Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Human Resource Intelligence as a Higher-Order Capability: Evidence from HR Professionals in Thai Listed Companies

Chairat Nateeprasittiporn and Boon-Anan Phinaitrup*
Graduate School of Public Administration, National Institute of Development Administration, Bangkok, Thailand
E-mail: chairat_nat@cmru.ac.th and boon@nida.ac.th*
*Corresponding author
(Received: 18 March 2026, Revised: 8 July 2026, Accepted: 9 July 2026)
https://doi.org/10.57260/csdj.2026.287914

Abstract

This study conceptualizes and empirically validates Human Resource Intelligence (HRI) as a higher-order capability for HR professionals in the AI era. Drawing on data from 255 HR managers and practitioners in companies listed on the Stock Exchange of Thailand (SET), the study examines how six intelligence domains—Artificial Intelligence, Business Intelligence, Cultural Intelligence, Digital Intelligence, Emotional Intelligence, and Functional Intelligence—jointly constitute HRI. Using PLS-SEM, the results support HRI as a reliable and valid second-order construct, with acceptable model fit (SRMR = 0.066). All six dimensions contributed significantly to HRI. Digital Intelligence showed the strongest structural contribution (w = 0.262), followed by Emotional Intelligence (w = 0.245) and Functional Intelligence (w = 0.244), indicating that digital capability functions as the central anchor of HRI. Descriptive findings, however, showed that HR professionals reported the highest proficiency in Functional Intelligence and the lowest proficiency in Artificial Intelligence and Business Intelligence. This divergence reveals a capability imbalance: the areas in which practitioners feel most confident are not necessarily those that most strongly define HRI in AI-enabled organizations. The study contributes to HRM literature by showing that HRI is better understood not as a list of isolated competencies, but as an empirically validated higher-order capability. Practically, the findings suggest that HR development in Thai listed firms should prioritize AI literacy, digital fluency, and business analytics capability.

Keywords: Human resource intelligence, Artificial intelligence, Digital transformation, Higher-order construct, Stock exchange of Thailand, Human resource management

Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Introduction

The rapid infiltration of artificial intelligence (AI) and data-centric technologies has fundamentally redefined the landscape of modern human resource management (HRM). Organizations globally are transitioning from traditional administrative functions to AI-enabled processes, utilizing algorithms for talent acquisition, performance auditing, and predictive workforce analytics (Dutta & Naveen, 2025; Garcia & Kwok, 2025; Qamar et al., 2021). Industry estimates suggest that roughly seven in ten organizations have integrated some form of AI into their HR operations (McKinsey & Company, 2025); although such figures derive from consulting surveys rather than peer-reviewed research, the scholarly literature converges on the same underlying problem: a persistent value gap. Many firms struggle to derive sustainable strategic advantage from these tools, largely because HR systems remain decoupled from broader organizational decision-making and from the nuanced realities of human judgment (Enholm et al., 2021; Chowdhury et al., 2024).

This challenge is particularly acute in emerging economies such as Thailand, where digital transformation has accelerated across industries and the expectations placed on HR leaders have intensified accordingly. Yet a readiness deficit remains a critical bottleneck: a substantial share of HR leaders in Asia—by some accounts approaching 40%—report being underprepared to manage advanced analytics or mitigate algorithmic bias (Budhwar et al., 2023; Tambe et al., 2023). Technological adoption alone, in other words, is insufficient to catalyze meaningful organizational outcomes.

Companies listed on the Stock Exchange of Thailand (SET) constitute a particularly instructive context in which to examine this problem. Listed firms operate under formal governance and disclosure requirements, maintain professionalized HR functions, and are among the earliest Thai adopters of HR technology; they are therefore the setting in which the tension between technological adoption and practitioner readiness is most visible. At the same time, Thai organizational life is characterized by comparatively collectivist values and hierarchical norms, conditions under which the relational and human-centred dimensions of HR work retain particular weight. Studying HR professionals in SET-listed companies thus captures the socio-technical tension at its sharpest point, while explicitly bounding the interpretation of findings to this population rather than to HR professionals at large.

Traditional HR competency models, such as the seminal framework of Ulrich & Brockbank (2005), provided a vital foundation for HR's role as a strategic partner, but were architected prior to the era of pervasive automation and cognitive computing. As organizations increasingly delegate managerial processes to machines, a new tension has emerged: the automation–augmentation paradox—the proposition that automating routine processing simultaneously heightens, rather than reduces, the demand for human transparency, ethical oversight, and relational trust (Raisch & Krakowski, 2021; Jarrahi et al., 2022). In response, Human Resource Intelligence (HRI) has been proposed as an integrative construct: not a collection of isolated digital skills, but a socio-technical capability that synthesizes technological fluency with strategic foresight and human-centric judgment (Deepa et al., 2024; Prentice et al., 2023; Marler & Boudreau, 2017). In this study, HRI is conceptualized as a multidimensional construct comprising six intelligence domains: Artificial Intelligence, Business Intelligence, Cultural Intelligence, Digital Intelligence, Emotional Intelligence, and Functional Intelligence. The Artificial Intelligence dimension is interpreted operationally as AI literacy because it captures practitioners' capacity to understand, interpret, and critically evaluate AI systems rather than the technology itself; however, the construct label Artificial Intelligence (AI) is retained to preserve consistency with the HRI framework.

Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Despite this theoretical promise, empirical evidence on HRI's structural hierarchy remains scarce. Prior work has examined the components largely in isolation—digital literacy, people analytics capability, or AI adoption in HR—and predominantly in developed-economy settings; to the authors' knowledge, no study has yet validated an integrated, higher-order HRI construct with data from an emerging Southeast Asian market. This study addresses that gap by examining the HRI architecture among HR executives and practitioners in SET-listed companies using PLS-SEM, identifying which intelligence dimensions anchor the construct and thereby providing an empirical blueprint for HR capability development in AI-enabled organizations.

Research Objectives and Hypotheses

The specific objectives of this study are threefold:

1. To assess the current proficiency levels of the six HRI dimensions among HR professionals in SET-listed firms.
2. To validate the multidimensional architecture of HRI, examining how technological, strategic, and human-centric intelligence domains converge into a higher-order capability construct.
3. To analyze the relative contribution (hierarchical importance) of each intelligence dimension to the higher-order HRI construct.

Consistent with the second-order measurement model, three hypotheses were formulated. H1: each first-order intelligence dimension demonstrates satisfactory reliability, convergent validity, and discriminant validity. H2: all six intelligence dimensions contribute positively and significantly to the higher-order HRI construct. H3: the six dimensions differ in their relative contribution to HRI, forming an identifiable hierarchy of importance. These hypotheses correspond directly to the analytical sequence in Section 4: H1 is examined through the measurement model assessment (Sections 4.3–4.4), and H2 and H3 through the higher-order construct assessment (Section 4.5).

