

Artificial Intelligence in Human Resource Information Systems: Measurement and Validation

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The rapidly increasing applications of artificial intelligence (AI) within Human Resource Information Systems (HRIS) is revolutionizing human resource management, transforming traditional practices, and enabling enhanced decision-making, efficiency, and strategic alignment. However, the extent of AI integration and its implications remain underexplored. This research addresses this gap by developing and validating an AI-enabled HRIS reflectively measured construct. Through a rigorous methodology encompassing qualitative interviews, survey-based quantitative analyses, and scale validation procedures, a 16-item scale was constructed to assess AI's role across various human resources functions. Findings demonstrate the scale is reliable and valid, providing a comprehensive tool for measuring AI integration in HRIS. Theoretical contributions include extending the technology acceptance models to the context of artificial intelligence in human resources management, while practical implications suggest pathways for organizations to leverage artificial intelligence technologies within HRIS optimally. This research bridges a critical gap in HRIS literature, offering a standardized measure of artificial intelligence integration and highlighting its strategic importance in modern human resource management.

Keywords: artificial intelligence, HRIS, human resource management

INTRODUCTION

Artificial intelligence (AI) is reshaping the business world, society and the economy, as well as the experiences workers have as they interact with the different AI functions inside organizations (Loureiro et al., 2021). In particular, AI continues to play an increasing role in how work itself is transformed with substantial changes occurring in knowledge management, risk management, and decision support systems (Aicardi et al., 2018; Cesta et al., 2014; Kolbjørnsrud et al., 2017). These changes can be observed in the

integration of artificial intelligence within Human Resource Information Systems (HRIS). This integration marks a substantial evolution in the field of Human Resource Management (HRM).

Integrating AI technologies into HRIS platforms has transformed HR information systems from passive data repositories to dynamic systems capable of optimizing routine tasks, providing data-driven insights, and facilitating strategic decision-making processes. Almost overnight, organizations are wrestling with important questions surrounding how to manage and implement AI systems into their organizations, the ways employees use AI in their day-to-day work, how employees engage in the development of AI, and the support AI can provide to enhance the efficiency and effectiveness of organizations (Loureiro et al., 2021). As a result, valid and reliable measures are essential to assess the extent of AI integration within organizational systems and plan for future applications to minimize system disruptions.

All human resource (HR) functions utilize HRIS, yet there is often a disconnect between the various platforms used (Jemine & Guillaume, 2022). A series of qualitative interviews with working HR professionals was conducted to fully capture the extent of AI technology present in these disconnected platforms. This qualitative process was followed by three rounds of survey-based quantitative data collection and analysis. The results of the data collection and analysis efforts produced a 16-item reflectively measured instrument of AIHR in HR activities. The items in the scale represent different aspects of task specific usage frequency, whereas the scale score reflects an overall assessment of AIHR. In other words, the items measure the frequency of usage for different HR functional tasks (e.g., recruitment, training, compensation) and the overall score indicates the general frequency of AI usage across relevant functional tasks.

LITERATURE REVIEW

Human Resource Information Systems

HRIS is defined as an integrated system employed to compile, store, and analyze data concerning an organization's human resources. The evolution of HRIS dates back to the 1960s when organizations began automating HR tasks through the use of early computer systems (Ball, 2001). Subsequent advances in technology have led to the development of sophisticated HRIS platforms capable of handling diverse HR functions (Kavanagh et al., 2011). Within these functions, HRIS encompasses databases, computer applications, hardware, and software essential for planning, decision-making, and record keeping (DeSanctis, 1986). This includes collecting, recording, managing, delivering, presenting, and processing data throughout the full life of HR management (Hendrickson, 2003). From recruiting and selection, onboarding, training and development, performance management, pay and reward systems, and beyond, these HR functions are enhanced by the integration of information systems (DeSanctis, 1986; Hendrickson, 2003).

HRIS offer numerous benefits to organizations through the increased efficiency, accuracy, and accessibility of HR data (Lengnick-Hall & Moritz, 2003). By centralizing HR information, organizations can streamline processes such as payroll, recruitment, and performance management (Sánchez et al., 2008), leading to cost savings and improved decision-making (Stone, 2006). Despite the advantages and efficiencies afforded by HRIS, several challenges have been noted in the literature. These challenges include issues related to data security and privacy (Bélanger & Maier, 2022), employee resistance (Bondarouk & Ruël, 2009), and the need for ongoing training and support (Sambasivan et al., 2021).

A quite meaningful trend shaping the future of HRIS is the increasing integration of AI and machine learning capabilities into each of the functions of HR management (Parry & Tyson, 2011). Table 1 provides examples of the HR activities that HRIS are facing pressure to change through the integration of AI capabilities.

TABLE 1
EXAMPLES OF ARTIFICIAL INTELLIGENCE APPLICATIONS FOR
HR FUNCTIONS IN HRIS

HR Function	Examples & Applications
Recruitment	job postings, application management
Selection	applicant screening, applicant testing, interviews
Hiring	background and credit checks, drug screenings
Onboarding	employment authorization, new hire onboarding, orientation
Training	upskilling, cross training
Development	career development, career counseling
Performance	performance appraisals, feedback and coaching
Retention	attitude, engagement, and satisfaction surveys
Compensation	salary administration, PTO, leave management
Incentives	incentive programs, equity compensation
Policies	policy development, employee handbook
Legal Compliance	labor law compliance and reporting, accommodations, labor relations
Benefits	benefits administration / support, retirement plan, profit-sharing
Wellness	health and wellness program, EAP
Communication	information sharing / management, employee-facing communications
Strategic Planning	data analytics, work design & analysis, workforce planning / forecasting / benchmarking

Artificial Intelligence

In this research, AI is defined as a computer system able to perform tasks normally requiring human intelligence. AI is different from automation. Automation is usually rule-based and follows predetermined instructions, while AI-supported systems learn from data and make real-time decisions based on the data (Tyson & Zysman, 2022).

Organizations are increasingly adopting AI-powered HRIS applications to optimize HR administrative tasks, enhance decision-making processes, and improve the overall efficiency of HR operations (Marler & Boudreau, 2017; Votto et al., 2021). The integration of AI in HRIS offers numerous benefits to organizations. AI-powered algorithms can analyze vast amounts of HR data to identify patterns, trends, and insights to drive improved outcomes across many HR functions. These outcomes include, but are not limited to, recruitment, talent management, and workforce planning (Davenport & Harris, 2017). Additionally, AI-driven chatbots and virtual assistants deployed within HRIS platforms can provide personalized support to employees, improve user experiences, and increase engagement (Bishop et al., 2019).

AI-enabled HRIS (AIHR)

The proposed construct of AIHR is defined as the constellation of components in an HRIS that have integrated artificial intelligence to improve HR-related processes and outcomes. Scholars and organizations need an instrument to measure the extent of AI use to better understand the challenges associated with AIHR, the levels of adoption in an organization, and how AI is affecting HR professionals and employees. The ability to measure AI integration and impact will enable researchers and organizations to assess how AI technologies are influencing specific HR functions. This understanding will facilitate the evaluation of AI's effectiveness in improving HR processes and outcomes. Extant literature focusing on the extent of technology use by employees, such as AIHR, has been published in the information systems and human resources literature (Doll & Torkzadeh, 1998; Hussain et al., 2007; Rosen et al., 2013; Tambe et al., 2019; Yawalkar, 2019) for a number of years. The methodology applied, and scale development procedures applied in this study were designed in line with extant literature.

