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Artificial Intelligence Adoption and Human Resource Agility Through Digital HR Capabilities

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ABSTRACT

Although the AI adoption for human resource management can support responsive management, its organisational value is partly dependent on the capabilities that it can bring through digital information in day-to-day decisions. This study aims to investigate the relationships between artificial intelligence adoption, human resource agility, and explore the mediating relationships between these factors and determine the effects of artificial intelligence adoption on human resource agility. The sample includes 390 HR eligible respondents in a three-construct partial least squares (PLS) structural equation model (SEM) and five indicators per construct. The results of the measurement assessment indicate that the indicators of the measurement have good reliability, internal consistency, convergent validity, and discriminant validity. The direct association between Artificial Intelligence adoption and human resource agility is positive (standardised coefficient 0.220) as is the relationship between Artificial Intelligence adoption and digital HR capabilities (standardised coefficient 0.420). The coefficient value of digital HR capabilities is 0.451 and positive, this means that digital HR capabilities are correlated with human resource agility. The specific indirect effect is 0.189 (95th confidence interval = 0.142, 0.242), which supports complementary partial mediation. The model explains 17.6 per cent of the variance in digital HR capabilities and 33.5 per cent in human resource agility. Small differences between the partial least squares and linear benchmarks were found in the individual indicators when using predictive comparisons. The findings place digital HR capabilities as a concrete path towards organisational responsiveness and adopting AI. The adoption of AI for HR should be paired with manager's skills, accurate employee information, data analytics understanding and digital platform coordination.

INTRODUCTION

The human resource functions need to understand the shifting needs of the workforce, while still being able to offer reliable services to both employees and management. The needs of staffing can shift before staffing cycles are completed, new assignments may involve new skills, and operational priorities may shift the appropriateness of existing HR processes. With these responses, the ability to be responsive hinges on whether HR professionals can come to an understanding of the data and act accordingly. Agility in HR is thus the ability to sense the shifts in the workforce and make timely changes in HR priorities, decisions, and services (Tanantong & Wongras, 2024).

AI has various uses that can apply to this process. Pattern recognition tools can help identify patterns, build content, predict outcomes, and suggest recommendations for recruitment, employee communication, workforce analysis, and administration. Their involvement is contingent on the use in organisational routines. Not using a tool consistently or using it for different HR activities does not make it a decision support tool. Adoption, based on this present study, is thus defined by routine use, by integration into the workflow, by the breadth of use, and by routine adoption of the AI outputs (Agarwal, 2023).

There's the HR function that utilizes the technology and adoption that needs to be paid attention to. A recommendation is operationally useful if it can be understood by employees, related to accurate reporting and facilitate the coordination of action. Digital HR capabilities refer to this ability to be effective with digital systems and information (Ogbeibu *et al.*, 2024). They involve staff expertise, staff data managing, information integration from various sources, interpreting digital reports, and coordination via digital platforms (Bian *et al.*, 2025). These capacities can link technology applications to organisation responses at the appropriate time.

A completely adoption-centred assessment might identify 'responsiveness' as the property of AI but not take into account the organisational processes by which technology becomes useful. In contrast, a capabilities-centred assessment may not give credit for the use of AI tools in information processing, and in repetitive digital practice (Alam *et al.*, 2024). To explain more precisely, both of the relationships within the same model should be looked at. It differentiates between the direct link between adoption and agility and the indirect link working through digital HR capabilities, whilst maintaining the conceptual integrity of both constructs.

In turn, the empirical analysis speaks to a single research question: What's the relationship between the adoption of artificial intelligence and human resource agility—both directly and indirectly via digital HR capabilities? The investigation has three aims. The first is to look at the relationship between the adoption of AI and HR agility.

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The second is to understand the correlation between the adoption of artificial intelligence and the digital HR capabilities and HR agility. The third is to find out if there is an intermediate step between the adoption and agility: is there a digital HR capability? These objectives structure the measurement assessment, hypothesis testing and interpretation of the structural results.

The study provides a concentrated description of the use of technology and of organisational responsiveness based on 390 respondent records. Its findings link to a positive direct link with adoption with an additional capability mediated. The importance of this distinction lies in the fact that it mentions capabilities that should be attended to, in addition to the technological implementation, in management. The analysis also makes the distinction between explanatory relationship and predictive performance, which means that substantive conclusions are kept linked to the concrete statistical evidence on which they draw.

LITERATURE REVIEW

Artificial Intelligence Adoption in HR

The adoption of AI in HR is the degree to which AI tools are employed in existing HR processes. The relevant technologies provide information, detect patterns, make predictions, or suggest actions to help make decisions. When not used for these functions, ordinary electronic recordkeeping and basic rule-based payroll processing are not considered to be part of this definition. This boundary provides a particular technological definition to adoption and avoids the risk of having a broad definition of computer use be interpreted as evidence of AI adoption (Halid *et al.*, 2024).

The adoption process includes both routine and organisational aspects. The frequent use suggests that AI is an integral part of a broader work, not just a one-off demonstration. Workflow integration is about how it relates to existing processes (Taufeeq Ahmad & Rabia Majeed, 2025). Breadth refers to its use in a variety of HR activities, while consideration of generated outputs suggests the technology becomes part of the decision-making process. These dimensions are combined and distinguish operational engagement from awareness or intention. If the HR function at an organisation hasn't been using the technology, then it can express interest in AI but report on low adoption (Chen, 2023).

Digital HR Capabilities

Digital HR capabilities relate to what the HR function is capable of doing with digital. But capability is only being capable of doing something well, which is more than mere technical access. Staff need to be aware of the systems they have access to, keep accurate employee information, combine relevant data, decipher reports, and sync activities via shared platforms (Böhmer & Schinnenburg, 2023). Such activities serve as a foundation for the use of information in a consistent way in HR decisions. The construct is therefore not a number of software products or digital subscriptions, but a functionality (Ogbeibu *et al.*, 2024).

A capabilities perspective can help to understand how similar technologies can lead to different organisational outcomes. A staffing problem could be detected in one HR function, which might then be part of a report to the Digital Comms Function to explain the issue and update a recruitment plan (setiawati, 2026). Another might produce the same report but not include it in the decision. Analytical – interpretive skills to coordinate action. This ability is conceived outside of the framework of AI adoption to assess technological engagement and functional competence together (Singh *et al.*, 2025).

