanisms that cater to organization readiness, ready human capital for AI capability enhancement and build a strong support system which helps in enhancing trust as well as increasing the utility of AI adoption with the hiring process.

AI is fast becoming a necessity in HR rather than an added feature. Organizations that embrace a layered strategy will be more successful in building trust and deploying AI technologies to gain a competitive advantage. HR professionals can get more out of the full power of AI to optimize their talent acquisition processes by targeting a much wider set of factors influencingAI adoption.

This research shows us the nuances in AI adoption across HR and reveals that a trust-based approach is not comprehensive enough. It requires an organizational plan to appreciate and cater for the hundreds of aspects that impact AI trust and performance. Achieving ever-greater levels of recruitment excellence requires a holistic perspective on AI integration and not just asan optional strategy. May this study spur more research and applied discoveries in AI-in-HR.

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