From Digital Tools to Institutional Capability: Artificial Intelligence, Human Resource Analytics, and Strategic HRM in Indian Higher Education

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Abstract

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Purpose. Indian higher education institutions are expanding while simultaneously con-fronting faculty shortages, uneven digital maturity, and pressure to improve institutional quality. Artificial intelligence (AI) and human resource analytics (HRA) are often presented as solutions, yet the literature rarely explains how technological tools become durable human resource man-agement (HRM) capabilities in universities. This article critically reviews that relationship and develops an India-sensitive capability and governance framework.

Design/methodology/approach. The article is a critical narrative review rather than an empirical or systematic review. Google Scholar was the sole literature-discovery platform, supplemented by backward and forward citation searching, during July–August 2026. The review audits the 32 references in the source manuscript, retains 22 traceable and relevant seed sources, and adds 29 scholarly, policy, and legal sources. A structured narrative process covered identification, relevance screening, design-sensitive appraisal, thematic coding, and narrative synthesis. Dynamic capabilities theory structures the analysis.

Findings. AI does not independently improve institutional outcomes. Its value is realized through HRA capability—the routines, expertise, data architecture, and interpretive practices that turn workforce data into defensible decisions—and through redesigned HRM practices. Leadership, digital skills, interoperable data, employee participation, and responsible-AI gover-nance condition this process. Evidence specific to AI-enabled HRM in Indian universities remains sparse; most positive claims are transferred from corporate or non-Indian higher education settings and are predominantly cross-sectional.

Originality/value. The review replaces a technology-adoption narrative with a capability-conversion explanation. It contributes a five-stage digital HR transformation framework, an AI–HRA–HRM relationship model, and testable propositions that distinguish technological affordances from analytics capability, HRM redesign, governance, and institutional outcomes.

Keywords: artificial intelligence; human resource analytics; strategic human resource management; higher education; India; dynamic capabilities; responsible AI; digital transformation

1 Introduction

India's higher education system combines exceptional scale with marked institutional heterogeneity. The All India Survey on Higher Education (AISHE) 2023–24 records approximately 4.5 crore students and more than 64,000 registered higher education institutions (HEIs), including universities, colleges, and standalone institutions (Department of Higher Education, Ministry of Education, Government of India, 2026). Expansion on this scale intensifies familiar massification and dif-ferentiation pressures (Altbach et al., 2017), including recruiting and retaining qualified faculty, developing interdisciplinary capability, evaluating performance without reducing academic work to narrow metrics, and coordinating administrative and academic talent across diverse institutional forms. The National Education Policy (NEP) 2020 adds further expectations concerning autonomy, multidisciplinary education, research, digitalization, and faculty development (Ministry of Education, Government of India, 2020). These expectations make people management a strategic issue rather than a back-office activity.

Strategic HRM research argues that coherent systems of recruitment, development, performance management, rewards, and employee participation can shape organizational capabilities and outcomes (Armstrong & Taylor, 2023; Becker & Huselid, 2006; Boxall & Purcell, 2016; Jiang et al., 2012; Paauwe & Boselie, 2005; Wright & McMahan, 1992). In universities, however, the transfer of corporate HRM assumptions is not straightforward. Academic work depends on professional autonomy, peer judgment, disciplinary norms, collegial governance, and long time horizons. Faculty performance is multidimensional and difficult to represent through a single dashboard. Studies of academic talent systems and engagement consequently warn that managerial control, opaque criteria, and narrow performance measures can undermine the commitment that HR practices are intended to strengthen (Guest, 2017; Raina & Khatri, 2015; van den Brink et al., 2013).

AI and HRA have entered this contested setting as part of the wider development of digital HRM (Bondarouk & Brewster, 2016; Strohmeier, 2020). AI-enabled applications can assist vacancy analysis, candidate matching, service queries, learning recommendations, workload forecasting, and pattern detection. HRA can combine workforce data to support planning, retention, capability development, and evaluation (Margherita, 2022; Marler & Boudreau, 2017; Tursunbayeva et al., 2018). Yet the evidence also documents data-quality problems, weak analytical expertise, organizational resistance, algorithmic opacity, surveillance concerns, and the risk of reproducing historical discrimination (Angrave et al., 2016; Bujold et al., 2024; Edwards et al., 2024; Leicht-Deobald et al., 2019; Tambe et al., 2019). Technology can therefore augment judgment, distort it, or simply automate an inadequate process.