Human Resource Agility

Human resource agility is the capacity to readjust the staff needs and now react to them in a timely way. The construct involves identifying changes, responding to unforeseen staffing needs, changing priorities, changing procedures and identifying appropriate responses to new workforce challenges as it arises (Kaur *et al.*, 2023). These attributes link awareness with action. A function that identifies a change, but cannot change a procedure, would indicate only part of the responsiveness of the construct. Appropriateness of the response is part of Agility. Speed is organisational where there is a need to do so for the relevant workforce requirement. Quickly passing on incorrect information or modifying a procedure without knowing what it does, would not satisfy the basic idea. The measurement statements are therefore related to changes in organisational needs and responses. With this context, agility can be seen as a controlled 'adaptability' in HR, rather than just a speed-up of HR tasks (Singh *et al.*, 2025).

Direct Relationship Between Adoption and Agility

AI applications can support HR professionals by structuring information, spotting key patterns, and compiling content for decision making. These functions can speed up part of the procedures related to the reception of information and deliberation on response (Deepa *et al.*, 2024). For instance, during recruitment, an AI-aided process might streamline the organisation of candidate information for analysis. Analytical outputs in workforce planning may alert managers to workforce changes they need to consider. These kinds of applications give a conceptual foundation for a positive correlation between adoption and HR agility (Wuisan *et al.*, 2023).

The direct relationship is preserved even when digital HR capabilities are added since AI can have operand meaning, beyond the capabilities explicitly shown in the mediator. Daily activities and portions of tasks can reinforce specific responses even if more global capacity building is not done (Jatobá *et al.*, 2023). Thus, this model enables association of the concept of adoption with the concept of agility both directly and indirectly. H1 posits that there is a positive direct influence of adoption of artificial intelligence on human resource agility. The hypothesised

effect is used as a statistical association in the sense of being directional in understanding the empirical results (Shahzad *et al.*, 2023).

Adoption and Digital HR Capabilities

The demands on HR's digital practices are present when operational AI use is present. Relevant information is needed for outputs, employees must have a knowledge of how to use the tools and processes must link technological recommendations to current records and responsibilities (Fenwick *et al.*, 2024). These practices may be enhanced during repeated use. It could foster building up digital competencies and can help to coordinate systems in a more structured and systematic way, depending on the way in which it is implemented (Raji N *et al.*, 2024).

The proposed relationship is thus based on technological involvement and the functional capacity. Organisations that report more widespread use should report higher capacity to use systems, manage information and to interpret digital output (Mer & Virdi, 2023). The model tests this association among respondents at various phases of AI usage. In H2's opinion, artificial intelligence has a positive impact on digital HR capabilities. The construct is still larger than AI specific skill as it encompasses the digital base that underlies the HR function generally (Islam *et al.*, 2022).

Digital HR Capabilities and Agility

Information must be accessible, understandable and usable to be HR responsive. Having accurate digital records makes it easier to understand the workforce scenario and blending help to understand the changing requirements in a coherent manner. Interpretation serves as a bridge between information and decision; coordination is a bridge between decision and implementation. These skills directly apply to the situations depicted by human resource agility (Nawaz *et al.*, 2024).

Therefore, a good digital HR should be better able to shift priorities and procedures given changes in requirements. It can enable sharing and coordination of information, across responsibilities and minimize delays from disjointed digital practices (Siradhana & Arora, 2023). This isn't reliant upon all tasks using AI. It finds a general capability relationship without regard to adoption. H3 asserts that digital HR abilities have a positive impact on human resource agility (Dr. Bijja Vishwanath, Dr. Surendar Vaddepalli, 2023).

The Mediating Pathway

The mediation hypothesis incorporates the foregoing relationships. Expect greater agility to be linked with stronger digital HR capabilities, which in turn is linked with greater adoption. In this series the use of technology is related to the skill to interpret the information and organize a response. This indirect pathway is more specific than an adoption outcome relationship as it reflects the existence of an intervening organisational capability (Dr. Ritesh Kumar Singhal, 2024).

H4 says that digital HR capabilities mediate the relationship between the adoption of artificial intelligence and human resource agility in a positive manner. Then the indirect effect is equal to the product of the adoption to capability and capability to agility. This hypothesis is supported by a positive indirect effect which did not contain zero in its confidence interval. When the direct and indirect effects are both positive and statistically significant from zero, the pattern is said to be complementary partial mediation. The entire conceptual framework is given in Fig. 1.

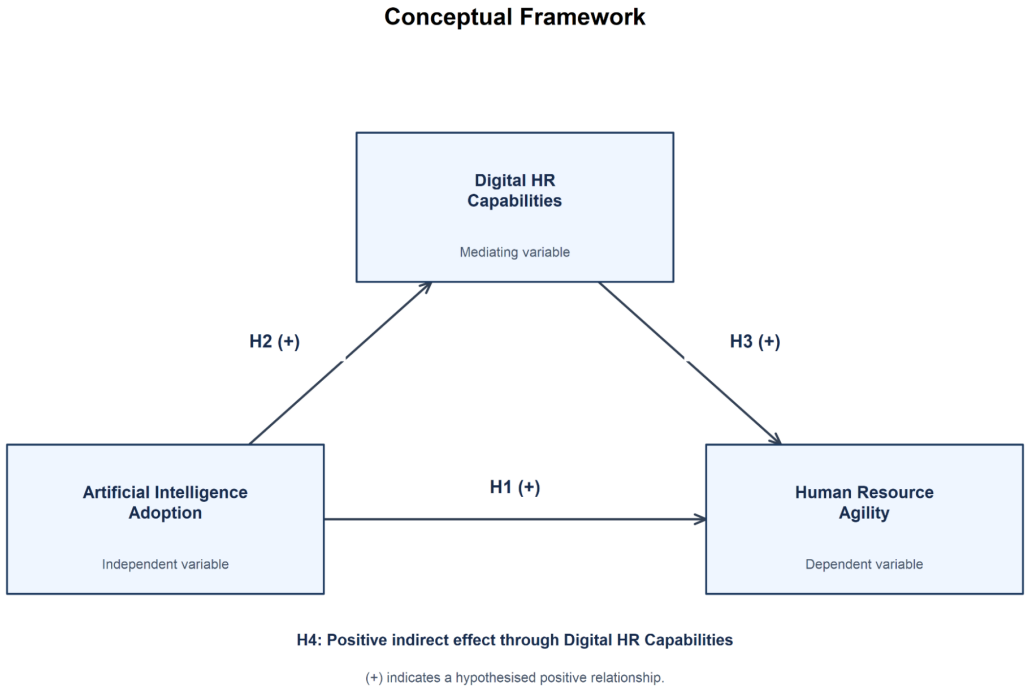


Figure 1: Conceptual framework

MATERIALS AND METHODS

The study employs purposive sampling to recruit HR professionals and managers with HR responsibilities from organisations in Dhaka, Bangladesh. Eligible participants are aged 18 years or above, have at least six months of service in their current organisation, and possess sufficient knowledge of its HR practices and digital technologies. Recruitment takes place through professional networks and organisational contacts. Data collection uses a structured questionnaire measuring artificial intelligence adoption, digital HR capabilities, and human resource agility. Participation is voluntary, and participants provide informed consent before completing the questionnaire. Responses remain anonymous and undergo screening for eligibility, completeness, and duplicate submissions before analysis.