SCALE DEVELOPMENT METHODOLOGY

Item Generation and Practitioner Interviews

After an extensive review of the relevant literature, a pool of items was developed. Items were generated to be both exhaustive and exclusive to identify and avoid gaps in measuring AI usage and to minimize overlap in measuring AI usage. The resulting pool contained five items spanning each of the five primary functions of HRM (Lussier & Hendon, 2017). Each item asked to what extent does the participants' organization use AI-assisted technology to help with hiring employees, developing employees, retaining employees, communicating with employees and HR administration. Item measurement was a 7-point Likert-type scale ranging from never to always.

In the next stage of the scale development process, cognitive interviews were conducted with five HR professionals. Cognitive interviewing has support in the literature as an effective tool for gathering information about the functioning of the survey items (Lenzner et al., 2023; Willis, 2015). The participants' years of HR experience ranged from 1.5-30 years, all had college-level degrees and/or professional certifications in HR, and worked in the functional areas of compensation, recruitment, administration, and employee development.

Participants were provided with an invitation to interview containing a specific definition of AI, a brief overview of basic AI processes within HRIS, and examples of AI in HR systems. The choice to provide a formal invitation to interview was undertaken because initial requests for interviews were declined by HR professionals who indicated they did not work with AI in their jobs. This led to the conclusion that some HR professionals did not realize they are interacting with AI within their HR systems.

The participants were asked about their primary job functions and the types of systems they interacted with for their primary job functions. Once the participants had shared information on their job functions and relevant information systems, they were presented with the initial list of five items generated from extant literature. Participants were first asked to score the items as a survey respondent would. The interviewer then probed the participants to obtain detailed information as to why they scored the item in the manner it was scored. Next, they were asked about their opinions on the wording, clarity, and scope of the items. The interviews were recorded, reviewed by two members of the research team, and utilized for item expansion and refinement. The major identified theme that surfaced across all five interviews was that each interview participant suggested changing one or more items from covering a major functional area of HR to specific HR tasks. Based on the interview feedback, the items were expanded from five to sixteen.

Qualitative Pretesting with OpenAI ChatGPT

A second round of qualitative item testing was conducted using OpenAI ChatGPT 3.5, which has recently been recognized in the literature as having considerable promise in the research process for pretesting design choices and qualitative analysis (Hair & Sabol, 2025; Sarstedt et al., 2024; Tai et al., 2024). The expanded and refined items were entered into OpenAI ChatGPT with instructions to evaluate each item's quality and appropriateness and to provide suggestions for improvement.

The OpenAI ChatGPT evaluation identified eight items measuring AI in the activities of recruitment, hiring, training, performance evaluation, and compensation as clear and specific, and needing no improvement. The OpenAI ChatGPT evaluation of AI in the selection, onboarding, development, and retention provided suggestions to be more specific and add additional activities. While the suggested revisions were in line with activities present in HRIS and could have AI integration, the decision was made not to further expand the items due to concerns with the length of the questionnaire and potential issues with cognitive load on human subjects participating in the study (Galesic & Bosnjak, 2009). A copy of the OpenAI ChatGPT script and final scale items can be found in the appendix.

Pilot Study 1

Once the qualitative testing and analysis of items was complete, the resulting questionnaire was approved by an institutional review board and pretested with an online panel of working HR professionals in the Amazon Mechanical Turk (MTurk) platform web services. A definition of AI and examples of AI in

HR tasks were provided at the top of the landing page for the items. Providing definitions and examples for survey participants has been shown to aid in communicating the researchers' intended meaning and improve the accuracy of participants' responses (Peytchev et al., 2010; Haraldsen, 2023). The survey concluded with demographic-related questions. The average time to complete was two minutes and one second. The pilot sample consisted of 90 respondents.

Data quality was assessed and missing values were addressed using mean imputation. Once data quality was confirmed, a correlation analysis confirmed the data matrix had sufficient correlations to apply exploratory factor analysis (EFA). The model sampling adequacy was assessed by conducting a Kaiser-Meyer-Olkin (KMO) test (Kaiser, 1970), which measures sampling adequacy (MSA) of the model as a whole and for each indicator. KMO and MSA evaluation measures the proportion of common variance; a higher value indicates greater suitability (Taherdoost et al., 2022). With sampling adequacy established, the data was subjected to Bartlett's test of sphericity (Bartlett, 1950), to determine whether the observed correlation matrix conforms to an identity matrix wherein all non-diagonal elements are zero (Howard, 2016). The KMO value was .839 and Bartlett's test results were statistically significant ensuring the data was appropriate for submitting to an EFA.

An EFA enables researchers to evaluate whether the collected data are consistent with the expected pattern, or structure, of the target construct (Matsunaga, 2010). A parallel analysis EFA was applied using JASP 0.13.1.0 software for Windows (JASP team, 2024) to determine the number of potential factors. The parallel analysis approach is supported in the literature as superior to other methods in more accurately identifying the ideal number of factors to extract (Finch, 2020; Iacobucci et al., 2022). Since the items were found to correlate, an oblique promax rotation was applied.

The parallel analysis identified a single factor. As displayed in Table 2, a majority of the item factor loadings exceeded the threshold of .40 (Hair et al., 2019). Items 3, 8, and 16 were not included in the single factor due to loadings below .40.

TABLE 2
PARALLEL ANALYSIS RESULTS – PILOT 1

Bartlett's test			Factor Characteristics			
X ²	df	p	SumSq. Loadings	Proportion var.	Cumulative	KMO
229.4831	104	< .001	4.981	0.311	0.311	0.7862

Factor Metrics			
Item	Factor 1	Uniqueness	MSA
AIHR_1		0.636	0.596
AIHR_2		0.708	0.499
AIHR_3			0.896
AIHR_4		0.581	0.662
AIHR_5		0.586	0.657
AIHR_6		0.569	0.676
AIHR_7		0.411	0.831
AIHR_8			0.900
AIHR_9		0.550	0.698
AIHR_10		0.676	0.543
AIHR_11		0.663	0.561
AIHR_12		0.550	0.697
AIHR_13		0.567	0.679
AIHR_14		0.687	0.528
AIHR_15		0.563	0.683
AIHR_16			0.912

Note . Applied rotation method is promax. KMO=Kaiser-Meyer-Olkin test

Pilot Study 2

A second questionnaire pilot study was conducted with an online panel of working HR professionals using the Prolific platform. The second pilot survey followed the same format and flow as the first pilot. The same 16 items used in the first pilot study were used for this second pilot study. The average time to complete was three minutes and thirty seconds. The pilot sample consisted of 50 respondents.

Once data quality was confirmed, the model sampling adequacy was assessed. The KMO value for the pilot one model was .839, and the MSA for each item exceeds .5, indicating sample adequacy. (Shrestha, 2021). Bartlett's test of sphericity was statistically significant, suggesting that factor analysis is appropriate for the dataset (Hair et al., 2019). Both the KMO and Bartlett's tests suggest the data did not violate the assumptions needed to conduct an EFA.