Literature Review

Human Resource Intelligence: An Integrative Capability Framework

The rapid advance of AI, coupled with digital technologies and big data analytics, is profoundly altering the contours of HRM within organizations (Strohmeier & Piazza, 2015). HR professionals, once custodians of routine administrative functions, now bear the onus of fusing technological acumen with strategic foresight and empathetic insight to underpin evidence-based people management (Deepa et al., 2024; Bandara et al., 2025). This study conceptualizes Human Resource Intelligence (HRI) as a multifaceted, integrative capability that embodies the HR practitioner's proficiency in weaving technology, business acumen, and human-centered perspectives into cohesive organizational strategies. Departing from fragmented skill-based models, HRI is framed as an architectural construct wherein individual competencies interlock to form a resilient whole (Deepa et al., 2024).

This framing resonates with the automation-augmentation paradox, which posits that AI augments rather than supplants human cognition, particularly in navigating ambiguity and ethical dilemmas (Raisch & Krakowski, 2021). Yet, while prior research underscores the perils of over-reliance on automation—such as diminished relational depth in HR interactions—few inquiries interrogate how integrated capabilities might mitigate these risks (e.g., Meijerink & Bondarouk, 2023). By positing HRI as a second-order latent construct, this framework extends dynamic capabilities theory, suggesting that HR's adaptive prowess emerges from the interplay of technological and humanistic elements, ultimately enhancing organizational resilience in volatile digital ecosystems.

The conceptualization of Human Resource Intelligence (HRI) is grounded in three complementary theoretical perspectives: the Resource-Based View (RBV), dynamic capability theory, and socio-technical systems theory. The Resource-Based View suggests that organizations gain sustainable competitive advantage through valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). Within this perspective, human capital capabilities—such as HR professionals' analytical, strategic, and relational competencies—represent critical strategic assets that influence organizational performance.

Building on RBV, dynamic capability theory emphasizes the ability of organizations to integrate, build, and reconfigure internal and external competencies in rapidly changing environments (Teece et al., 1997). In the context of AI-driven organizations, HR professionals must continuously adapt their capabilities to interpret technological insights, respond to workforce changes, and support strategic decision-making.

In addition, socio-technical systems theory highlights the interdependence between technological infrastructures and human capabilities within organizational systems. As AI technologies increasingly influence HR processes such as recruitment, performance evaluation, and workforce analytics, HR professionals must develop competencies that bridge technological systems and human judgment.

Integrating these theoretical perspectives, Human Resource Intelligence (HRI) is conceptualized as a multidimensional capability architecture in which technological intelligence, strategic intelligence, and human-centered intelligence interact to enhance HR's strategic contribution in digitally transformed organizations.

The Six Dimensions of HRI

HRI's architecture draws from a synthesis of six mutually reinforcing dimensions, each calibrated to the exigencies of AI-infused HRM. These are not discrete attributes but interdependent facets that collectively fortify HR's strategic mandate.

Artificial Intelligence (AI): Extending beyond superficial tool proficiency, this dimension entails a discerning grasp of AI algorithms' mechanics, interpretative pitfalls, and contextual applicability in HR contexts (Tambe & Cappelli, 2019). Critically, HR professionals must interrogate algorithmic outputs for embedded biases, ensuring that recommendations in areas like predictive hiring do not perpetuate inequities—a challenge amplified in diverse workforces (Meijerink & Bondarouk, 2023). Empirical evidence indicates that such evaluative competence correlates with more equitable outcomes, yet its underdevelopment in practice risks entrenching discriminatory practices.

Business Intelligence (BI): Here, HRI manifests as the HR leader's adeptness at translating organizational imperatives into actionable workforce strategies, leveraging data analytics to align talent deployment with competitive objectives (Ulrich & Brockbank, 2005; Boudreau et al., 2015). This involves not only descriptive reporting but predictive modeling to forecast talent gaps, thereby linking HR metrics to firm-level performance indicators (Marler & Boudreau, 2017; McCartney & Fu, 2022). However, studies reveal a persistent disconnect: many HR functions remain siloed from executive strategy, underscoring the need for BI to evolve from tactical support to a pivotal driver of business sustainability.

Cultural Intelligence (CI): In an era of globalized operations, CI equips HR practitioners to navigate multicultural dynamics, fostering inclusive practices that counteract AI's tendency toward cultural homogenization (Ang & Van Dyne, 2008). This capability demands sensitivity to cross-cultural nuances in team formation and conflict resolution, mitigating biases in automated assessments that often favor dominant cultural norms (Bader et al., 2019; Schlaegel et al., 2021). While CI's value in international HRM is well-documented, its integration with AI tools remains underexplored, potentially leaving organizations vulnerable to intercultural frictions in hybrid work models.

Digital Intelligence (DI): DI encompasses the agile mastery of digital platforms for HR execution, from cloud-based systems to real-time collaboration tools, enabling seamless data-driven interventions (Bondarouk & Brewster, 2016; Mithas & McFarlan, 2017). Modern HR practitioners must possess advanced digital competencies to effectively identify and manage organizational talent. Specialized roles, such as HR data analysts, have become increasingly important because they use analytics and automation to support evidence-based decision-making. By leveraging digital tools, HR functions can improve talent acquisition, performance management, and operational efficiency while strengthening their strategic contribution to the organization (Strohmeier, 2020; Wiblen & Marler, 2021).

Emotional Intelligence (EI): As the humanistic counterweight to technological determinism, EI empowers HR professionals to discern and modulate emotional undercurrents in employee interactions, from performance feedback to crisis management (Goleman, 1995). Rooted in self-awareness and relational empathy, it is indispensable for addressing AI's emotional blind spots, such as impersonal algorithmic notifications (Joseph et al., 2015). Longitudinal data suggest EI buffers against burnout in high-stakes HR roles, yet its erosion in tech-heavy environments poses a critical threat to organizational morale.

Functional Intelligence (FI): Anchoring HRI's practical foundation, FI denotes deep-seated expertise in HR domains, including regulatory compliance, talent lifecycle management, and policy formulation (Wright & Snell, 2005). It facilitates the application of specialized knowledge to resolve multifaceted issues, such as integrating AI ethics into labor contracts (Rodgers et al., 2023). Although FI underpins professional legitimacy, evolving regulations in AI governance demand its continual recalibration, revealing tensions between traditional HR orthodoxy and emergent techno-legal paradigms.