Research Design and Analytical Focus

A quantitative questionnaire type of study is used in analyzing the relationship between three constructs of organisational practice. For each respondent, assessment comprises their current organisation and practices over the previous 12 months. The unit of analysis is the individual respondent evaluating the HR function. The number of respondents should not be interpreted as a validated number of organisations as these categories are organisational profiles that describe the context of these responses (Aithal & Aithal, 2020).

The explanatory construct in this research was the adoption of artificial intelligence, which was placed in the structural specification, the mediated variable was digital human resource competencies, and the dependent variable was human resource agility. There are 3 direct paths and one particular indirect pathway in the model. These relationships can be tested using partial least squares (PLS) structural equation modelling, which views each construct as reflected by several indicators (Wu *et al.*, 2022). The quality of measurement is tested prior to the interpretation of the structural coefficients, and the relationships tested are evaluated with regard both to the relationships' consistency and to the distinctiveness of the constructs.

Participant Eligibility and Questionnaire Procedures

The questionnaire explicitly states discretionary consent, as well as four criteria for eligibility. The participants should be at least 18 years old, have HR responsibilities and have been working for a minimum of 6 months in the organization, and be sufficiently knowledgeable of the HR practices and digital tools used in the organization. HR responsibilities are related to HR managers and practitioners who are engaged in HR activities. These conditions ensure a linkage with the participation required by the organisational knowledge of the measurement statements.

The participant information indicates that there is no obligatory participation and that anyone may refuse to answer questions and even refuse to submit. Does not ask for the name of the respondent; does not ask for the name of the organisation and asks participants to not provide information. Responses are designed for study as a group. The consent and confidentiality agreements outlined in the research instrument are provided for in these questionnaire provisions but not subjected to extra institutional procedures (Mirzaei *et al.*, 2022).

There is no requirement to use AI for organisations to be able to have their representatives participate. This approach of including people at different points in adoption allows for this range of variation to observe adoption as a process. The instructions clarify the difference between disagree and not being able to assess. Respondents from organisations that don't use AI are directed to select the disagreement option that aligns with them, and others that do not know enough to agree or disagree can select the explicit 'unable to assess' option.

Measurement Specification

There are five indicators in the questionnaire for each construct. AI adoption is assessed based on its use on a daily basis, frequent use, integration with existing processes, use throughout multiple HR activities, and whether AI-generated information is taken into consideration when making HR decisions. The degree to which Digital HR functions are rated by staff competency, employee data accuracy, the use of digital information, understanding of reports, and the use of platforms for coordination (Braun *et al.*, 2021). Human resource agility is the recognition of changes in the workforce and swift adaptation of staffing responses, priorities, procedures, and practices.

A five-point agreement scale ("strongly disagree" to "strongly agree") is used to categorize all substantive statements. There is a specific “do not know/unable to assess” option available. The analytical workbook provides complete information on construct items for all cases that qualify. All indicators in the measurement model were regarded as reflective measures of the constructs. Outer loadings, internal consistency, average variance extracted, and heterotrait monotrait ratios are used to evaluate the resulting measurement structure (Holtom *et al.*, 2022).

Screening and Statistical Assessment

Screening examines consent/eligibility data, completeness of construct responses, similarity of answers with other items of the profile, and presence of the same response for all the substantive items. Thirty-nine hundred records were initially entered in the workbook and all 390 were retained for analysis. No cases with any of the 15 indicators have a response of unknown or have failed to meet the eligibility criteria, no screening responses have been missed, nor do there appear to be any construct records that are incomplete, multiple matching profiles, or identical responses across all 15 indicators. The screening results are shown in Table 1.

Measurement assessment is in relation to indicator loadings with the cutoff of 0.708 and internal

Table 1: Data Screening and Analysis Sample

Screening metric	Count
Initial records	390
Records missing one or more screening responses	0
Records failing one or more screening conditions	0
Eligible records	390
Missing construct-item cells among eligible records	0
Eligible records excluded for incomplete construct items	0
Additional matching answer profiles; retained	0
Final cases with identical responses across all 15 items; retained	0
Total records excluded	0
Final analytical sample	390

consistency is tested with alpha, rhoA and composite reliability. Average variance extracted measures the amount of variance that is shared by each construct and its indicators. Discriminant validity is analyzed by the HTMT point values and their confidence intervals (CI) from the workbook's 0.90 comparison value. These are considered in combination with each other and not as an individual statistic as a full measurement evaluation.

They are inner variance inflation factors, standardised path coefficients, bootstrap standard errors, confidence intervals, explained variance and effect sizes. The significance probabilities reported are normal approximations to the bootstrap standard errors. The specific indirect effect and its confidence interval is calculated for mediation. The predictive assessment is the comparison of level prediction errors obtained with the partial least squares model and with a linear model benchmark both in terms of the mean absolute error and the root mean squared error.

RESULTS AND DISCUSSION

Respondent and Organisational Characteristics

The highest age group is age 25 to 34 accounting for 44.87% of the respondents followed by age 35-44 with 28.72%. Male 53,59 percent and female 43,85 percent. 86.41 per cent of the sample has Bachelor's or master's degree. Professional distribution comprises HR executives or senior executives (32.56 percent), HR managers (28.97 percent) and heads of HR or HR directors (13.08 percent). HR responsibility is there for non-HR managers 16.15 percent.

Events are spread out over categories. Those with four to six years of HR experience make up 28.46 percent of respondents while those with seven to 10 years make up 25.38 percent. An additional 18.46 per cent state over 10 years. There is also a mix in terms of organisational tenure – around a quarter say 6-11 months and the same number say 1-3 years. The assessments contain organisational experience as well as longer service as can be seen from these distributions. The respondent profile is detailed in table 2 (Complete Respondent Profile).

The main categories of manufacturing and banking or financial services account for the largest shares, 19.23 percent and 18.72 percent, respectively. The share of IT and telecom is 14.10 percent. The private domestic organisations account for 54.10% of the responses while Multinational organisations account for 17.95% and public sector organisations account for 15.38%.