As presented in Table 3, the item factor loadings all exceeded the threshold of .40 (Hair et al., 2019). The parallel analysis identified a single factor. The lowest loading was .687. The resulting scale can be described as having high loadings and a high number of variables with a simple one-factor structure. Extant literature supports a sample size of 50 as being appropriate for this type of scale (de Winter et al., 2009; MacCallum et al., 1999).

TABLE 3
PARALLEL ANALYSIS RESULTS – PILOT 2

Bartlett's test			Factor Characteristics			
X ²	df	p	SumSq. Loadings	Proportion var.	Cumulative	KMO
774.2397	120	< .001	9.551	0.597	0.597	0.839

Factor Metrics			
Item	Factor 1	Uniqueness	MSA
AIHR_1	0.668	0.554	0.763
AIHR_2	0.716	0.487	0.897
AIHR_3	0.712	0.493	0.787
AIHR_4	0.715	0.489	0.914
AIHR_5	0.791	0.375	0.882
AIHR_6	0.815	0.336	0.817
AIHR_7	0.687	0.529	0.772
AIHR_8	0.720	0.481	0.793
AIHR_9	0.810	0.345	0.790
AIHR_10	0.795	0.369	0.752
AIHR_11	0.806	0.350	0.875
AIHR_12	0.776	0.399	0.904
AIHR_13	0.891	0.206	0.904
AIHR_14	0.818	0.331	0.876
AIHR_15	0.761	0.421	0.852
AIHR_16	0.845	0.286	0.863

Note . Applied rotation method is promax KMO=Kaiser-Meyer-Olkin test

Scale Validation

Since both pilot studies support a single-factor scale, the decision was made to move forward with scale validation. Based on the results of pilot 2, the choice was made to retain all 16 items. A listing of the items can be found in the appendix.

An important phase in the scale development process is examining the nomological network to assess associations with closely related but dissimilar constructs (Jebb et al., 2021). A review of the AI HRM literature found AIHR has overlap with the following constructs as they relate to AI specifically: transparency, perceived usefulness, trust, effectiveness, and innovative work behavior (Agarwal & Prasad, 1997; Choung & Ross, 2023; Marangunić & Granić, 2015).

Transparency in AI refers to the openness and comprehensibility of the algorithms, decision-making processes, and data usage within these systems. In other words, transparency describes knowledge available to the system and the reasoning process utilized (Vorm & Combs, 2022). According to the principle of algorithmic transparency (Diakopoulos, 2017), transparency is essential for building trust, fostering accountability, and mitigating potential biases and discrimination in AI systems. Transparency impacts trust because employees are more likely to trust and engage with AIHR when they understand how these systems work, how decisions are made, and how their data is used (Glikson & Woolley, 2020; Goodman & Flaxman, 2017). Transparency also provides a mechanism for organizations to identify and address issues related to AI system performance and fairness (Veale & Binns, 2017). As such, the following hypothesis is offered:

H1. AI transparency is positively associated with AI Trust.

Trust in AI technologies refers to the confidence and belief that these systems will operate reliably, ethically, and in the best interests of users and the organization as a whole (Gillath et al., 2021). According to organizational trust theory (Mayer et al., 1995), trust is built upon perceptions of competence, integrity, benevolence, and predictability. Employees are more likely to utilize AIHR when they trust these systems will maintain data privacy, provide accurate recommendations, and support fair decision-making processes (Bélanger & Carter, 2008). Trust also fosters collaboration between employees and AI systems, leading to positive evaluations of AI usefulness (Bhattacharjee, 2001). Because trust in AI plays a fundamental role in the adoption and effective utilization of AIHR within organizations (Ardion et al., 2018; Yu & Li, 2022), the following hypotheses are offered:

H2. AI Trust is positively associated with perceived AI usefulness.

H3. AI Trust is positively associated with AIHR.

Perceived usefulness holds an established position in the technology adoption and utilization literature (Abdullah et al., 2016; Hampshire, 2017; Hess et al., 2014). Thus, its position is logically extended to also apply to the field of AIHR within organizations. In the technology acceptance model (TAM; Davis, 1989), employees' perceptions of the usefulness of integrated technologies significantly influence their acceptance and continued use. Perceived usefulness encompasses the subjective belief that utilizing technologies such as AIHR can positively impact job performance and contribute to achieving organizational goals (Venkatesh et al., 2003). Extant literature suggests employees are more inclined to embrace technologies like AIHR when they perceive tangible benefits such as increased efficiency (Venkatesh & Davis, 2000). Perceived usefulness has been supported in the literature as positively relating to trust and technology use (Pitardi & Marriott, 2021; Zhang et al., 2021). As such, the following hypotheses are proposed:

H4. Perceived AI usefulness is positively associated with AIHR.

H5. Perceived AI usefulness will mediate the relationship between trust and AIHR.

Perceived AI effectiveness refers to employees' evaluation of AI decision-making. AI effectiveness is considered to be a measure of user satisfaction with the ability of the output information to meet user requirements (Nicolau, 2000). Put simply, when users engage in using a technology, their experiences enable them to form perceptions of the technology's effectiveness. Although perceived AI effectiveness has been modeled as an outcome of technology use (Castelo et al., 2019), it has also been supported in the

literature as a potential outcome of technology use and continuation of use (Lowerison et al., 2006; Zhang et al., 2017). Therefore, the following hypothesis is proposed:

H6. *AIHR is positively associated with perceived effectiveness.*

Innovative work behavior (IWB) refers to the proactive generation, adoption, and implementation of novel ideas, processes, or products by employees (Janssen, 2000). IWB has support in the extant literature as a component of the nomological network that encompasses the adoption of AI-integrated technologies (Schechter et al., 2023). Because AI algorithms can effectively analyze large volumes of data to identify patterns, trends, and opportunities for innovation, the literature suggests creativity and experimentation are positively impacted (Chuang et al., 2016) by freeing up employees' time and cognitive resources, allowing them to focus on more creative and strategic endeavors (Verma & Singh, 2022). Simply put, the usefulness and satisfactory quality of AI decisions facilitates reduced job demands and greater job autonomy, which positively impacts IWB. This relationship is expected to be meaningful in this study, therefore, so the following is hypothesized:

H7. *Perceived AI effectiveness is positively associated with IWB.*

SCALE VALIDATION METHODOLOGY

Data Collection

The validation study was conducted with an online panel of working HR professionals using the Survey Monkey (SM) audience platform. SM has support in the literature as having high data quality in line with more expensive panel options for survey-based data collection (Bentley et al., 2020). The survey settings prequalified participants based on age, working status, and HR job type. The survey flow and structure followed the same format as the pilot studies. The average time to complete was six minutes and seven seconds. The sample consisted of 53 respondents. The data supporting this study's findings are available from the corresponding author upon request.

Measurement and Analysis

Previously established scales with a seven-point Likert-like scale were used to reflectively measure the constructs in the validation model. Examples include IWB (De Jong & Den Hartog, 2010), Perceived Usefulness (Davis et al., 1989), AI effectiveness (Yu & Li, 2022), and Transparency (Zhao et al., 2019). Trust was measured by combining two three-item scales for a six-item measure (Hoddinghaus et al., 2021; McKnight et al., 2002).