Theoretical Synergy and Higher-Order Capability

These six dimensions do not function in isolation but converge into a higher-order Human Resource Intelligence (HRI) capability, where technological foundations (AI and DI) provide robust analytical infrastructure, strategic pillars (BI and FI) guide foresight-driven navigation, and humanistic facets (EI and CI) ensure ethical alignment and relational resilience. This triadic synergy embodies an extended resource-based view (RBV), framing HRI as a valuable, rare, and inimitable resource that elevates HRM from compliance-oriented tactics to proactive, value-generating orchestration (Barney, 1991; Wright & McMahan, 2011). In parallel domains like IT management, integrative models of this nature have demonstrated enhanced adaptability and performance under uncertainty, yet HRM research trails in adapting such architectures to AI-driven ecosystems—a critical void this study addresses via SEM analysis of HRI's latent architecture and predictive pathways (Boxall & Purcell, 2022; Strohmeier, 2020).

Ultimately, HRI positions HR professionals as architects of hybrid intelligence ecosystems, resolving the automation-augmentation paradox to foster ethically sound, strategically agile HRM in digital-era organizations. Subsequent research could validate this framework's causal impacts, especially in culturally nuanced settings like Thailand's financial sector, where regulatory and societal factors heighten its transformative potential (Budhwar et al., 2023)

Figure 1 Human Resource Intelligence (HRI) framework

This framework illustrates the concept of Human Resource Intelligence (HRI) as an integrated capability composed of six complementary forms of intelligence that support value creation in human resource management. At the center of the model is Human Resource Intelligence (HRI), which represents the overall strategic capacity of HR professionals to integrate data, technology, human understanding, and professional expertise into organizational decision-making. HRI is not a single skill but a multidimensional capability emerging from the interaction of several types of intelligence.

Methodology

Research Design

This study employed a quantitative, cross-sectional survey design to develop and empirically assess Human Resource Intelligence (HRI) as a higher-order capability construct. A survey approach was appropriate because the constructs of interest are perceptual capabilities self-assessed by practitioners, and because the study's aim was the structural validation of a newly integrated construct rather than the confirmation of causal paths among mature theoretical variables.

Population, Sampling, and Participants

The target population comprised HR executives and practitioners in companies listed on the Stock Exchange of Thailand (SET), a group recognized for advanced adoption of digital infrastructure and strategic HR practices (Deepa et al., 2024). The population frame consisted of all 816 companies listed on the SET at the time of data collection. Questionnaires were addressed to the HR managers of these firms and distributed through three complementary channels—the Personnel Management Association of Thailand (PMAT), corporate email, and company HR departments—to facilitate rapid, cost-efficient dissemination and follow-up. Following ethical approval on August 21, 2025, data were collected from late August to December 2025, a period of rapid diffusion of AI-related applications in Thai organizational and HR contexts. A total of 272 responses were returned (returned response rate = 33.33%). Inclusion criteria required respondents to (a) hold an HR executive or practitioner position and (b) be currently employed in a SET-listed company. After data screening, 17 responses were excluded for incompleteness or unusable response patterns, yielding 255 valid cases for analysis (usable response rate = 31.25%; 93.75% of returned responses were valid).

The sample size was justified against PLS-SEM-specific guidelines rather than the general covariance-based heuristic. Applying the inverse square root method (Kock & Hadaya, 2018), a minimum of approximately 155 cases is required to detect path coefficients of 0.20 at the 5% significance level with 80% power. The obtained sample of 255 exceeds this threshold, as well as the ten-times rule relative to the maximum number of indicators pointing at any construct (Hair et al., 2022).

Instrument Development and Validation

The research instrument was developed through an extensive review of the literature on HR capabilities in the digital and AI era. The HRI construct was operationalized through six dimensions, each measured with four reflective indicators adapted from established frameworks (Table 1). Rather than adopting any single existing scale, the item pool for each dimension was synthesized from established source frameworks in the corresponding domain and adapted to the HR professional context. All 24 indicators used a five-point application scale ranging from 1 (not applied at all) to 5 (applied proficiently and continuously).

Table 1 Measurement Items of Human Resource Intelligence (HRI)

Construct	Code	Measurement Item	Source
Artificial Intelligence (AI)	AI1	You apply AI to analyze data for HR decision-making.	Tambe et al. (2019) ; Dwivedi et al. (2021)
	AI2	You apply AI to support collaboration between personnel and technology within the HR team.	Tambe et al. (2019); Li & Kim (2024)
	AI3	You apply AI to monitor and evaluate the quality of HR processes, such as recruitment and training.	Tambe et al. (2019); Chee et al. (2024)
	AI4	You apply AI to forecast trends, such as employee turnover rates or workforce demand.	Tambe et al. (2019); Budhwar et al. (2022)
Business Intelligence (BI)	BI1	You use business data, such as revenue, market share, or costs, to plan workforce requirements and skill development.	Chaudhuri et al. (2011); Ulrich & Brockbank (2005)
	BI2	You use business intelligence to analyze and improve the effectiveness of HR processes.	Chen et al. (2012); Gurcan et al. (2023)
	BI3	You are able to use business intelligence to forecast and manage workforce-related risks.	Chen et al. (2012); Tavera Romero et al. (2021)
	BI4	You are able to measure and analyze the ROI of HR projects or activities to demonstrate business value.	Levenson (2018); Boon et al. (2019)
Cultural Intelligence (CI)	CI1	You are able to adapt communication methods, task assignments, and feedback approaches to suit employees from different cultural backgrounds.	Ang et al. (2007)
	CI2	You are able to manage culturally diverse teams so that they can work together effectively.	Ang et al. (2007); Tang & Zhang (2024)
	CI3	You are able to accept and respect differing opinions from colleagues from different cultural backgrounds.	Ang et al. (2007)
	CI4	You are able to use conflict resolution skills when facing misunderstandings among employees from diverse cultural backgrounds.	Ang et al. (2007); Tang & Zhang (2024)
Digital Intelligence (DI)	DI1	You are able to use HR software, such as HRIS, ATS, or PMS, to reduce work time and improve accuracy.	Ferrari (2013); Bondarouk & Brewster (2016)
	DI2	You are able to use digital technologies to manage HR data and support strategic decision-making.	Ferrari (2013); Levenson (2018)
	DI3	You are able to learn and adapt quickly to new digital technologies in HR work.	Ferrari (2013); Shahzad et al. (2022)
	DI4	You are able to use digital technologies to communicate and coordinate with HR teams and other departments.	Ferrari (2013); Strohmeier (2020)
Emotional Intelligence (EI)	EI1	You are able to regulate your emotions and express yourself appropriately in high-pressure situations, such as communicating performance appraisal results or negotiations.	Salovey & Mayer (1990); Goleman (1995)
	EI2	You are able to understand and respond appropriately to employees' emotions in the workplace.	Salovey & Mayer (1990); Cherniss (2010)
	EI3	You are able to manage relationships and work effectively with teams under complex situations.	Salovey & Mayer (1990); Goleman (1995)
	EI4	You are able to manage your own stress and your team's stress effectively during crisis situations.	Salovey & Mayer (1990); Cherniss (2010)
Functional Intelligence (FI)	FI1	You possess specialized competencies essential for HR work.	Boyatzis (1982); Ulrich & Brockbank (2005)
	FI2	You are able to solve day-to-day work problems using professional experience and specialized knowledge.	Boyatzis (1982); Ulrich et al. (2012)
	FI3	You are able to plan and manage HR strategies using specialized HR knowledge.	Ulrich & Brockbank (2005); Ulrich et al. (2012)
	FI4	You continuously and systematically develop specialized knowledge and skills in HR work.	Boyatzis (1982); Ulrich et al. (2012)

Note: n = 255. Response scale (level of application): 5 = applied proficiently and continuously; 4 = applied well in many situations; 3 = applied in some situations; 2 = applied very little; 1 = not applied at all. Items were administered in Thai; the English wording above reflects the fielded instrument. The item pool for each dimension was synthesized from the source frameworks listed rather than adopted from a single existing scale.