The central problem is not whether AI and HRA are "used" but how an institution converts them into legitimate and repeatable HRM capability. Existing scholarship is divided among strategic HRM, digital transformation in higher education, HRA, AI-enabled HRM, and responsible-AI governance (Budhwar et al., 2022; Chowdhury et al., 2023; Dwivedi et al., 2021). Much of it examines one component in isolation. Direct evidence from Indian HEIs is particularly thin: India-based research has examined faculty engagement and corporate HR digitalization, but it does not establish that AI-enabled HRA improves HRM outcomes in universities (Kaur et al., 2025; Murugesan et al., 2023). This absence matters because public, private, deemed, autonomous, and affiliating institutions operate under different resource, governance, and employment conditions.

1.1 Research gap and questions

The literature presents four connected gaps. First, it often treats AI adoption as the explanatory variable, overlooking the organizational routines needed to interpret and act on AI outputs. Second, HRA research frequently measures tool use or analytical maturity without tracing how insights alter HR decisions. Third, higher education research concentrates on teaching, learning, and institutional digitalization rather than employee-facing AI and HRA. Fourth, evidence from India is fragmented and rarely integrates institutional diversity, employee voice, and the country's evolving data-protection environment.

The review addresses the following questions:

RQ1: How are AI, HRA, and strategic HRM connected in the higher education literature?

RQ2: Which organizational capabilities and governance conditions enable or constrain the conversion of AI and HRA into HRM value?

RQ3: What can be concluded—and what cannot be concluded—about Indian HEIs from the available evidence?

RQ4: What theoretically grounded framework can guide implementation and future empirical testing?

1.2 Novelty and contribution

The contribution is more specific than combining AI with HRA. *Theoretically*, the review uses dynamic capabilities theory to explain the conversion process from sensing workforce problems to seizing digital opportunities and reconfiguring HR routines. *Conceptually*, it positions HRA as the translation mechanism between AI affordances and strategic HRM, rather than treating AI and HRA as parallel independent variables. *Methodologically*, it separates reviewed evidence from proposed relationships and identifies the limits of cross-sectional, self-reported research. *Practically*, it proposes a staged transformation framework in which data governance, participation, validation, and human oversight are design requirements rather than post-implementation controls.

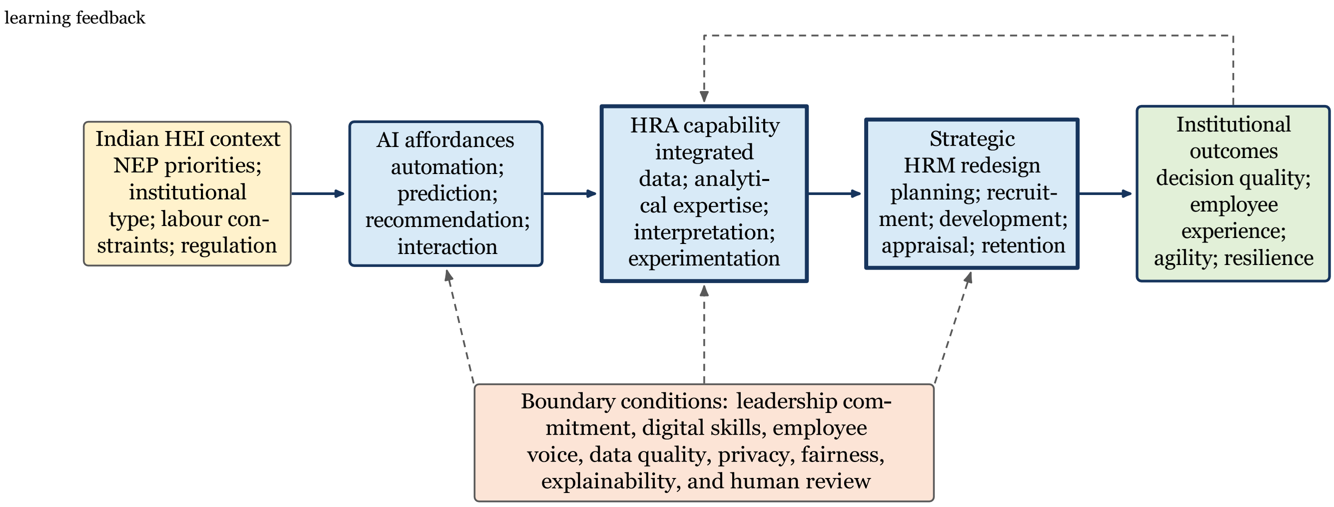

Figure 1: Conceptual framework: converting AI affordances into institutional HRM capability

2 Review Method

2.1 Rationale for a critical narrative review

This article adopts a critical narrative review because its purpose is explanatory and theory-building: to connect research streams that use different concepts and methods, evaluate the limits of their claims, identify unresolved gaps, and develop an implementation framework for Indian HEIs. The design is informed by the quality domains in the Scale for the Assessment of Narrative Review Articles (SANRA) (Baethge et al., 2019).