To assess the reliability and validity of the measurement models and investigate the nomological validity of the structural model, partial least squares structural equation modeling (PLS-SEM) analysis was utilized (Wold, 1982; Lohmöller, 1989; Hair et al., 2022). Hair et al. (2020) confirms the relevance of PLS-SEM for scale development and validation. Confirmatory composite analysis (CCA) was used to evaluate the measures and structural models. CCA is a useful tool for developing and validating measures within a nomological network (Hair et al., 2020).

Measurement Model Results

To estimate the proposed model with the obtained data, we use the statistical software SmartPLS 4 (Ringle et al., 2024). The default settings of Mode A with 3,000 iterations were used in estimating the models (Cheah et al., 2024). For the measurement model assessment, we apply the criteria and guidelines provided by Hair et al. (2022). The results support the reliability and validity of the measurement model. All indicators have high loadings, which ensures indicator reliability (Table 4).

TABLE 4
INDICATOR LOADING

Construct	Item	Outer Loading	Construct	Item	Outer Loading
AIHR	AIHR1	0.854	Innovative Work Behavior	INV1	0.805
	AIHR2	0.877		INV2	0.807
	AIHR3	0.854		INV3	0.852
	AIHR4	0.922		INV4	0.873
	AIHR5	0.908		INV5	0.769
	AIHR6	0.937		INV6	0.838
	AIHR7	0.909	Perceived Usefulness	PU1	0.905
	AIHR8	0.923		PU2	0.960
	AIHR9	0.904	Transparency	PU3	0.951
	AIHR10	0.898		TRNS1	0.907
	AIHR11	0.871		TRNS2	0.933
	AIHR12	0.871	Trust	TRNS3	0.901
	AIHR13	0.941		Trust1	0.819
	AIHR14	0.913		Trust2	0.890
	AIHR15	0.879		Trust3	0.871
Perceived Effectiveness	AIHR16	0.937		Trust4	0.844
	EFCT1	0.901		Trust5	0.822
	EFCT2	0.940		Trust6	0.872
	EFCT3	0.904			

Furthermore, the latent variables exceed the .708 accepted threshold for $\hat{\eta}_A$, which supports internal consistency reliability (Table 5). However, some $\hat{\eta}_A$ values are quite high (i.e., >.90), which may indicate redundancy of items per construct (i.e., the use of indicators with slightly changed wordings of the underlying questions, which, thereby represent very similar content). However, high correlations between items are acceptable when items are sufficiently different (Relling et al., 2016). An inspection of the indicators per construct shows each indicator provides sufficiently different content, and we conclude that we revealed reliable scales. Moreover, all measures exhibit convergent validity by exceeding the recommended average variance extracted (AVE) threshold of .50.

TABLE 5
MEASUREMENT MODEL ASSESSMENT

		1	2	3	4	5	6	Cronbach's alpha	Composite reliability (rho_a)	Mean	SD
1.	AIHR	.810	.668	.370	.708	.840	.796	.984	.986	4.663	2.045
2.	EFCT	.635	.838	.631	.866	.832	.835	.903	.908	4.730	1.823
3.	INV	.357	.583	.680	.486	.487	.585	.906	.919	5.217	1.628
4.	PU	.686	.798	.459	.882	.890	.784	.933	.945	4.610	1.899
5.	TRNS	.791	.752	.445	.821	.835	.752	.901	.902	4.516	1.932
6.	Trust	.769	.768	.538	.739	.694	.728	.925	.931	4.601	1.890

Notes: AVEs are provided in diagonal, inter-construct correlations are provided in sub-diagonal, and HTMT metrics are provided in the super-diagonal.

Lastly, all measures demonstrate discriminant validity with all heterotrait-monotrait ratio of correlations (HTMT) below .90 (Table 6). Moreover, all HTMT results are statistically significantly below 1.00 but we find that some outcomes are not statistically significantly below .90, which indicates some limitations to our establishment of discriminant validity.

TABLE 6
HTMT RESULTS AND CONFIDENCE INTERVALS

Constructs	HTMT results	5.0%	95.0%
EFCT <-> AIHR	0.680	0.531	0.817
INV <-> AIHR	0.382	0.241	0.573
INV <-> EFCT	0.631	0.411	0.834
PU <-> AIHR	0.713	0.567	0.832
PU <-> EFCT	0.866	0.745	0.966
PU <-> INV	0.486	0.291	0.687
TRNS <-> AIHR	0.845	0.739	0.937
TRNS <-> EFCT	0.832	0.675	0.986
TRNS <-> INV	0.487	0.265	0.726
TRNS <-> PU	0.890	0.792	0.981
Trust <-> AIHR	0.803	0.684	0.911
Trust <-> EFCT	0.835	0.690	0.948
Trust <-> INV	0.585	0.368	0.803
Trust <-> PU	0.784	0.639	0.892
Trust <-> TRNS	0.752	0.567	0.916

Structural Model Results

Once the measurement model was assessed as having valid and reliable measures, the structural model was evaluated to assess the significance and relevance of path coefficients and to measure the model's explanatory power (Hair et al, 2022). First, the model was tested for collinearity issues. All variance inflation factor (VIF) values were lower than 3.0, indicating collinearity is not a critical issue. Next, the path coefficients were evaluated in terms of significance and relevance. Bias-corrected bootstrapping analysis using the percentile was conducted using 10,000 subsamples. All hypotheses were confirmed based on the path coefficients' direction and statistical significance based on a 95% confidence interval. Table 7 shows the results of the collinearity analysis and path coefficients' evaluation.

TABLE 7
STRUCTURAL MODEL ASSESSMENT

Structural paths	VIF	β	2.50%	97.50%	Standard deviation (STDEV)	P values	f-square	Hypothesis testing
TRNS -> Trust	1.00	0.694	0.475	0.844	0.091	0.000	0.927	H1 supported
Trust -> PU	1.00	0.739	0.548	0.849	0.071	0.000	1.204	H2 supported
Trust -> AIHR	2.20	0.577	0.302	0.772	0.116	0.000	0.399	H3 supported
PU -> AIHR	2.20	0.260	0.045	0.492	0.114	0.023	0.081	H4 supported
AIHR -> EFCT	1.00	0.635	0.447	0.775	0.083	0.000	0.676	H5supported
EFCT -> INV	1.68	0.597	0.106	0.860	0.187	0.001	0.322	H6 supported

Mediation Analysis

In H5, perceived usefulness was hypothesized to mediate the relationship between trust and AIHR. The indirect and direct paths were both positive and statistically significant, suggesting complementary partial mediation (Nitzl et al., 2016; Sarstedt et al., 2020). Once mediation was established, effect size metrics relevant to mediating relationships were assessed. Two mediation effect sizes appropriate for complementary mediation are total effect (TE) and variance accounted for (VAF). While a majority of mediation analysis research focuses on the size and significance of the indirect path (Lachowicz *et al.*, 2018), assessing the total effect (TE) can be useful in providing information on the entire mediation model, especially in exploratory studies with complementary mediation (Hair *et al.*, 2022). The TE is the sum of the direct (c') and indirect effects (ab). The TE for H5 was .961. The VAF determines the extent to which the mediation model explains the variance of the dependent variable (Nitzl et al., 2016). The VAF is the TE divided by the indirect effect. The VAF value was .200, indicating limited mediation (Hair et al., 2023). As reported in Table 8, perceived usefulness is a significant mediator of the relationship between trust and AIHR. H7 is therefore supported.