Validity was established through the Index of Item-Objective Congruence (IOC) evaluated by three experts: a statistics specialist, an HR practitioner experienced in applying AI in HR work, and a PLS-SEM specialist. For the initial 30-item HRI item pool, IOC values ranged from 0.33 to 1.00, with an overall mean of 0.81; 28 items met the acceptance criterion of 0.67, and items with low or borderline values were revised or removed following the experts' qualitative comments—for example, clarifying the descriptions of AI applications—before the final 24-item questionnaire was administered. The study protocol received ethical approval from the Ethics Committee in Human Research, National Institute of Development Administration (NIDA), under the expedited review procedure (COA No. 2025/0142; Protocol ID No. ECNIDA 2025/0155), approved on August 21, 2025.

Common Method Bias

Because all data were self-reported by a single respondent per questionnaire, both procedural and statistical remedies for common method bias were applied (Podsakoff et al., 2003). Procedurally, respondents were assured of anonymity, were informed that there were no right or wrong answers, and completed construct blocks that were separated in the questionnaire. Statistically, Harman's single-factor test indicated that the first unrotated factor accounted for 31.13% of the total variance, below the 50% threshold. In addition, a full collinearity assessment produced VIF values ranging from 2.248 to 2.784, all below the conservative threshold of 3.3 (Kock, 2015), indicating that common method bias is unlikely to threaten the validity of the findings.

Data Analysis

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. PLS-SEM was selected over covariance-based SEM for three reasons aligned with the study's purpose: the research aim is the development and assessment of a newly integrated higher-order capability construct rather than the confirmation of a mature theory; the model is complex, comprising six first-order constructs and 24 indicators converging on a second-order construct; and the analytical emphasis is on the relative contribution (prediction-oriented weighting) of dimensions rather than on covariance reproduction (Hair et al., 2022; Sarstedt et al., 2019).

The higher-order HRI construct was specified as reflective–formative and estimated using a two-stage approach (Sarstedt et al., 2019): in the first stage, the six first-order reflective constructs were assessed for reliability and validity; in the second stage, the latent variable scores of Artificial Intelligence, Business Intelligence, Cultural Intelligence, Digital Intelligence, Emotional Intelligence, and Functional Intelligence served as formative indicators of the second-order HRI construct. Statistical significance was assessed through bootstrapping with 5,000 subsamples using bias-corrected and accelerated (BCa) confidence intervals at the 95% level. Measurement quality was evaluated against conventional thresholds: indicator loadings ≥ 0.70; Cronbach's alpha, rho_A, and composite reliability (CR) ≥ 0.70; average variance extracted (AVE) ≥ 0.50; HTMT < 0.85 complemented by the Fornell-Larcker criterion; and standardized root mean square residual (SRMR) < 0.08.

Results

The results are reported in the sequence of the three research objectives: the respondent and descriptive profiles address Objective 1 (Sections 4.1–4.2); the measurement model, discriminant validity, and higher-order validation address Objective 2 (Sections 4.3–4.5); and the hierarchy of dimension contributions within Section 4.5, together with the model fit assessment in Section 4.6, addresses Objective 3.

Respondent Profile

Table 2 summarizes the demographic characteristics of the 255 respondents.

Table 2 Demographic Profile of Respondents (n = 255)

Characteristic	Category	n	%
Gender	Female	126	49.40
	Male	102	40.00
	LGBTQ+	18	7.10
	Prefer not to say	9	3.50
Age (years)	Under 25	6	2.40
	25–34	45	17.60
	35–44	90	35.30
	45–54	81	31.80
	55 and above	33	12.90
Education	Below a bachelor's degree	4	1.60
	Bachelor's degree	85	33.30
	Master's degree	141	55.30
	Doctoral degree	25	9.80
Position level	Officer / operational staff	63	24.70
	Manager / supervisor	132	51.80
	Director / executive	58	22.70
	C-level	2	0.80
Tenure in current position	Less than 1 year	7	2.70
	1–3 years	48	18.80
	4–6 years	67	26.30
	7–10 years	61	23.90
	More than 10 years	72	28.20
Organization size (employees)	Fewer than 50	24	9.40
	50–200	31	12.20
	201–500	57	22.40
	More than 500	143	56.10

The sample was broadly gender-balanced (49.40% female, 40.00% male) and concentrated in the experienced working-age range, with 67.1% of respondents aged 35–54. Educational attainment was high—65.10% held a graduate degree—and three quarters (75.30%) occupied managerial positions or above, with 78.40% having served four or more years in their current role. A majority (56.10%) worked in organizations employing more than 500 people, a profile consistent with the professionalized HR functions characteristic of listed companies and appropriate for assessing capability at the professional level.

Descriptive Profile of HRI Dimensions (Objective 1)

Descriptive statistics for the six HRI dimensions are presented in Table 3. The overall level of Human Resource Intelligence was moderately high (mean = 3.441, SD = 0.551). Practitioners reported the highest proficiency in Functional Intelligence (mean = 3.811), followed by Emotional (3.684) and Cultural Intelligence (3.551), while Artificial Intelligence (3.074) and Business Intelligence (3.062) recorded the lowest scores. Skewness values ranged from −0.602 to 0.044 and kurtosis values from 0.264 to 1.444, well within the conventional ±2 bounds, indicating no severe departure from univariate normality.

Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Table 3 Descriptive Statistics of HRI Dimensions (n = 255)

Dimension	Mean	SD	Min	Max	Skewness	Kurtosis
Functional Intelligence	3.811	0.677	1.000	5.000	−0.602	1.444
Emotional Intelligence	3.684	0.645	1.000	5.000	−0.063	0.803
Cultural Intelligence	3.551	0.689	1.000	5.000	−0.317	1.174
Digital Intelligence	3.464	0.760	1.000	5.000	−0.227	0.264
Artificial Intelligence	3.074	0.819	1.000	5.000	−0.159	0.728
Business Intelligence	3.062	0.831	1.000	5.000	−0.479	0.460
Overall HRI	3.441	0.551	1.542	5.000	0.044	0.919

It should be emphasized that these mean scores represent respondents' perceived level of proficiency in each dimension. They describe the current capability profile of the workforce and are conceptually distinct from the structural contribution of each dimension to the HRI construct, which is examined in Section 4.5.