A systematic literature review would be appropriate for an exhaustive, protocol-led answer to a narrowly bounded question, but the present project did not begin with archived search exports, independent duplicate screening, or a pre-registered protocol. A scoping review would map the breadth and characteristics of an emerging field, whereas this article goes beyond mapping to compare explanations and build a capability-conversion argument. Meta-analysis is not appropriate because the corpus combines conceptual articles, reviews, books, policy documents, and empirical studies with non-equivalent constructs, outcomes, and designs; comparable effect sizes are unavailable. An empirical study is also inappropriate because no primary dataset was collected. The critical narrative format therefore provides the best fit without overstating reproducibility or causal evidence.

2.2 Google Scholar search and source identification

Google Scholar was the sole platform used to identify literature. Searches were conducted during July–August 2026, with the final search performed on 5 August 2026. Google Scholar was selected for its cross-disciplinary coverage of HRM, information systems, higher education, books, and policy material. Its use is reported as a practical discovery strategy, not as evidence of exhaustive database coverage. Publisher pages, DOI records, and official government documents were consulted only to verify bibliographic details and authoritative versions after a source had been identified; they were not additional literature-search databases.

The search was iterative. Exact phrases, synonyms, acronyms, and contextual terms were combined with Boolean operators. The principal search strings were:

- ("artificial intelligence" OR AI) AND ("human resource analytics" OR "people analytics") AND ("human resource management" OR HRM) AND ("higher education" OR university OR universities) AND India;
- ("artificial intelligence" OR AI) AND (HRM OR "human resource management");
- ("artificial intelligence" OR AI) AND ("higher education" OR university OR universities);
- ("human resource analytics" OR "people analytics") AND (universities OR "higher education");
- ("strategic HRM" OR "strategic human resource management") AND ("higher education" OR universities);
- ("digital HRM" OR "digital human resource management") AND India; and
- ("responsible AI" OR fairness OR explainability) AND (HRM OR employees), together with targeted searches connecting "dynamic capabilities" and "digital transformation" to higher education.

The review began with all 32 reference entries in the source manuscript. Each was checked for a traceable title, complete authorship, outlet, year, and DOI or official institutional source. Twenty-two seed sources were retained. Ten were excluded because they were untraceable as cited, bibliographically incomplete, peripheral to the review questions, or redundant with stronger evidence. Google Scholar searching and citation chaining identified 29 supplementary sources, producing the existing cited corpus of 51 scholarly, theoretical, policy, and legal works. Backward searching examined reference lists, while forward searching used Google Scholar's "Cited by" links to locate later extensions, critiques, and applications.

2.3 Eligibility and structured review process

The review followed a structured narrative process involving literature identification, screening for relevance, critical appraisal, thematic coding, and narrative synthesis. It does not claim PRISMA compliance. Titles and available abstracts or summaries were first assessed against the review questions; potentially relevant works were then examined in full or through complete bibliographic and substantive records where full text was unavailable.

Eligible sources were English-language peer-reviewed journal articles; books from established academic publishers; government reports; policy and legal documents; and higher education, AI-

HRM, digital HRM, strategic HRM, or HRA scholarship that directly informed the review questions or theoretical framework. Conference abstracts, blogs, editorials, news reports, duplicate records, non-English publications, and works unrelated to HRM or institutional workforce management were excluded. Policy and legal documents were retained for context and obligations, not as evidence of organizational effectiveness.

Table 1: Transparent review protocol

Element	Decision
Review type	Critical narrative review focused on theory development, conceptual integration, gap identification, and framework construction; no PRISMA claim.
Discovery platform	Google Scholar only, supplemented by backward reference searching and Google Scholar forward-citation searching.
Seed material	32 references in the uploaded manuscript; 22 retained after traceability and relevance checks.
Search period	July–August 2026; final search completed on 5 August 2026.
Supplementary identification	Google Scholar searches and citation chaining; 29 sources added to the retained seed literature.
Time coverage	Primarily 2015–5 August 2026, with earlier seminal theory, books, and meta-analytic research retained.
Inclusion	English-language peer-reviewed articles; established academic books; government, policy, and legal documents; directly relevant higher education, AI-HRM, digital HRM, strategic HRM, HRA, responsible-AI, and theory sources.
Exclusion	Non-English publications; conference abstracts; blogs; editorials; news articles; duplicates; untraceable or irreparably incomplete citations; and studies unrelated to HRM or institutional workforce management.
Appraisal	Bibliographic traceability, fit between method and claim, contextual relevance, transparency of sample or review process, and attention to limitations or ethics.
Extraction	Country/context, method, sample, theory, constructs, major findings, limitations, research gap, and managerial implications.
Synthesis	Thematic comparison organized by strategic HRM, AI affordances, HRA capability, digital transformation, and responsible governance.