Table 2: Respondent Demographic and Professional Profile

Variable	Category	n	%
Age group	18–24 years	30	7.69
	25–34 years	175	44.87
	35–44 years	112	28.72
	45–54 years	55	14.10
	55 years or above	18	4.62
	Prefer not to say	0	0.00
Gender	Woman	171	43.85
	Man	209	53.59
	Another gender identity	2	0.51
	Prefer not to say	8	2.05
Education	Secondary or below	5	1.28
	Higher secondary or equivalent	3	0.77
	Diploma or professional qualification	34	8.72

	Bachelor's degree	171	43.85
	Master's degree	166	42.56
	Doctoral degree	11	2.82
	Other	0	0.00
Position	HR assistant/officer	31	7.95
	HR executive/senior executive	127	32.56
	HR manager	113	28.97
	Head of HR/HR director	51	13.08
	Non-HR manager with HR responsibilities	63	16.15
	Other HR-related position	5	1.28
HR experience	Less than 1 year	21	5.38
	1–3 years	87	22.31
	4–6 years	111	28.46
	7–10 years	99	25.38
	More than 10 years	72	18.46
Organisation tenure	6–11 months	100	25.64
	1–3 years	101	25.90
	4–6 years	86	22.05
	7–10 years	65	16.67
	More than 10 years	38	9.74

Percentages use N = 390 and may not sum to 100 because of rounding.

The categories of employee size range from smaller to (at least) larger organisations, giving a description of the organisational context represented (Agarwal, 2023).

There is a significant difference in implementation phases of AI. Operational use in selected HR activities (30.26 percent usage), pilot or trial use (24.87 percent) and operational use across a few activities (16.67 percent) were the operational levels. The percentage of no current use and consideration without current implementation is 13.85 percent and 14.36 percent respectively. So, 46.92 percent say that they use some form operationally. These percentages represent the assessment by the respondents of the stages of adoption and are not an accurate reflection of the prevalence of AI in a broader population of organisations. The detailed organisational profile is provided in Table 3.

Table 3: Organisational Profile and AI Adoption Stage

Variable	**Category**	**n**	**%**
Sector	Manufacturing	75	19.23
	Banking/financial services	73	18.72
	IT/telecommunications	55	14.10
	Healthcare	37	9.49
	Education	28	7.18
	Retail/wholesale	36	9.23
	Hospitality/tourism	28	7.18
	Public administration	17	4.36
	NGO/development	35	8.97
	Other	6	1.54
Organisation type	Private domestic	211	54.10
	Multinational	70	17.95
	Public sector	60	15.38
	NGO/non-profit	40	10.26
	Other	9	2.31
Employees	1–49 employees	52	13.33

	50–99 employees	41	10.51
	100–249 employees	81	20.77
	250–499 employees	68	17.44
	500–999 employees	64	16.41
	1,000 or more employees	84	21.54
	Do not know	0	0.00
AI stage	No current use	54	13.85
	Under consideration	56	14.36
	Pilot/trial use	97	24.87
	Operational use in selected HR activities	118	30.26
	Operational use across several HR activities	65	16.67
	Do not know	0	0.00

Percentages use N = 390 and may not sum to 100 because of rounding.

Item and Construct Descriptions

Items have a range for AI adoption from 2.903 to 3.205. The mean score is highest for regular use; the mean score for integration into existing workflow is lowest. This is a pattern that separates frequency of engagement from embedding AI into organisational procedures. Digital HR capability means range from 3.162 to 3.497. Accurate employee information is rated highest and combining employee information from various digital sources is rated lowest. Whereas the two factors are for agility, where "responding quickly to unexpected staffing needs" has the highest mean of 3.487, and "adjusting priorities" has the lowest mean of 3.195.

All indicators are reported across the entire range of responses of 1-to-5. Standard deviations vary between 1.178 and 1.434 for each of the 15 items, measuring the variation from the average. The descriptive pattern indicates a distinction between the practical aspects of adoption, capability and agility. It is also a good starting point for managerial interpretation as the relatively less

Table 4: Descriptive Statistics of Measurement Items

Construct	Item	N	Mean	SD	Min	Max
AIA	AIA1	390	3.059	1.397	1	5
AIA	AIA2	390	3.205	1.434	1	5
AIA	AIA3	390	2.903	1.359	1	5
AIA	AIA4	390	3.105	1.406	1	5
AIA	AIA5	390	3.023	1.367	1	5
DHC	DHC1	390	3.313	1.236	1	5
DHC	DHC2	390	3.497	1.221	1	5
DHC	DHC3	390	3.162	1.259	1	5
DHC	DHC4	390	3.428	1.260	1	5
DHC	DHC5	390	3.238	1.271	1	5
HRA	HRA1	390	3.356	1.178	1	5
HRA	HRA2	390	3.487	1.184	1	5
HRA	HRA3	390	3.195	1.229	1	5
HRA	HRA4	390	3.364	1.207	1	5
HRA	HRA5	390	3.303	1.271	1	5

rated activities are related to the integration of workflows, the combination of information, and the HR priority adjustment. Table 4 shows item statistics.

The mean for adoption of AI is 3.059, while it is 3.328 for digital HR capabilities and 3.341 for HR agility at the construct level. The largest standard deviation is for AI, where it is 1.226. The correlation between adoption and capabilities is 0.415, and that between adoption and agility is 0.404. There is a higher correlation at 0.539 between capabilities and agility. The positive bivariate relationship is in line with the directional framework, and the structural analysis looks at direct relations in the selected model (Alam *et al.*, 2024). Construct statistics and correllations are shown on Table 5.

Table 5: Construct Descriptive Statistics and Correlations

Construct	N	Mean	SD	AIA	DHC	HRA
AIA	390	3.059	1.226	1.000	0.415	0.404
DHC	390	3.328	1.026	0.415	1.000	0.539
HRA	390	3.341	0.957	0.404	0.539	1.000

Correlations are the descriptive construct correlations reported in the workbook.

Measurement Quality

All other loadings are greater than 0.708. The valid range for AI adoption loadings is between 0.863 and 0.897, for digital HR capability loadings is between 0.800 and 0.845 and for agility loadings is between 0.748 and 0.811. An indicator's squared loadings fall in the range of 0.560-0.804, which identifies their reliability. As a result, over half of the variance of each retained item is therefore consistent with its assigned construct in the context of the measurement specification. Results indicate that the five-item representation per construct should be kept. The values for the individuals are summarised in Table 6.