Measurement Model Assessment (Objective 2)

The measurement model was assessed for indicator reliability, internal consistency, and convergent validity (Table 4). All indicator loadings exceeded 0.70 (overall range 0.77–0.92). Cronbach's alpha (0.831–0.882), rho_A (0.835–0.906), and composite reliability (0.887–0.918) all surpassed the 0.70 threshold, and AVE values (0.663–0.737) exceeded 0.50, confirming satisfactory reliability and convergent validity across all six constructs. H1 is therefore supported with respect to reliability and convergent validity.

Table 4 Reliability and Convergent Validity of First-Order Constructs

Construct	Loading range	α	rho_A	CR	AVE
Artificial Intelligence	0.77–0.92	0.869	0.901	0.909	0.715
Business Intelligence	0.81–0.92	0.882	0.906	0.918	0.737
Cultural Intelligence	0.79–0.83	0.831	0.835	0.887	0.663
Digital Intelligence	0.81–0.86	0.855	0.855	0.902	0.696
Emotional Intelligence	0.81–0.87	0.872	0.875	0.912	0.722
Functional Intelligence	0.79–0.91	0.874	0.875	0.913	0.725

Discriminant Validity (Objective 2)

Discriminant validity was assessed using two complementary criteria. First, heterotrait–monotrait (HTMT) ratios among the six dimensions ranged from 0.245 to 0.754, all below the conservative 0.85 threshold (Henseler et al., 2015), with the highest value observed between Emotional and Functional Intelligence (HTMT = 0.754). Second, the Fornell–Larcker criterion was satisfied: the square root of each construct's AVE exceeded its correlations with all other constructs (Table 5; Fornell & Larcker, 1981). Together, these results confirm that the six dimensions are empirically distinct facets of HRI, completing the support for H1. The proximity of Emotional and Functional Intelligence, while comfortably within acceptable bounds, reflects meaningful conceptual adjacency between interpersonal-emotional capability and professional HR expertise; this relationship is examined further in the Discussion.

Table 5 Discriminant Validity: Fornell–Larcker Criterion and HTMT Ratios

	AI	BI	CI	DI	EI	FI
AI	**0.846**	0.673	0.516	0.627	0.334	0.374
BI	0.581	**0.859**	0.513	0.489	0.245	0.269
CI	0.446	0.444	**0.814**	0.643	0.725	0.688
DI	0.553	0.430	0.545	**0.835**	0.686	0.726
EI	0.311	0.221	0.622	0.595	**0.850**	0.754
FI	0.334	0.238	0.589	0.627	0.661	**0.852**

Note: Bold diagonal values are the square roots of AVE; values below the diagonal are construct correlations (Fornell–Larcker criterion); values above the diagonal are HTMT ratios.

Higher-Order Construct Assessment (Objectives 2 and 3)

HRI was assessed as a reflective–formative second-order construct using the two-stage approach described in Section 3.5. Given the formative specification of the higher-order layer, collinearity among the dimension scores was examined first: all outer VIF values ranged from 1.689 to 2.324, below the conservative 3.3 threshold (Table 6), indicating no collinearity concerns. All six dimensions contributed positively and significantly to HRI ($p < .001$), with 95% BCa confidence intervals excluding zero, supporting H2.

Table 6 Higher-Order Construct Assessment: Outer Weights of HRI Dimensions

Dimension	Outer weight	t	p	95% BCa CI	VIF	Rank
Digital Intelligence	0.262	23.919	< .001	[0.240, 0.282]	2.324	1
Emotional Intelligence	0.245	19.441	< .001	[0.218, 0.267]	2.236	2
Functional Intelligence	0.244	21.567	< .001	[0.221, 0.264]	2.218	3
Cultural Intelligence	0.220	17.058	< .001	[0.190, 0.242]	2.116	4
Artificial Intelligence	0.197	12.400	< .001	[0.169, 0.229]	1.847	5
Business Intelligence	0.138	6.398	< .001	[0.093, 0.177]	1.689	6

Note: t statistics and bias-corrected and accelerated (BCa) 95% confidence intervals are based on 5,000 bootstrap resamples of the respondent-level data.

Addressing Objective 3, the outer weights reveal a clear hierarchy of contribution, supporting H3. Digital Intelligence emerged as the strongest anchor of the HRI architecture ($w = 0.262$), followed closely by Emotional ($w = 0.245$) and Functional Intelligence ($w = 0.244$), with Cultural Intelligence ($w = 0.220$), Artificial Intelligence ($w = 0.197$), and Business Intelligence ($w = 0.138$) contributing progressively less. Two readings of these results must be kept distinct. The outer weight expresses each dimension's structural contribution to what constitutes HRI as a capability construct; it does not indicate the level at which practitioners currently perform. Thus, although Functional Intelligence recorded the highest mean proficiency (Section 4.2), Digital Intelligence carries the greatest weight in defining professional intelligence—while Artificial Intelligence and Business Intelligence are simultaneously the weakest contributors and the least developed proficiencies, marking them as a compound capability gap.

Model Fit and Scope of the Structural Assessment

Overall model fit was evaluated using the standardized root mean square residual, yielding SRMR = 0.066, below the 0.08 threshold and indicating acceptable fit (Hair et al., 2022). Because the present model is a measurement-focused, higher-order validation model with no endogenous outcome variable, statistics that presuppose structural dependence—R^2, f^2, and Q^2/PLSpredict—are not applicable and are therefore not reported. The model estimates how six intelligence dimensions constitute a higher-order capability; it does not, and is not intended to, test causal effects of HRI on downstream outcomes such as HR effectiveness or organizational performance. This boundary is addressed explicitly in the Discussion and in the directions for future research.

Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Discussions

Perceived Proficiency versus Structural Contribution

Perhaps the most consequential pattern in the findings is the divergence between what HR practitioners are good at and what most strongly defines their professional intelligence. Descriptively, respondents reported the highest proficiency in Functional Intelligence—the traditional core of the HR craft—yet structurally, Digital Intelligence carried the greatest weight in constituting HRI. Mean scores capture perceived proficiency; outer weights capture each dimension's contribution to the construct. Conflating the two would lead to the mistaken inference that the highest-scoring dimension is the most important one. Read together, they tell a sharper story: the profession's centre of gravity has shifted toward digital fluency faster than practitioners' self-assessed capabilities have followed, and the dimensions where proficiency is lowest—Artificial Intelligence and Business Intelligence—are precisely those where deliberate development effort is most needed.