TABLE 8
MEDIATION RESULTS

	β	t Statistic	p Values	BCBCI 2%	BCBCI 97.5%	Total Effect	VAF
H3b Effects						0.961	0.200
Direct Effects							
(a)Trust -> PU	0.739	10.356	0.000	0.548	0.849		
(b)PU -> AIHR	0.259	2.250	0.025	0.044	0.497		
(c')Trust -> AIHR	0.769	11.410	0.000	0.596	0.874		
Indirect Effect							
(ab)Trust -> PU- ->AIHR	0.192	2.072	0.038	0.038	0.405		

Note. BCBCI= Bias corrected bootstrap confidence interval, \hat{v} =upsilon, VAF= Variance accounted for.

Once the path coefficient analysis and hypothesis testing were complete, the model's explanatory power was assessed. As presented in Figure 1 the model's dependent variable INV has an R2 value of .34 which is considered suitable for models that investigate the impact of workplace resources on innovative behavior (Chang et al., 2013; Madrid & Patterson, 2020). Trust, Perceived Usefulness, AIHR, and Perceived Effectiveness show R2 values of .481, .546, .622, and .403, respectively, which aligns with extant research on technology usage (Al-Jabri & Roztocki, 2015; Mou et al., 2017). In comparison to a recent meta-analysis of technology use models that included innovativeness (Blut et al., 2021), and in consideration of the exploratory focus of this research, the explanatory power of the model can be considered more than adequate.

Once the explanatory power within the sample was evaluated, a cross-validated predictive ability test (CVPAT) was utilized to assess and compare the out-of sample predictive capabilities of the hypothesized models (Hair, 2021; Sarstedt et al., 2023). The CVPAT method, introduced by Liengaard et al. (2021), conducts an inferential analysis to determine whether an alternative model shows significantly improved predictive abilities compared to a well-established model. Sharma et al. (2023) expanded the use of CVPAT from simultaneous model comparison to also include a comparison of the target construct and naïve benchmarking. The model's predictive abilities based on the PLS-SEM results were tested against predictions using the indicator averages and linear model benchmarks (Table 9). The PLS-SEM results have a significantly lower average loss model than the indicator averages benchmark. Moreover, we find that the PLS-SEM results have a slightly lower average loss than the linear model benchmark, which, however, is not statistically significant. Based on these CVPAT results we conclude that the hypothesized model has moderate predictive power.

FIGURE 1
HYPOTHESIZED MODEL

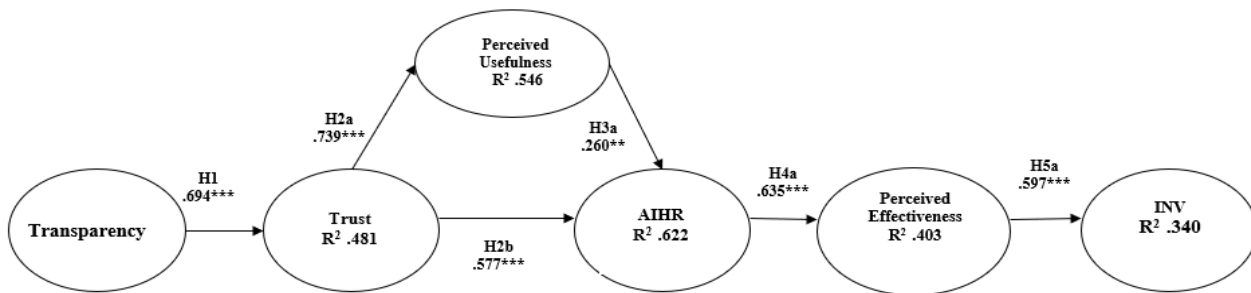


TABLE 9
PREDICTION ASSESSMENT

	Average loss difference				Average loss difference		
	PLS loss	IA loss	PLS: IA	p-value	LM loss	PLS: LM	p-value
			PLS: IA	PLS: IA		PLS: LM	PLS: LM
Overall Model	2.401	3.794	-1.393	0.000	2.402	-0.001	0.991

Note. IA- indicator average, LM= linear model

DISCUSSION

The Integration of AI in HRIS is a rapidly emerging and substantial evolution in the domain of HRM, transforming HR systems from static data repositories to dynamic, decision-supportive platforms. This study contributes to the growing field of AI-supported HRM by developing and validating a reflective measure of AI integration within HRIS. The resulting 16-item scale quantifies the extent of AI utilization across diverse HR functions and presents an opportunity for practitioners and researchers to understand better how AIHR can impact employee perceptions and behavior.

Our findings indicate when employees perceive AIHR as useful and effective, there is greater potential for improved employee outcomes, such as innovative behavior. The newly developed scale's high reliability and validity demonstrate its robustness and applicability across a wide range of HR tasks, enabling a standardized assessment of AI's integration into HRIS.

This paper highlights the importance of organizations fostering an environment of trust and transparency regarding AI applications in HRM. Such an environment not only facilitates the acceptance of AI technologies but can also play an important role in effectively achieving HR objectives.

IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

Theoretically, this research enriches the HRIS and AI literature by providing a novel instrument to measure AI integration in HRIS, thereby addressing a substantial gap in the extant research. It also offers an opportunity to measure and, therefore, better understand the relationship between AI integration and key constructs such as trust, transparency, and perceived usefulness, thereby contributing to the broader discourse on technology acceptance models in the context of HRIS.

For practitioners, the validated scale is a vital tool for assessing the current state of AI integration in their HRIS, facilitating benchmarking against industry standards, and identifying areas for enhancement. Organizations can leverage insights from this measure to strategically plan AI initiatives, aligning them with HR objectives to optimize HR operations and improve decision-making processes. Moreover, by

highlighting the importance of transparency and trust in adopting AIHR, this study underscores the need for organizations to adopt ethical AI practices and ensure clear communication regarding AI use in HR processes.

The study's cross-sectional design provides a snapshot of AI integration within HRIS at a single point in time. This design limits the ability to capture the dynamic nature of AI integration and its evolving impact on HRM practices over time. Longitudinal studies are recommended to track changes in AI integration and its effects on organizational outcomes, employee satisfaction, and HR efficiency. Acknowledging these limitations is crucial for interpreting the study's findings within the appropriate context and for guiding future research efforts to advance our understanding of AI integration in HRIS and its implications for HRM.