Table 6: Indicator Reliability

Construct	Item	Outer loading	Indicator reliability
AIA	AIA1	0.864	0.747
AIA	AIA2	0.897	0.804
AIA	AIA3	0.863	0.744
AIA	AIA4	0.894	0.800
AIA	AIA5	0.882	0.778
DHC	DHC1	0.819	0.670
DHC	DHC2	0.800	0.641
DHC	DHC3	0.845	0.714
DHC	DHC4	0.824	0.679
DHC	DHC5	0.815	0.665
HRA	HRA1	0.748	0.560
HRA	HRA2	0.811	0.658
HRA	HRA3	0.794	0.631
HRA	HRA4	0.802	0.644
HRA	HRA5	0.785	0.616

Constructs have satisfactory internal consistency. The alpha value is 0.927 when it comes to AI adoption, 0.879 for digital HR capabilities, and 0.848 for HR agility. Corresponding rhoA values are 0.933, 0.883, and 0.850, while composite reliability values are 0.945, 0.912, and 0.891. The overlapping of these reliability measures validates the coherence of each set of indicators. The content of the statements is considered in relation to reliability, which is to maintain statistical consistency and to keep it in relation to the intended construct meaning (Ogbeibu *et al.*, 2024).

The average variance extracted is: adoption (0.775), capabilities (0.674) and agility (0.622). All values are above 0.50, demonstrating that the construct explains most of the variance of its indicators on average. These results are evidence for convergent validity. These measurement results show that the three constructs can be represented in a coherent way at the level of their respective indicators prior to the examination of their structural relationship. Table 7 summarises reliability and convergent validity.

Table 7: Internal Consistency Reliability and Convergent Validity

Construct	Alpha	rhoA	Composite reliability	AVE
AIA	0.927	0.933	0.945	0.775
DHC	0.879	0.883	0.912	0.674
HRA	0.848	0.850	0.891	0.622

These HTMT values are: 0.459 (adoption and capabilities), 0.456 (adoption and agility) and 0.625 (capabilities and agility). The highest upper confidence bound is 0.698, which is less than the specified value of 0.90, and less than the more conservative value of 0.85. Hence the constructs demonstrate empirical distinctiveness in addition to the positive relationships (Deepa *et al.*, 2024). Substantive results suggest the separation of the use of AI, the competency of digital HR work, and HR responsiveness. The HTMT assessment and intervals are given in Table 8.

Table 8: Discriminant Validity Assessment Using HTMT

Construct pair	HTMT	95% CI	Threshold
AIA and DHC	0.459	0.365 to 0.546	0.90
AIA and HRA	0.456	0.366 to 0.541	0.90
DHC and HRA	0.625	0.545 to 0.698	0.90

Structural Relationships and Explanatory Power

These inner VIFs are 1.000 for predicting adopters' capabilities and 1.214 for each predictor for agility. These values suggest there is no significant multicollinearity between the structural predictors within the equations listed. Coefficients for adoption and capabilities can thus be read without concern for an inflated predictor overlap from this assessment. The structural collinearity statistics are shown in Table 9.

H1 is supported. With the other variables (digital HR capabilities) controlled for, there is a positive direct relationship between AI adoption and HR agility (beta = 0.220, standard error = 0.043, t = 5.085). The 95% confidence interval is from 0.136 to 0.305, and the probability reported is less than 0.001. The difference between one standard deviation of change in adoption and one standard deviation of change in agility (conditional on the capability construct in this model) is 0.220 (Wuisan *et al.*, 2023).

Table 9: Structural Model Collinearity Assessment

Predictor	Outcome	Inner VIF
AIA	DHC	1.000
AIA	HRA	1.214
DHC	HRA	1.214

H2 also is supported. Adoption to capability coefficient is 0.420 and the standard error is 0.041 while the t statistic is 10.127. A 95 per cent confidence interval for the difference μB - μA would be (0.339, 0.500) without zero. The capability of H3 is supported with an agility coefficient of 0.451, standard error of 0.041 and t statistic of 11.130. Its confidence interval is 0.372 to 0.530. The two probabilities are both < 0.001. The results of the hypothesis tests are reported in Table 10 and the structure model in Figure 2.

Table 10: Direct Effects and Hypothesis Testing

Hypothesis and path	Beta	SE	t	95% CI	p	Decision
H1 AIA → HRA	0.220	0.043	5.085	0.136 to 0.305	<0.001	Supported
H2 AIA → DHC	0.420	0.041	10.127	0.339 to 0.500	<0.001	Supported
H3 DHC → HRA	0.451	0.041	11.130	0.372 to 0.530	<0.001	Supported

SE is the bootstrap standard error. Reported p values use normal approximation.

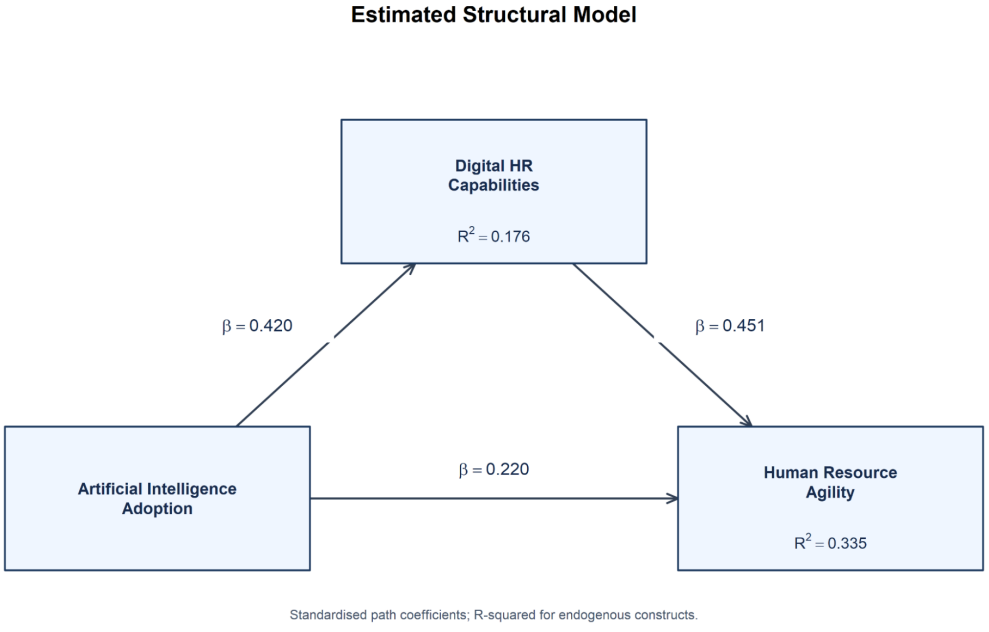


Figure 2: Structural model with standardised coefficients and explained variance

The model accounts for 17.63 per cent of the variance in digital HR capabilities and 33.51 per cent in HR agility. These numbers are 17.42 percent and 33.17 percent when adjusted. The low levels of difference between the ordinary and adjusted values indicate that the adjustment for the number of predictors is not significant enough to affect the explanatory summary. These are statistics about the variance accounted for in an analytical sample. They are not the same as the prediction error comparisons that are reported later (Islam *et al.*, 2022). The results of the explanatory power are given in table 11.