The Implementation Paradox and the Interpretative Gap

The validation of HRI reveals what we term an implementation paradox in the Thai corporate context: organizations demonstrate a firm foundation for digital execution—reflected in the anchoring strength of Digital Intelligence—while AI-specific intelligence remains only moderate, indicating that technological adoption has outpaced the cognitive readiness of practitioners to interrogate and govern those technologies. This is consistent with Strohmeier and Piazza (2015), who emphasize that AI techniques demand a higher level of analytical maturity than conventional digital tools, and reinforces the caution of Deepa et al. (2024) and Akbarighatar et al. (2023) that digital readiness alone does not guarantee the socio-technical competencies required to manage AI responsibly.

Relatedly, the comparatively low weight of Business Intelligence points to an interpretative gap: a disconnect between the availability of workforce data and practitioners' capacity to translate it into strategic organizational narratives. This aligns with Rasmussen et al. (2023), who argue that the value of people analytics depends on precisely this translational ability, and is consistent with the automation–augmentation paradox (Raisch & Krakowski, 2021): as AI absorbs routine processing, the premium on human strategic oversight and contextual judgment rises rather than falls.

High-Tech and High-Touch: A Triadic Reading of the Architecture

The balance between high-tech and high-touch remains a defining feature of the HRI architecture. The enduring strength of the functional and emotional domains is consistent with evidence that emotional intelligence operates as a critical personal resource for navigating career-related challenges (Pirsoul et al., 2023), while research on algorithmic management shows that algorithm-mediated governance can be experienced as impersonal and can elicit negative emotional reactions when human support is absent (Hu et al., 2026; Kellogg et al., 2020). The emergence of Digital Intelligence as the primary anchor likewise coheres with a broader shift in professional legitimacy toward value creation through people analytics and AI capability building (Bottesch et al., 2025; Chowdhury et al., 2023; Margherita, 2022), and with contemporary HRM scholarship urging HR to actively shape how AI is designed and deployed rather than treating it as a technical substitution for human judgment (Charlwood & Guenole, 2022; Gong et al., 2025; Vrontis et al., 2022).

Interpretively, the six dimensions can be read as forming three capability layers: a technological layer (Artificial and Digital Intelligence), a strategic layer (Business and Functional Intelligence), and a human layer (Emotional and Cultural Intelligence). We stress that this triadic grouping is offered as a conceptual interpretation of the validated six-dimension structure, not as a statistically tested third-order model; formally testing the triadic layer—for instance, through a third-order specification or clustering of dimension scores—is a task for future research. Within this reading, the conceptual proximity between Emotional and Functional Intelligence observed in the discriminant validity assessment (the highest HTMT ratio, 0.754) is theoretically sensible: empathy, sensitive communication, and interpersonal judgment are embedded in the everyday exercise of professional HR expertise, even as the two constructs remain empirically distinct. The triadic reading also clarifies why the technological layer currently rests more heavily on Digital Intelligence than on AI Literacy: platform fluency has become infrastructural to Thai HR practice, whereas the capacity to interrogate algorithmic systems is still consolidating.

Limitations

Three limitations bound the interpretation of these findings. First, the cross-sectional design captures the HRI architecture at a single point in time and cannot speak to how the hierarchy of dimensions evolves as AI adoption matures. Second, the sample is drawn from a single country and, within it, from listed companies only; generalization to SMEs, the public sector, or other institutional contexts should be made with caution. Third, all measures are self-reported perceptions of capability, which—despite the procedural and statistical remedies reported in Section 3.4—remain subject to self-assessment and common-method concerns.

Future Research

Three extensions follow directly. Longitudinal designs could trace whether the weights of Artificial Intelligence and Business Intelligence rise as organizational AI maturity deepens, converting the present architecture into a dynamic account of capability evolution. Cross-country comparative studies—for example, across ASEAN markets at different stages of digital transformation—could test the boundary conditions of the hierarchy identified here. Most importantly, linking HRI to downstream outcomes such as HR effectiveness, decision quality, or firm performance would convert the validated measurement architecture into a full structural model, directly testing the effectiveness claims that the present study deliberately refrains from making.

Conclusion and suggestions

Conclusion

This research mapped the architecture of Human Resource Intelligence among HR executives and practitioners in SET-listed companies. The evidence indicates that HRI is not a singular technical skill but a validated, multidimensional capability constituted by six intelligence domains. Practitioners remain strongest in their high-touch foundations—Functional and Emotional Intelligence—while a visible capability gap persists in Artificial Intelligence and Business Intelligence. Structurally, Digital Intelligence serves as the primary anchor of the construct, bridging traditional human-centred management and increasingly automated decision environments. These conclusions describe the composition and internal hierarchy of HRI; claims about its effects on HR effectiveness or organizational competitiveness lie beyond the scope of the data and are framed here only as implications for practice and future inquiry.

Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Managerial and Policy Implications

Three implications follow directly from the empirical pattern of results and are offered as potential managerial implications rather than causal prescriptions. First, because Artificial Intelligence and Business Intelligence recorded both the lowest proficiency means and the lowest structural weights, development investment should shift from general digital training toward specialized AI literacy and data-interpretation programs that equip HR professionals to interrogate algorithmic outputs rather than merely operate the tools. Second, the interpretative gap identified in Business Intelligence suggests cultivating professionals who are conversant in both human behavior and data analytics—able to translate workforce data into business-relevant narratives. Third, the anchoring role of Digital Intelligence implies that evidence-based practice should be institutionalized as the default mode of talent decisions, so that the profession's strongest structural asset is exercised routinely rather than episodically.

New knowledge and the effects on society and communities

This study contributes to the HRM literature in three ways. First, it extends the discussion of digital transformation in HR by conceptualizing HRI as an empirically validated higher-order capability rather than a set of isolated competencies. Second, it empirically validates HRI as a second-order construct comprising six intelligence dimensions, demonstrating that HR capability in AI-driven organizations emerges from the synergistic interaction of multiple forms of intelligence rather than from any single technological competence. Third, it contributes to the automation–augmentation debate: the simultaneous strength of digital and human-centred dimensions is consistent with the argument that AI amplifies, rather than diminishes, the need for integrative human judgment (Raisch & Krakowski, 2021). It should be noted that the six constituent dimensions are individually well established in prior literature; the study's novelty resides in their second-order integration and in the empirical identification of the hierarchy among them in an emerging-market context. Table 7 positions this contribution against the most closely related prior frameworks.