REFERENCES

- Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. *Computers in human behavior*, 63, 75–90.
- Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences*, 28(3), 557–582.
- Aicardi, C., Fothergill, B.T., Rainey, S., Stahl, B.C., & Harris, E. (2018). Accompanying technology development in the Human Brain Project: From foresight to ethics management. *Futures*, 102, 114–124. <https://doi.org/10.1016/j.futures.2018.01.005>
- Alam, M.F.B., Hosen, M.I., Mridha, J.H., Chowdhury, S.E., & Rahman, M.A. (2023). Assessing the barriers of integrating technological innovations in textiles sector: Implications towards sustainable production. *Green Technologies and Sustainability*, 1(3), 100039.
- Al-Jabri, I.M., & Roztock, N. (2015). Adoption of ERP systems: Does information transparency matter?. *Telematics and Informatics*, 32(2), 300–310.
- Beldad, A.D., & Hegner, S.M. (2018). Expanding the Technology Acceptance Model with the Inclusion of Trust, Social Influence, and Health Valuation to Determine the Predictors of German Users' Willingness to Continue using a Fitness App: A Structural Equation Modeling Approach. *International Journal of Human–Computer Interaction*, 34(9), 882–893.
- Ball, K.S. (2001). The use of human resource information systems: a survey. *Personnel Review*, 30(6), 677–693.
- Bélanger, F., & Carter, L. (2008). Trust and risk in e-government adoption. *The Journal of Strategic Information Systems*, 17(2), 165–176.
- Bélanger, F., Maier, J., & Maier, M. (2022). A longitudinal study on improving employee information protective knowledge and behaviors. *Computers & Security*, 116, 102641.
- Bentley, F., O'Neill, K., Quehl, K., & Lottridge, D. (2020, April). Exploring the quality, efficiency, and representative nature of responses across multiple survey panels. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–12).
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, pp. 351–370.
- Bishop, L., van Maris, A., Dogramadzi, S., & Zook, N. (2019). Social robots: The influence of human and robot characteristics on acceptance. *Paladyn, Journal of Behavioral Robotics*, 10(1), 346–358.
- Blut, M., Chong, A., Tsiga, Z., & Venkatesh, V. (2021). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting A research agenda in the red ocean. *Journal of the Association for Information Systems*, forthcoming.
- Bondarouk, T.V., & Ruël, H.J. (2009). Electronic Human Resource Management: Challenges in the digital era. *The International Journal of Human Resource Management*, 20(3), 505–514.
- Castelo, N., Bos, M.W., & Lehmann, D.R. (2019). Task-dependent algorithm aversion. *J. Mark. Res.*, 56, 809–825.

- Cesta, A., Cortellessa, G., & De Benedictis, R. (2014). Training for crisis decision making—An approach based on plan adaptation. *Knowledge-Based Systems*, 58, 98–112.
- Chang, H.T., Hsu, H.M., Liou, J.W., & Tsai, C.T. (2013). Psychological contracts and innovative behavior: A moderated path analysis of work engagement and job resources. *Journal of Applied Social Psychology*, 43(10), 2120–2135.
- Cheah, J.H., Magno, F., & Cassia, F. (2024). Reviewing the SmartPLS 4 software: The latest features and enhancements. *Journal of Marketing Analytics*, 12, 97–107.
- Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction*, 39(9), 1727–1739.
- Chuang, Y.T., Jackson, S.E., & Jiang, Y. (2016). Can knowledge-intensive teamwork be managed? Examining the roles of HRM systems, leadership, and tacit knowledge. *Journal of Management*, 42(2), 524–554.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning*. Harvard Business Press.
- De Jong, J.P., & Den Hartog, D.N. (2008). Innovative work behavior: Measurement and validation. *EIM Business and Policy Research*, 8(1), 1–27.
- DeSanctis, G. (1986). Human resource information systems: A current assessment. *MIS Quarterly*, pp.15–27. <https://doi.org/10.2307/248875>
- de Winter, J.C., Dodou, D.I., & Wieringa, P.A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate Behavioral Research*, 44(2), 147–181.
- Diakopoulos, N. (2017). Enabling accountability of algorithmic media: Transparency as a constructive and critical lens. In T. Cerquitelli, D. Quercia, & F. Pasquale (Eds.), *Transparent Data Mining for Big and Small Data* (pp. 25–43). Springer International Publishing.
- Doll, W.J., & Torkzadeh, G. (1998). Developing a multidimensional measure of system-use in an organizational context. *Information & Management*, 33(4), 171–185.
- Finch, W.H. (2020). Using fit statistic differences to determine the optimal number of factors to retain in an exploratory factor analysis. *Educational and Psychological Measurement*, 80(2), 217–241.
- Galesic, M., & Bosnjak, M. (2009). Effects of Questionnaire Length on Participation and Indicators of Response Quality in a Web Survey. *Public Opinion Quarterly*, pp. 349–360.
- Gaskin, J., Ogbeibu, S., & Lowry, P.B. (2023). Demystifying prediction in mediation research and the use of specific indirect effects and indirect effect sizes. In H. Latan, J.F. Hair, & R. Noonan (Eds.), *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 209–228). Cham: Springer International Publishing.
- Gillath, O., Ai, T., Branicky, M.S., Keshmiri, S., Davison, R.B., & Spaulding, R. (2021). Attachment and trust in artificial intelligence. *Computers in Human Behavior*, 115, 106607.
- Glikson, E., & Woolley, A.W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2), 627–660.
- Goodman, B., & Flaxman, S. (2017). European Union regulations on algorithmic decision-making and a “right to explanation”. *AI Magazine*, 38(3), 50–57.
- Hair, J.F. (2021). Next-generation prediction metrics for composite-based PLS-SEM. *Industrial Management & Data Systems*, 121, 5–11.
- Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2019). *Multivariate data analysis* (8th ed.). Boston: Cengage, U.K.
- Hair, J.F., Jr., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Hair, J.F., Jr., Howard, M.C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 109, 101–110.
- Hair, J.F., Risher, J.J., Sarstedt, M., & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.

- Hair, J.F., Jr., Sarstedt, M., Ringle, C.M., & Gudergan, S.P. (2024), *Advanced issues in partial least squares structural equation modeling* (2nd ed.), Sage.
- Hair, J.F., & Sabol, M. (2025). Leveraging Artificial Intelligence (AI) in Competitive Intelligence (CI) Research. *Journal of Sustainable Competitive Intelligence*, 15, e0469–e0469.
- Hampshire, C. (2017). A mixed methods empirical exploration of UK consumer perceptions of trust, risk and usefulness of mobile payments. *International Journal of Bank Marketing*, 35(3), 354–369.
- Haraldsen, G. (2023). What computerized business questionnaires and questionnaire management tools can offer. *Advances in Business Statistics, Methods and Data Collection*, pp. 335–355.
- Hendrickson, A.R. (2003). Human resource information systems: Backbone technology of contemporary human resources. *Journal of Labor Research*, 24(3), 381.
- Hess, T.J., McNab, A.L., & Basoglu, K.A. (2014). Reliability generalization of perceived ease of use, perceived usefulness, and behavioral intentions. *MIS Quarterly*, 38(1), 1–28.
- Höddinghaus, M., Sondern, D., & Hertel, G. (2021). The automation of leadership functions: Would people trust decision algorithms?. *Computers in Human Behavior*, 116, 106635.
- Howard, M.C. (2016). A review of exploratory factor analysis decisions and overview of current practices: What we are doing and how can we improve? *International Journal of Human-Computer Interaction*, 32(1), 51–62.
- Hussain, Z., Wallace, J., & Cornelius, N.E. (2007). The use and impact of human resource information systems on human resource management professionals. *Information & Management*, 44(1), 74–89.
- Iacobucci, D., Ruvio, A., Román, S., Moon, S., & Herr, P.M. (2022). How many factors in factor analysis? New insights about parallel analysis with confidence intervals. *Journal of Business Research*, 139, 1026–1043.
- Janssen, O. (2000). Job demands, perceptions of effort-reward fairness, and innovative work behavior. *Journal of Occupational and Organizational Psychology*, 73(3), 287–302.
- JASP Team. (2024). *JASP (Version 0.18.3)* [Computer software].
- Jemine, G., & Guillaume, K. (2022). Lifting the veil on HRIS adoption: The role of vendors and consultants in the diffusion of HR innovations. *Information Technology and People*, 35(7), 2418–2440.
- Jebb, A.T., Ng, V., & Tay, L. (2021). A review of key Likert scale development advances: 1995–2019. *Frontiers in Psychology*, 12, 637547.
- Kaiser, H.F. (1970). A second-Generation little jiffy. *Psychometrika*, 35(4), 401–415.
- Kavanaugh, A., Fox, E.A., Sheetz, S., Yang, S., Li, L.T., Whalen, T. . . . Xie, L. (2011, June). Social media use by government: From the routine to the critical. In *Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times* (pp. 121–130).
- Kolbjørnsrud, V., Amico, R., & Thomas, R.J. (2017). Partnering with AI: How organizations can win over skeptical managers. *Strategy & Leadership*, 45(1), 37–43.
- Lachowicz, M.J., Preacher, K.J., & Kelley, K. (2018). A novel measure of effect size for mediation analysis. *Psychological Methods*, 23(2), 244.
- Latan, H., Hair Jr., J.F., Noonan, R., & Sabol, M. (2023). Introduction to the partial least squares path modeling: Basic concepts and recent methodological enhancements. In *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 3–21). Springer.
- Lengnick-Hall, M.L., & Moritz, S. (2003). The impact of e-HR on the human resource management function. *Journal of Labor Research*, 24(3), 365.
- Lenzner, T., Hadler, P., & Neuert, C. (2023). An experimental test of the effectiveness of cognitive interviewing in pretesting questionnaires. *Quality & Quantity*, 57(4), 3199–3217.
- Liengaard, B.D., Sharma, P.N., Hult, G.T.M., Jensen, M.B., Sarstedt, M., Hair, J.F., & Ringle, C.M. (2021). Prediction–coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. *Decision Sciences*, 52(2), 362–392.
- Lohmöller, J.-B. (1989). Latent Variable Path Modeling with Partial Least Squares. *Physica*.