Effect sizes tell the difference between the relative impact of individual predictors and statistical support. The effect size associated with determining capabilities in adoption is equal to 0.214. The capability effect size for agility is 0.247 and the direct adoption effect size is 0.060. The first two are medium contribution points, as is the direct adoption contribution, using the conventional points of 0.02, 0.15, and 0.35. The pattern recognizes that capabilities within the agility equation have substantive meaning and that a capability, distinct from the main adoption relationship, can have a direct relationship. The following effect sizes are provided in table 12.

Table 11: Explanatory Power of the Structural Model

Construct	R squared	Adjusted R squared	N
DHC	0.176	0.174	390
HRA	0.335	0.332	390

Table 12: Effect Sizes of Structural Relationships

Path	f squared	Interpretation
AIA → DHC	0.214	Medium
AIA → HRA	0.060	Small
DHC → HRA	0.247	Medium

Mediation Analysis

The indirect effect via capabilities to agility is specific to the question of adoption, and is equal to 0.189, with a bootstrap standard error of 0.026 and a t statistic of 7.376. The 95% confidence interval for this value ranges from 0.142 to 0.242, and the p value is less than 0.001. The positive interval supports H4. Two component path coefficients are multiplied to replicate the mediation result between the mediation result and the relationship between the adoption capability and capability agility (Fenwick *et al.*, 2024).

The direct effect is still positive (0.220) once the mediator is taken into account, and the total effect is 0.410. The total effect confidence interval is (0.332, 0.488). Relationships between the direct and indirect are positive and supported, thus the pattern can be termed as complementary partial mediation. The specified indirect pathway accounts for about 46.22 percent of the total statistical effect. This is not to say that capabilities have the same percentage of variation in agility accounted for by the decomposition in the model. The results of the mediation are summarized in Table 13.

Table 13: Mediation Analysis

Effect	Beta	SE	t	95% CI	p
Indirect AIA → DHC → HRA	0.189	0.026	7.376	0.142 to 0.242	<0.001
Direct AIA → HRA	0.220	0.043	5.085	0.136 to 0.305	<0.001
Total AIA → HRA	0.410	0.040	10.247	0.332 to 0.488	<0.001

H4 is supported by the indirect effect. Direct and indirect effects show complementary partial mediation.

Predictive Assessment

Indicator level prediction assessment is conducted between the partial least squares (PLS) errors and linear model (LM) errors. The partial least squares model accounts for smaller portions of the RMSE in three of the five capability indicators and in three of the five agility indicators. In this criterion, six comparisons favour the partial least squares, across all 10 indicators. Despite

Table 14: Out-of-Sample Predictive Assessment

Item	PLS RMSE	LM RMSE	PLS MAE	LM MAE
DHC1	1.172	1.176	0.986	0.985
DHC2	1.173	1.172	0.971	0.967
DHC3	1.169	1.173	0.985	0.979
DHC4	1.173	1.172	0.976	0.966
DHC5	1.201	1.207	1.010	1.011
HRA1	1.136	1.141	0.947	0.949

HRA2	1.120	1.118	0.916	0.918
HRA3	1.135	1.133	0.955	0.937
HRA4	1.152	1.159	0.955	0.960
HRA5	1.220	1.226	1.034	1.035

PLS = partial least squares; LM = linear model; RMSE = root mean squared error; MAE = mean absolute error. Lower error indicates closer prediction.

numerical differences ranging from ~ -0.0068 to 0.0020 (partial least squares minus linear model error), the magnitude of the differences is rather small (Wuisan *et al.*, 2023).

Partial least squares show lower error mean absolute for one capability indicator and four agility indicators. Hence, the pattern varies according to the error measures and indicators. The results argue for a careful reading of the reported benchmarks and careful conclusions regarding comparative predictive performance, but not for any sort of overall superiority. The prediction comparisons form a separate account of the closer one gets to predictor responses and the structural conclusions are based on the path and mediation evidence. Both error measures are reported for each endogenous indicator in Table 14.

Discussion

Adoption and Organisational Responsiveness

The positive direct relationship also suggests that as reported adoption increases, so does HR agility even accounting for capabilities. This finding aligns with the function of AI within the framework: operation. Embedded tools for information processing can help making decisions at any stage that a response is needed. This positive direct relationship is still significant in the context of the other variables which constitute the HR function's overall digital competence as reflected in the coefficient of 0.220.

The direct effect should be interpreted in conjunction with the effect size (0.060). It has a positive relationship in the mentioned model based on its statistical support and it has a lesser contribution in explaining the model incrementally compared to digital HR capabilities. The distinction impacts management priorities. There's an adoption programme that may be related to responsiveness but is not enough to explain how HR gets agile (Nawaz *et al.*, 2024). The decision-making process in relation to training, information management, and coordination remains as central for interpreting the bigger capability relationship.

Operationally detail is added with descriptive findings. Incorporation into existing workflows has the lowest adoption item mean, and regular use has the highest. While the study does not test for statistically significant differences between these means, this ordering serves as a helpful benchmark to review. An organisation can determine if frequent use is aligned with specific HR processes, decision makers and the subsequent steps following an AI output. Linking the adoption construct to observable management practices (Deepa *et al.*, 2024).

Capabilities as an Organisational Mechanism

The largest of the two direct coefficients that enter into the agility equation is the capability to move at an agility coefficient of 0.451. Its effect size is 0.247, which is also larger than the direct adoption effect size. These results combined give a significant place to capabilities in the given explanation of responsiveness. But it is the capacity to deal with and decipher digital information that is pertinent in relation to the extent of technological use by the HR function (Singh *et al.*, 2025).

The process of the relationship has a clear interpretation. Digital information is of value if staff decide what it means for a staff need. Then, interpretation needs to be followed by coordination in order to notify the correct people about the recruitment decision, staffing adjustment or change in procedure. These activities are a reflection of the content of the capability indicators (Halid *et al.*, 2024). The measured relationship is thus between a specified set of HR competence and the practical activities indicated by agility.

This mechanism is linked with technological engagement by the positive coefficient on adoption to capability of 0.420. Those who say that they have adopted more strongly say they are more digitally capable. That relationship with agility is later incorporated into the mediation finding. The ability-based explanation is consistent with this pattern, which is characterised by organisational competence, which in turn serves as a means of facilitating the AI's use to responsive HR work. The overall interpretive context is cross sectional relationship and it is not a valid temporal sequence (Raji N *et al.*, 2024).

Meaning of Complementary Partial Mediation

Complementary partial mediation suggests that adoption and capabilities work through similar pathways. This indirect effect (0.189) is significant compared with the overall effect (0.410), and the direct relationship is also observed. A capability-based account, in turn, accounts for an appreciable portion of the adoption agility relationship, but doesn't encompass it all. This finding tentatively lends to the notion of an integrated approach to the implementation of HR technology where both tool utilization and functionality are considered (setiawati, 2026).