Table 7 Positioning HRI against Related Frameworks

Framework	Primary focus	Structure	What HRI adds
Marler & Boudreau (2017)	HR analytics: evidence-based review	Narrative review; no latent construct	Integrates analytics capability into a validated multidimensional construct
Chowdhury et al. (2023)	AI capability in HRM	Capability framework grounded in the resource-based view	Extends AI capability into a six-domain, HR-specific architecture
Deepa et al. (2024)	HR capability in the digital/AI era	Integrative conceptual framework	Provides second-order empirical validation with PLS-SEM in an emerging market
This study (HRI)	Integrative socio-technical HR capability	Second-order construct; six dimensions; n = 255, SET-listed firms	Validated hierarchy: DI as structural anchor; AI/BI as compound gap

Potential Social and Policy Implications

Beyond the firm level, the findings carry potential implications—offered as interpretive extensions rather than empirically demonstrated impacts—for the broader labor market. HR professionals equipped with stronger AI literacy are better positioned to implement algorithmic tools transparently and to detect embedded bias, supporting fairness in employment decisions. At the level of national workforce policy, the compound gap in AI and business analytics identified here suggests a concrete target for professional development curricula in the Thai HR community. Finally, the persistent structural weight of emotional and cultural intelligence indicates that responsible automation in HR need not come at the expense of the human element; within this architecture, the two are complementary.

Acknowledgments

This research is part of the doctoral dissertation titled "The Influence of Human Resource Intelligence on Sustainable Value Creation: The Mediating Role of Wisdom and the Moderating Role of Algorithmic Ethics from the Perspective of Human Resource Managers in Companies Listed on the Stock Exchange of Thailand" conducted in partial fulfillment of the requirements for the Doctor of Philosophy Program in Public Administration, Graduate School of Public Administration, National Institute of Development Administration (NIDA), Thailand.

Declarations

Ethical approval: Ethics Committee in Human Research, National Institute of Development Administration (NIDA); COA No. 2025/0142; Protocol ID No. ECNIDA 2025/0155; approved August 21, 2025 (expedited review). Conflict of interest: The authors declare no conflict of interest. Data availability statement: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

References

Akbarighatar, P., Pappas, I. O., & Vassilakopoulou, P. (2023). A sociotechnical perspective for responsible AI maturity models: Findings from a mixed-method literature review. *International Journal of Information Management Data Insights, 3*(2), 100193. https://doi.org/10.1016/j.jjimei.2023.100193

Ang, S., & Van Dyne, L. (2008). *Handbook of cultural intelligence: Theory, measurement, and applications*. M. E. Sharpe.

Ang, S., Van Dyne, L., Koh, C., Ng, K. Y., Templer, K. J., Tay, C., & Chandrasekar, N. A. (2007). Cultural intelligence: Its measurement and effects on cultural judgment and decision making, cultural adaptation and task performance. *Management and Organization Review, 3*(3), 335–371. https://doi.org/10.1111/j.1740-8784.2007.00082.x

Bader, B., Schuster, T., Bader, A. K., & Shaffer, M. (2019). The dark side of expatriation: Dysfunctional relationships, expatriate crises, prejudice and a VUCA world. *Journal of Global Mobility, 7*(2), 126–136. https://doi.org/10.1108/JGM-06-2019-070

Bandara, R., Biswas, K., Akter, S., Shafique, S., & Rahman, M. (2025). Addressing algorithmic bias in AI-driven HRM systems: Implications for strategic HRM effectiveness. *Human Resource Management Journal, 35*(4), 1047-1063. https://doi.org/10.1111/1748-8583.12609

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bondarouk, T., & Brewster, C. (2016). Conceptualising the future of HRM and technology research. *The International Journal of Human Resource Management, 27*(21), 2652–2671. https://doi.org/10.1080/09585192.2016.1232296

Boon, C., Den Hartog, D. N., & Lepak, D. P. (2019). A systematic review of human resource management systems and their measurement. *Journal of Management, 45*(6), 2498–2537. https://doi.org/10.1177/0149206318818718

Bottesch, S., Schwenke, C., Förster, M. *et al.* Driving business value through people analytics: Literature review and research agenda from an information systems perspective. *Electron Markets 35, 106*(2025), 1-38. https://doi.org/10.1007/s12525-025-00842-3

Boudreau, J. W., Cascio, W. F., Conger, J. A., Lawler, E. E., Lewin, D., Ulrich, D., Vicere, A. A., & Welbourne, T. M. (2015). *Pursue insight*. Three: The Human Resources Emerging Executive. Wiley.

Boxall, P., & Purcell, J. (2022). *Strategy and human resource management*. (5th ed.). Bloomsbury Academic.

Boyatzis, R. E. (1982). *The competent manager: A model for effective performance*. Wiley.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G.J., Beltran, J.R., Boselie, P., Cooke, F. L., Decker, S., Denisi, A., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V>, Ren, S., Rogelberg, S., Saunders, M. N. K., Tung, R. L., Varma, A. (2023) Human Resource Management in the Age of Generative Artificial Intelligence: Perspectives and Research Directions on Chatgpt. *Human Resource Management Journal*, *33*, 606-659. https://doi.org/10.1111/1748-8583.12524

Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. (2022). Artificial intelligence – Challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management, 33*(6), 1065–1097. https://doi.org/10.1080/09585192.2022.2035161

Carolus, A., Koch, M., Straka, S., Latoschik, M., & Wienrich, C. (2023). *MAILS – Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies.* https://doi.org/10.48550/arXiv.2302.09319

Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence?. *Human Resource Management Journal, 32*(4), 729–742. https://doi.org/10.1111/1748-8583.12433

Chee, H., Ahn, S., & Lee, J. (2024). A competency framework for AI literacy: Variations by different learner groups and an implied learning pathway. *British Journal of Educational Technology, 56*(5), 2146-2183. https://doi.org/10.1111/bjet.13556

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*(4), 1165–1188. https://doi.org/10.2307/41703503

Cherniss, C. (2010). Emotional intelligence: Toward clarification of a concept. *Industrial and Organizational Psychology, 3*(2), 110–126. https://doi.org/10.1111/j.1754-9434.2010.01231.x

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative artificial intelligence in business: Towards a strategic human resource management framework. *British Journal of Management, 35*(4), 1680-1691. https://doi.org/10.1111/1467-8551.12824

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review, 33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

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

Dutta, D., & Naveen, P. M. (2025). Transforming recruitment and selection practices in organizations through discriminative and generative AI adoption: A structuration lens. *Human Resource Management, 65*(1), 77-115. https://doi.org/10.1002/hrm.70018

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Medaglia, R., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57,* 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Enholm, I.M., Papagiannidis, E., Mikalef, P. and Krogstie, J. (2021) Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontiers*, *24*, 1709-1734. https://doi.org/10.1007/s10796-021-10186-w

Ferrari, A. (2013). *DIGCOMP: A framework for developing and understanding digital competence in Europe.* Publications Office of the European Union.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

Garcia, R., & Kwok, L. (2025). Generative artificial intelligence in human resource management: A critical reflection on impacts, resilience and roles. *International Journal of Contemporary Hospitality Management*, 37(9), 3136-3158. https://doi.org/10.1108/ijchm-01-2025-0159

Goleman, D. (1995). *Emotional intelligence: Why it can matter more than IQ*. Bantam Books.