- Loureiro, S.M.C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. *Journal of Business Research*, 129, 911–926.
- Lowerison, G., Sclater, J., Schmid, R.F., & Abrami, P.C. (2006). Student perceived effectiveness of computer technology use in post-secondary classrooms. *Computers & Education*, 47(4), 465–489.
- Lussier, R.N., & Hendon, J.R. (2017). *Human resource management: Functions, applications, and skill development*. Sage.
- MacCallum, R.C., Widaman, K.F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological Methods*, 4, 84–99.
- Madrid, H.P., & Patterson, M.G. (2020). How and for whom time control matter for innovation? The role of positive affect and problem-solving demands. *Applied Psychology*, 69(1), 93–119.
- Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, 14, 81–95.
- Marler, J.H., & Boudreau, J.W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, 28(1), 3–26.
- Matsunaga, M. (2010). How to Factor-Analyze Your Data Right: Do's, Don'ts, and How-To's. *International Journal of Psychological Research*, 3(1), 97–110.
- Mayer, R.C., Davis, J.H., & Schoorman, F.D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734.
- McKnight, D.H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *The Journal of Strategic Information Systems*, 11(3–4), 297–323.
- Mou, J., Shin, D.H., & Cohen, J. (2017). Understanding trust and perceived usefulness in the consumer acceptance of an e-service: A longitudinal investigation. *Behaviour & Information Technology*, 36(2), 125–139.
- Nicolaou, A.I. (2000). A contingency model of perceived effectiveness in accounting information systems: Organizational coordination and control effects. *International Journal of Accounting Information Systems*, 1(2), 91–105.
- Nitzl, C., Roldan, J.L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems*, 116(9), 1849–1864.
- Parry, E., & Tyson, S. (2013). *Managing people in a contemporary context*. Routledge.
- Peytchev, A., Conrad, F.G., Couper, M.P., & Tourangeau, R. (2010). Increasing respondents' use of definitions in web surveys. *Journal of Official Statistics*, 26(4), 633.
- Pitardi, V., & Marriott, H.R. (2021). Alexa, she's not human but... Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, 38(4), 626–642.
- Relling, M., Schnittka, O., Ringle, C.M., Sattler, H., & Johnen, M. (2016). Community members' perception of brand community character: Construction and validation of a new scale. *Journal of Interactive Marketing*, 36, 107–120.
- Ringle, C.M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4*. Retrieved from <https://www.smartpls.com/>
- Rosen, L.D., Whaling, K., Carrier, L.M., Cheever, N.A., & Rokkum, J. (2013). The media and technology usage and attitudes scale: An empirical investigation. *Computers in Human Behavior*, 29(6), 2501–2511.
- Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L.M. (2021). “Everyone wants to do the model work, not the data work”: Data Cascades in High-Stakes AI. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1–15).
- Sánchez Vidal, M.E., Sanz Valle, R., & Barba Aragón, M.I. (2008). International workers' satisfaction with the repatriation process. *The International Journal of Human Resource Management*, 19(9), 1683–1702.
- Sarstedt, M., Hair, J.F., Nitzl, C., Ringle, C.M. & Howard, M.C. (2020). Beyond a tandem analysis of SEM and PROCESS: Use PLS-SEM for mediation analyses! *International Journal of Market Research*, 62(3), 288–299.

- Sarstedt, M., Radomir, L., Moisescu, O.I., & Ringle, C.M. (2022). Latent class analysis in PLS-SEM: A review and recommendations for future applications. *Journal of Business Research*, 138, 398–407.
- Sarstedt, M., Adler, S.J., Rau, L., & Schmitt, B. (2024). Using large language models to generate silicon samples in consumer and marketing research: Challenges, opportunities, and guidelines. *Psychology & Marketing*, forthcoming.
- Sarstedt, M., Hair, J.F., & Ringle, C.M. (2023). “PLS-SEM: indeed a silver bullet”: Retrospective observations and recent advances. *Journal of Marketing Theory and Practice*, 31(3), 261–275.
- Schecter, A., Hohenstein, J., Larson, L., Harris, A., Hou, T.Y., Lee, W.Y., . . . Jung, M. (2023). Vero: An accessible method for studying human–AI teamwork. *Computers in Human Behavior*, 141, 107606.
- Sharma, P.N., Liengaard, B.D., Hair, J.F., Sarstedt, M., & Ringle, C.M. (2023). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing*, 57(6), 1662–1677.
- Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics*, 9(1), 4–11.
- Stone, D.L., Stone-Romero, E.F., & Lukaszewski, K. (2006). Factors affecting the acceptance and effectiveness of electronic human resource systems. *Human Resource Management Review*, 16(2), 229–244.
- Taherdoost, H., Sahibuddin, S. & Jalaliyoon, N. (2022). Exploratory factor analysis; concepts and theory. *Advances in Applied and Pure Mathematics*, 27, 375–382.
- Tai, R.H., Bentley, L.R., Xia, X., Sitt, J.M., Fankhauser, S.C., Chicas-Mosier, A.M., & Monteith, B.G. (2024). An Examination of the Use of Large Language Models to Aid Analysis of Textual Data. *International Journal of Qualitative Methods*, 23, 16094069241231168.
- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, 61(4), 15–42.
- Tyson, L.D., & Zysman, J. (2022). Automation, AI & work. *Daedalus*, 151(2), 256–271.
- Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204.
- Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, pp. 425–478.
- Verma, S., & Singh, V. (2022). Impact of artificial intelligence-enabled job characteristics and perceived substitution crisis on innovative work behavior of employees from high-tech firms. *Computers in Human Behavior*, 131, 107215.
- Veale, M., & Binns, R. (2017). Fairer machine learning in the real world: Mitigating discrimination without collecting sensitive data. *Big Data & Society*, 4(2), 2053951717743530.
- Vorm, E.S., & Combs, D.J. (2022). Integrating transparency, trust, and acceptance: The intelligent systems technology acceptance model (ISTAM). *International Journal of Human–Computer Interaction*, 38(18–20), 1828–1845.
- Willis, G.B. (2015). *Analysis of the cognitive interview in questionnaire design*. Oxford University Press.
- Wold, H. (1982). Soft modeling: The basic design and some extensions. In K.G. Jöreskog & H. Wold (eds.), *Systems under indirect observations: Part II* (pp. 1–54). North-Holland.
- Yu, L., & Li, Y. (2022). Artificial intelligence decision-making transparency and employees’ trust: The parallel multiple mediating effect of effectiveness and discomfort. *Behavioral Sciences*, 12(5), 127.
- Yawalkar, M.V.V. (2019). A study of artificial intelligence and its role in human resource management. *International Journal of Research and Analytical Reviews (IJRAR)*, 6(1), 20–24.
- Zhang, X., Jiang, S., Ordóñez de Pablos, P., Lytras, M.D., & Sun, Y. (2017). How virtual reality affects perceived learning effectiveness: A task–technology fit perspective. *Behaviour & Information Technology*, 36(5), 548–556.