The mediated portion of the total statistical relationship is explained by the mediated share, which is approximately 46.22 percent. It should be understood in the context of the original coefficients and confidence intervals. The pathway relates to the specific mediator measured in this pathway: effective digital HR practice through

systems, information, analysis, and coordination. It is not comprehensive of all of the organisation's processes for technology use, nor is the percentage indicative of an optimum investment in technology and staffing.

Sample Composition and Predictive Interpretation

Respondents across sectors, organisation sizes, job functions, and adoption stages are included in the sample. This categorisation is important, given that the model is presented in a range of organisational situations reported. Out of the responses, 46.92 percent indicated operational adopters, while the rest include pilots, consideration, and none currently. As a result, the analysis is an adoption gradient rather than comparing only those organisations that have operational use of AI.

These qualities characterize the extent of what is currently known while not necessarily suggesting that relationships are the same in all these categories. The structural results refer to combination of the sample. There are no sector, gender, organ size or adoption-stage subgroup coefficients to give a higher weighting to a sector, gender, organ size or adoption stage (Islam *et al.*, 2022). This maintains the interpretation consistent with the analyses carried out and maintains the descriptive nature of the profile tables.

The other needed distinction is the prediction error. A number of RMSE comparisons support PLS, but the differences are very small and do vary by item. Another distribution favoring comparisons occurs with mean absolute error. The right response is that the model is a supported explanation for the stated relationship, and that it has similar predictive errors across the board when compared to the linear model. These are descriptions of each claim and the specific statistic which supports it (Ogbeibu *et al.*, 2024).

Managerial Implications

Managers should relate AI application to an explicit process of HR-decision-making. The HR function should document the information that is used, output that is generated, employee who reviews it and subsequent action that may result for each application. This method endows workflow integration with an operational semantics. It also enables the evaluation of adoption based on use in activities that are already established and not just access to software alone. Review should be based around whether the application provides HR with a specific need in the workforce.

There needs to be capability development to accompany implementation. Training should focus on the actual activities that the capability construct reflects, such as utilizing online HR systems, ensuring accurate employee details, consolidating sources and interpreting reports, and planning for coordinated activity. Opportunities for staff to use these skills in appropriate HR decisions should be provided. The evaluation of the training programme can then be made through practice, e.g. generating a sustainable work force report and discussing the implications for staffing (Halid *et al.*, 2024).

This is especially true for data management as interpretation relies on data quality and consistency from underlying employee information. HR teams should designate who will ensure that records are kept and ensure there are no discrepancies between the different digital sources. The mean of combining information was relatively low to provide a potential area for practical evaluation. Managers can check to see if information needed to make an HR decision is collocated, and if they have an understanding of how other sources of data relate. Any improvement activity should be commensurate with the information need of the function.

Design for coordination in digital processes. When responsibilities and decision rights are clearly defined, shared platforms may be helpful in taking action from analysis. An AI output related to staffing, for instance, would put in a process identifiable by an authorised manager to review it and coordinate the appropriate response. Where recommendations impact employees, human review will still be used. These are not directly-measured outcomes of the proposed mechanism but are managerial recommendations.

Evaluates implementation, taking into account digital capability and HR responsiveness. Some of the operational measures that could be useful include the time it takes to recognise a staffing problem, make a decision and take an agreed action. They might also be able to check the accuracy of the records, the capability to synthesize information, and the clarity of analytical interpretation. These measures would manifest the conceptual framework in the practice and organisation. The results of the present findings are not numerical performance targets; these should be based on the organisation's own baseline and service needs.

Finally, the distribution according to the adoption stage allows for a differentiated approach in implementation. Organisations looking at AI might start with considering a specific HR use case, and then identifying the data and knowledge needed. Outputs can be tested in the Pilot users' workflows before application extension. Users can view the coordination of the AI activities in HR services. This evolution links technology decisions to the capability pathway uncovered by the mediation analysis, and focuses on the workforce response that the implementation is designed to support.

CONCLUSION

There is a direct positive relationship between the adoption of AI and HR agility, as well as an indirect relationship that includes digital HR capabilities. During the analysis of the 390 respondent assessments, all four hypotheses have been supported. Results from measurements create coherent and clear constructs, and structural estimates reveal positive adoption to agility, adoption to capabilities and capabilities to agility. The positive direct effect of 0.220 and the indirect effect of 0.189 indicate a case of complementary partial mediation.

The model explains 17.6% of the variance in digital HR capabilities and 33.5% of the variance in HR agility. In the agility equation, capabilities underpin in a more substantial way the importance of their contribution to understanding technological adoption. The predictive assessment presents small and mixed differences with the linear benchmark which offer an additional point of view on indicator prediction. The substantive conclusion is that the use of AI and the digital competence needed to interpret information and coordinate action is related to responsive HR management. AI must thus be considered within HR processes and the abilities that can enable a suitable answer to the evolving demands of the workforce.

REFERENCES

Agarwal, A. (2023). AI adoption by human resource management: A study of its antecedents and impact on HR system effectiveness. *Foresight, 25*(1), 67–81. https://doi.org/10.1108/FS-10-2021-0199

Aithal, A., & Aithal, P. S. (2020). Development and Validation of Survey Questionnaire & Experimental Data – A Systematical Review-based Statistical Approach. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3724105

Alam, M. S., Munira, K. S., Rahman, Md. S., Uddin, Md. A., & Akter, A. (2024). Artificial Intelligence (AI) for Talent Acquisition: Human Resource Professionals' Perspective. *International Journal of Human Capital and Information Technology Professionals, 13*(1), 1–18. https://doi.org/10.4018/IJHCITP.303950

Bian, X., Panyagometh, A., Wang, B., & Szabó, R. (2025). AI-Powered Digital Transformation of Government Human Resource Management: A Bibliometric and Systematic Literature Review. *Journal of Innovation Management, 13*(3), 66–95. https://doi.org/10.24840/2183-0606_013.003_0003

Böhmer, N., & Schinnenburg, H. (2023). Critical exploration of AI-driven HRM to build up organizational capabilities. *Employee Relations: The International Journal, 45*(5), 1057–1082. https://doi.org/10.1108/ER-04-2022-0202

Braun, V., Clarke, V., Boulton, E., Davey, L., & McEvoy, C. (2021). The online survey as a qualitative research tool. *International Journal of Social Research Methodology, 24*(6), 641–654. https://doi.org/10.1080/13645579.2020.1805550