Gong, Q., Fan, D., & Bartram, T. (2025). Integrating artificial intelligence and human resource management: A review and future research agenda. *The International Journal of Human Resource Management, 36*(1), 103-141. https://doi.org/10.1080/09585192.2024.2440065

Gurcan, F., Ayaz, A., Menekse Dalveren, G. G., & Derawi, M. (2023). Business intelligence strategies, best practices, and latest trends: Analysis of scientometric data from 2003 to 2023 using machine learning. *Sustainability, 15*(13), 9854. https://doi.org/10.3390/su15139854

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)*. (3rd ed.). Sage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hmoud, B. I., & Várallyai, L. (2020). Artificial intelligence in human resources information systems: Investigating its trust and adoption determinants. *International Journal of Engineering and Management Sciences, 5*(1), 749–765. https://doi.org/10.21791/IJEMS.2020.1.65

Hu, P., Wang, X., & Wang, J. (2026). Integrating human support with algorithmic control: Psychological reactance in platform work. *Technological Forecasting and Social Change, 225*, 124520. https://doi.org/10.1016/j.techfore.2025.124520

Jarrahi, M. H., Lutz, C., & Newlands, G. (2022). Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation. *Big Data & Society, 9*(2). https://doi.org/10.1177/20539517221142824

Joseph, D. L., Jin, J., Newman, D. A., & O'Boyle, E. H. (2015). Why Does Self-Reported Emotional Intelligence Predict Job Performance? A Meta-Analytic Investigation of Mixed EI. *Journal of Applied Psychology, 100,* 298-342. https://doi.org/10.1037/a0037681

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261. https://doi.org/10.1111/isj.12131

Levenson, A. (2018). Using workforce analytics to improve strategy execution. *Human Resource Management, 57*(3), 685–700. https://doi.org/10.1002/hrm.21850

Li, H., & Kim, S. (2024). Developing AI literacy in HRD: Competencies, approaches, and implications. *Human Resource Development International, 27*(4), 345–366. https://doi.org/10.1080/13678868.2024.2337962

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review, 32*(2), 100795. https://doi.org/10.1016/j.hrmr.2020.100795

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. https://doi.org/10.1080/09585192.2016.1244699

McCartney, S., & Fu, N. (2022). Bridging the gap: Why, how and when HR analytics can impact organizational performance. *Management Decision, 60*(13), 25-47. https://doi.org/10.1108/MD-12-2020-1581

McKinsey & Company. (2025). *HR Monitor 2025: A comprehensive look at the HR landscape*. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/hr-monitor-2025

Meijerink, J., & Bondarouk, T. (2023). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review, 33*(1), 100876. https://doi.org/10.1016/j.hrmr.2021.100876

Mithas, S., & McFarlan, F. W. (2017). What is digital intelligence?. *IT Professional, 19*(4), 3-6. https://doi.org/10.1109/MITP.2017.3051329

Pirsoul, T., Parmentier, M., Sovet, L., & Nils, F. (2023). Emotional intelligence and career-related outcomes: A meta-analysis. *Human Resource Management Review, 33*(3), 100967. https://doi.org/10.1016/j.hrmr.2023.100967

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Prentice, C., Wong, I. A., & Lin, Z. C. (2023). Artificial intelligence as a boundary-crossing object for employee engagement and performance. *Journal of Retailing and Consumer Services, 73,* 103376. https://doi.org/10.1016/j.jretconser.2023.103376

Qamar, Y., Agrawal, R. K., Samad, T. A., & Jabbour, C. J. C. (2021). When technology meets people: The interplay of artificial intelligence and human resource management. *Journal of Enterprise Information Management, 34*(5), 1339–1370. https://doi.org/10.1108/JEIM-11-2020-0436

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Rasmussen, T. H., Ulrich, M., & Ulrich, D. (2023). Moving people analytics from insight to impact. *Human Resource Development Review, 23*(1), 11-29. https://doi.org/10.1177/15344843231207220

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review, 33*(1), 100925. https://doi.org/10.1016/j.hrmr.2022.100925

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. *Imagination, Cognition and Personality, 9*(3), 185–211. https://doi.org/10.2190/DUGG-P24E-52WK-6CDG

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal, 27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003

Schlaegel, C., Richter, N. F., & Taras, V. (2021). Cultural intelligence and work-related outcomes: A meta-analytic examination of joint effects and incremental predictive validity. *Journal of World Business, 56*(4), 101209. https://doi.org/10.1016/j.jwb.2021.101209

Shahzad, K., Javed, Y., Khan, S. A., Iqbal, A., Hussain, I., & Jaweed, M. V. (2022). Relationship between IT self-efficacy and personal knowledge and information management for sustainable lifelong learning and organizational performance: A systematic review from 2000 to 2022. *Sustainability, 15*(1), 5. https://doi.org/10.3390/su15010005

Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management: Zeitschrift Für Personalforschung*, *34*(3), 345-365. https://doi.org/10.1177/2397002220921131

Strohmeier, S., & Piazza, F. (2015). Artificial intelligence techniques in human resource management—A conceptual exploration. *In Intelligent techniques in engineering management (pp. 149–172).* Springer. https://doi.org/10.1007/978-3-319-17906-3_7

Tambe, P., & Cappelli, P. (2019). Artificial intelligence in human resources management. *California Management Review, 61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Tang, L., & Zhang, C. (2024). Analysis and mapping of scientific literature on cross-cultural adaptation of global immigrants (1963–2022). *SAGE Open, 14*(2), 1-25. https://doi.org/10.1177/21582440241255684

Tavera Romero, C. A., Ortiz, J. H., Khalaf, O. I., & Prado, A. R. (2021). Business intelligence: Business evolution after Industry 4.0. *Sustainability, 13*(18), 10026. https://doi.org/10.3390/su131810026

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

Ulrich, D., & Brockbank, W. (2005). *The HR value proposition*. Harvard Business School Press.

Ulrich, D., Younger, J., Brockbank, W., & Ulrich, M. (2012). *HR from the outside in: Six competencies for the future of human resources.* McGraw-Hill.

Community and Social Development Journal : CSDJ
Vol 27 No 3 September–December 2026: e287914: TCI 1

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management, 33*(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398

Wiblen, S. L., & Marler, J. H. (2021). Digitalised talent management and automated talent decisions: The implications for HR professionals. *International Journal of Human Resource Management, 32*(12), 2592–2621. https://doi.org/10.1080/09585192.2021.1886149

Wright, P. M., & McMahan, G. C. (2011). Exploring human capital: Putting 'human' back into strategic human resource management. *Human Resource Management Journal, 21(*2), 93–104. https://doi.org/10.1111/j.1748-8583.2010.00165.x

Wright, P. M., & Snell, S. A. (2005). Partner or guardian? HR's challenge in balancing value and values. *Human Resource Management, 44*(2), 177–182. https://doi.org/10.1002/hrm.20061