- Zhang, S., Meng, Z., Chen, B., Yang, X., & Zhao, X. (2021). Motivation, Social Emotion, and the Acceptance of Artificial Intelligence Virtual Assistants—Trust-Based Mediating Effects. *Frontiers in Psychology*, 12, 728495.
- Zhao, R., Benbasat, I., & Cavusoglu, H. (2019, June 8–14). Do users always want to know more? Investigating the relationship between system transparency and users' trust in advice-giving systems. In *Proceedings of the 27th European Conference on Information Systems (ECIS)*, Stockholm & Uppsala, Sweden.

APPENDIX: OPENAI CHATGPT SCRIPT



You

evaluate the following survey questions regarding the quality and appropriateness of each question, please provide suggestions to improve the questions... Please indicate the extent to which your organization uses AI-assisted technologies to support HR activities in each of the categories below: Recruitment (e.g., job postings, application management); Selection (e.g., applicant screening, applicant testing, interviews); Hiring (e.g., background and credit checks, drug screenings); Onboarding (e.g., employment authorization, new hire onboarding, orientation); Training (e.g., upskilling, cross training); Development (e.g., career development, career counseling); Performance (e.g., performance appraisals, feedback and coaching); Retention (e.g., attitude, engagement, and satisfaction surveys); Compensation (e.g., salary administration, PTS, leave management); Incentives (e.g., incentive programs, equity compensation); Policies (e.g., policy development, employee handbook); Legal Compliance (e.g., labor law compliance and reporting, accommodations, labor relations); Benefits (e.g., benefits administration/support, retirement plan, profit sharing); Wellness (e.g., health and wellness programs, EAP); Communication (e.g., information sharing/management, employee facing communications); Strategic Planning (e.g., data analytics, work design and analysis, workforce planning/forecasting/benchmarking)



ChatGPT

Overall, the survey questions provide a comprehensive overview of various HR activities where AI-assisted technologies could be utilized. However, there are opportunities to improve the clarity, specificity, and alignment with the research objectives. Here's an evaluation of each question along with suggestions for improvement:

1. **Recruitment:** The question is clear and specific, asking about the use of AI in recruitment activities such as job postings and application management. No major improvements needed.
2. **Selection:** This question covers various aspects of applicant selection, but it could be more specific. For instance, instead of "applicant testing," specifying the types of tests (e.g., cognitive, personality) would provide clearer insights.
3. **Hiring:** The question is clear and covers relevant hiring activities. No major improvements needed.

4. **Onboarding:** Similar to the selection question, it could be more specific. For example, specifying the use of AI in document verification or compliance training during onboarding would enhance clarity.
5. **Training:** The question is clear and covers different aspects of training. No major improvements needed.
6. **Development:** This question could benefit from further specificity. For instance, asking about AI use in performance management systems or personalized learning recommendations would provide clearer insights into development activities.
7. **Performance:** The question is clear and specific, covering performance appraisals and feedback processes. No major improvements needed.
8. **Retention:** This question is clear, but it could be expanded to include AI use in predictive analytics for identifying flight risks or personalized retention strategies.
9. **Compensation:** The question is clear and covers various compensation-related activities. No major improvements needed.
10. **Incentives:** Similar to the retention question, it could be expanded to include AI use in identifying performance-based incentive structures or equity compensation adjustments.
11. **Policies:** The question is clear and covers policy-related activities. No major improvements needed.
12. **Legal Compliance:** This question covers a broad range of legal compliance activities, but it could be more specific. For instance, specifying AI use in auditing labor law compliance or analyzing accommodation requests would provide clearer insights.
13. **Benefits:** The question is clear and covers different aspects of benefits administration. No major improvements needed.
14. **Wellness:** Similar to other questions, it could be more specific. For example, asking about AI use in analyzing employee health data for wellness program recommendations would enhance clarity.
15. **Communication:** The question is clear and covers communication-related activities. No major improvements needed.
16. **Strategic Planning:** The question covers strategic planning activities, but it could be more specific. For example, asking about AI use in workforce forecasting models or strategic workforce planning tools would provide clearer insights.

In summary, while the survey questions generally cover relevant HR activities, enhancing specificity and alignment with research objectives would improve the clarity and appropriateness of each question. This can be achieved by providing more detailed examples or specifying particular AI applications within each HR function.

Final Scale Items: On a scale from 1(never) to 7 (always), please indicate the extent to which your organization uses AI-assisted technologies to support HR activities in each of the categories below:

1. Recruitment (e.g., job postings, application management)
2. Selection (e.g., applicant screening, applicant testing, interviews)
3. Hiring (e.g., background and credit checks, drug screenings)
4. Onboarding (e.g., employment authorization, new hire onboarding, orientation)
5. Training (e.g., upskilling, cross-training)
6. Development (e.g., career development, career counseling)
7. Performance (e.g., performance appraisals, feedback, and coaching)
8. Retention (e.g., attitude, engagement, and satisfaction surveys)
9. Compensation (e.g., salary administration, PTO, leave management)
10. Incentives (e.g., incentive programs, equity compensation)

11. Policies (e.g., policy development, employee handbook)
12. Legal Compliance (e.g., labor law compliance and reporting, accommodations, labor relations)
13. Benefits (e.g., benefits administration/support, retirement plan, profit-sharing)
14. Wellness (e.g., health and wellness program, EAP)
15. Communication (e.g., information sharing/management, employee-facing communications)
16. Strategic Planning (e.g., data analytics, work design, workforce planning)
17. Please indicate the extent to which your organization uses AI-assisted technologies in general