Chen, Z. (2023). Collaboration among recruiters and artificial intelligence: Removing human prejudices in employment. *Cognition, Technology & Work, 25*(1), 135–149. https://doi.org/10.1007/s10111-022-00716-0

Deepa, R., Sekar, S., Malik, A., Kumar, J., & Attri, R. (2024). Impact of AI-focussed technologies on social and technical competencies for HR managers – A systematic review and research agenda. *Technological Forecasting and Social Change, 202*, 123301. https://doi.org/10.1016/j.techfore.2024.123301

Dr. Bijja Vishwanath, Dr. Surendar Vaddepalli. (2023). The Future of Work: Implications of Artificial Intelligence on Hr Practices. *Tuijin Jishu/Journal of Propulsion Technology, 44*(3), 1711–1724. https://doi.org/10.52783/tjjpt.v44.i3.562

Dr. Ritesh Kumar Singhal, Dr. S. P., Dr. Ankit Garg, Dr. Tr Pandey,. (2024). Unveiling the Transformative Influence of Artificial Intelligence on Human Resource Management. *European Economic Letters (EEL), 14*(1), 1733–1739. https://doi.org/10.52783/eel.v14i1.1240

Fenwick, A., Molnar, G., & Frangos, P. (2024). Revisiting the role of HR in the age of AI: Bringing humans and machines closer together in the workplace. *Frontiers in Artificial Intelligence, 6*, 1272823. https://doi.org/10.3389/frai.2023.1272823

Halid, H., Ravesangar, K., Mahadzir, S. L., & Halim, S. N. A. (2024). Artificial Intelligence (AI) in Human Resource Management (HRM). In C. Machado (Ed.), *Building the Future with Human Resource Management* (pp. 37–70). Springer International Publishing. https://doi.org/10.1007/978-3-031-52811-8_2

Holtom, B., Baruch, Y., Aguinis, H., & A Ballinger, G. (2022). Survey response rates: Trends and a validity assessment framework. *Human Relations, 75*(8), 1560–1584. https://doi.org/10.1177/00187267211070769

Islam, M., Mamun, A. A., Afrin, S., Ali Quaosar, G. M. A., & Uddin, Md. A. (2022). Technology Adoption and Human Resource Management Practices: The Use of Artificial Intelligence for Recruitment in Bangladesh. *South Asian Journal of Human Resources Management, 9*(2), 324–349. https://doi.org/10.1177/23220937221122329

Jatobá, M. N., Ferreira, J. J., Fernandes, P. O., & Teixeira, J. P. (2023). Intelligent human resources for the adoption of artificial intelligence: A systematic literature review. *Journal of Organizational Change Management, 36*(7), 1099–1124. https://doi.org/10.1108/JOCM-03-2022-0075

Kaur, G., Gujrati, R., & Uygun, H. (2023). How does AI fit into the management of human resources? *Review of Artificial Intelligence in Education, 4*, e4. https://doi.org/10.37497/rev.artif.intell.education.v4i00.4

Mer, A., & Virdi, A. S. (2023). Navigating the Paradigm Shift in HRM Practices Through the Lens of Artificial Intelligence: A Post-pandemic Perspective. In P. Tyagi, N. Chilamkurti, S. Grima, K. Sood, & B. Balusamy (Eds.), *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part A* (pp. 123–154). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80382-027-920231007

Mirzaei, A., Carter, S. R., Patanwala, A. E., & Schneider, C. R. (2022). Missing data in surveys: Key concepts, approaches, and applications. *Research in Social and Administrative Pharmacy, 18*(2), 2308–2316. https://doi.org/10.1016/j.sapharm.2021.03.009

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. *International Journal of Information Management Data*

Insights, 4(1), 100208. https://doi.org/10.1016/j.jjimei.2023.100208

Ogbeibu, S., Emelifeonwu, J., Pereira, V., Oseghale, R., Gaskin, J., Sivarajah, U., & Gunasekaran, A. (2024). Demystifying the roles of organisational smart technology, artificial intelligence, robotics and algorithms capability: A strategy for green human resource management and environmental sustainability. *Business Strategy and the Environment, 33*(2), 369–388. https://doi.org/10.1002/bse.3495

Raji N, George, V., Iyer, R. S., Sharma, S., Pathan, F. I., & Basha S, M. (2024). Revolutionizing Recruitment: The Role of Artificial Intelligence in Talent Acquisition.*ShodhKosh: Journal of Visual and Performing Arts, 5*(1). https://doi.org/10.29121/shodhkosh.v5.i1.2024.2141

setiawati, rini. (2026). *Explainable AI and Transparency in AI-Based HR Systems: The Roles of Trust and Technology Readiness* [Data set]. Zenodo. https://doi.org/10.5281/ZENODO.18122990

Shahzad, M. F., Xu, S., Naveed, W., Nusrat, S., & Zahid, I. (2023). Investigating the impact of artificial intelligence on human resource functions in the health sector of China: A mediated moderation model. *Heliyon, 9*(11), e21818. https://doi.org/10.1016/j.heliyon.2023.e21818

Singh, R., Joshi, A., Dissanayake, H., Nainanayake, D., & Kumar, V. (2025). Harnessing Artificial Intelligence and Human Resource Management for Circular Economy and Sustainability: A Conceptual Integration. *Sustainability, 17*(15), 7054. https://doi.org/10.3390/su17157054

Siradhana, N. K., & Arora, Dr. R. G. (2023). The AI renaissance in HR: Exploring modern solutions. *International Journal of Research in Human Resource Management, 5*(2), 149–152. https://doi.org/10.33545/26633213.2023.v5.i2b.163

Tanantong, T., & Wongras, P. (2024). A UTAUT-Based Framework for Analyzing Users' Intention to Adopt Artificial Intelligence in Human Resource Recruitment: A Case Study of Thailand. *Systems, 12*(1), 28. https://doi.org/10.3390/systems12010028

Taufeeq Ahmad & Rabia Majeed. (2025). Artificial Intelligence in Human Resource Management: Exploring Public Policy Implications and Emerging Ethical Challenges. *Social Sciences & Humanity Research Review, 3*(4). https://doi.org/10.63468/sshrr.255

Wu, M.-J., Zhao, K., & Fils-Aime, F. (2022). Response rates of online surveys in published research: A meta-analysis. *Computers in Human Behavior Reports, 7*, 100206. https://doi.org/10.1016/j.chbr.2022.100206

Wuisan, D. S. S., Sunardjo, R. A., Aini, Q., Yusuf, N. A., & Rahardja, U. (2023). Integrating Artificial Intelligence in Human Resource Management: A SmartPLS Approach for Entrepreneurial Success. *Aptisi Transactions on Technopreneurship (ATT), 5*(3), 334–345. https://doi.org/10.34306/att.v5i3.355