2.4 Critical appraisal, coding, and synthesis

No single appraisal instrument is suitable for a corpus containing conceptual articles, systematic reviews, surveys, qualitative studies, books, and policy documents. The review therefore used design-sensitive appraisal. Empirical studies were assessed for sample transparency, context, measurement, analytic fit, and causal overreach. Reviews were assessed for search transparency, evidence boundaries, and the relationship between included studies and conclusions. Conceptual work was assessed for construct clarity and explanatory value. Policy and legal documents were used to establish context and obligations, not to infer HRM effects.

Data were extracted into a comparison matrix and coded around five questions: what technology or practice was examined; what mechanism was proposed; what outcome was reported; what contextual conditions were acknowledged; and what inference was justified. Codes were compared across five themes—strategic HRM, AI affordances, HRA capability, HEI digital transformation, and responsible governance—before being integrated narratively. The synthesis deliberately distinguishes association from causation, convergence from genuine replication, and reviewed findings from the propositions developed later in the article.

3 Theoretical Foundation: Dynamic Capabilities

The resource-based view identifies valuable and difficult-to-imitate human and organizational resources as potential sources of sustained advantage (Barney, 1991). It usefully explains why faculty expertise, institutional knowledge, analytical talent, and trusted employment relationships matter. Its limitation for the present problem is that possessing resources does not explain how an institution renews them during technological and policy change.

Other established theories illuminate parts of the problem but do not provide the same integrative mechanism. Technology acceptance models explain individual perceptions and intentions to use a system; this is relevant to continued use of AI-enabled HRM (Hammad & Alawad, 2026), but acceptance does not establish data quality, organizational learning, workflow redesign, or beneficial outcomes. Institutional theory explains how regulation, professional norms, and imitation create adoption pressure, yet it is less specific about how an HEI converts a symbolic or compliant adoption into operational capability (Paauwe & Boselie, 2005). The ability–motivation–opportunity perspective explains employee-level pathways between HR practices and outcomes (Jiang et al., 2012), but it does not primarily address the renewal of digital infrastructure and decision routines. These perspectives remain useful for explaining boundary conditions; none is treated as irrelevant.

Dynamic capabilities theory addresses the review's central question more directly. It defines higher-order capabilities through which organizations sense changes, seize opportunities, and reconfigure assets and routines (Teece, 2007). Digital transformation research applies this logic to strategic renewal: organizations must continually interpret technological change, make coordinated investment choices, and redesign structures, skills, and processes (Warner & Wager, 2019). The lens is especially appropriate for HEIs because digital HR transformation is not a one-time technology purchase. It is an iterative process in which an institution learns which workforce problems deserve attention, which data can legitimately be used, where human judgment is indispensable, and how practices should change. Dynamic capabilities is therefore the primary theory, while the resource-based view, acceptance, institutional, and ability–motivation–opportunity perspectives serve as complementary explanations of resource value, use, contextual pressure, and employee response.

In this review, *sensing* includes identifying faculty shortages, skill gaps, workload pressures, retention risks, and inequities. *Seizing* includes prioritizing use cases, creating interoperable data foundations, developing analytics expertise, and piloting tools with affected employees. *Transforming* includes redesigning HR workflows, decision rights, professional roles, performance criteria, and governance arrangements. HRA is the connective capability because it combines data, technology, domain knowledge, and interpretation. AI supplies affordances; HRA makes those affordances decision-relevant; strategic HRM embeds them in recurring organizational routines.

The theory also prevents a technocentric conclusion. Recent HEI evidence indicates that IT capabilities yield stronger innovation outcomes when organizational climate supports experimentation and learning (Galal & El Morsy, 2026). Similarly, sustained use of AI-enabled HR systems depends on organizational support, perceived usefulness, risk perceptions, and digital literacy (Hammad & Alawad, 2026). Dynamic capability is therefore both technical and social.

4 Critical Literature Synthesis

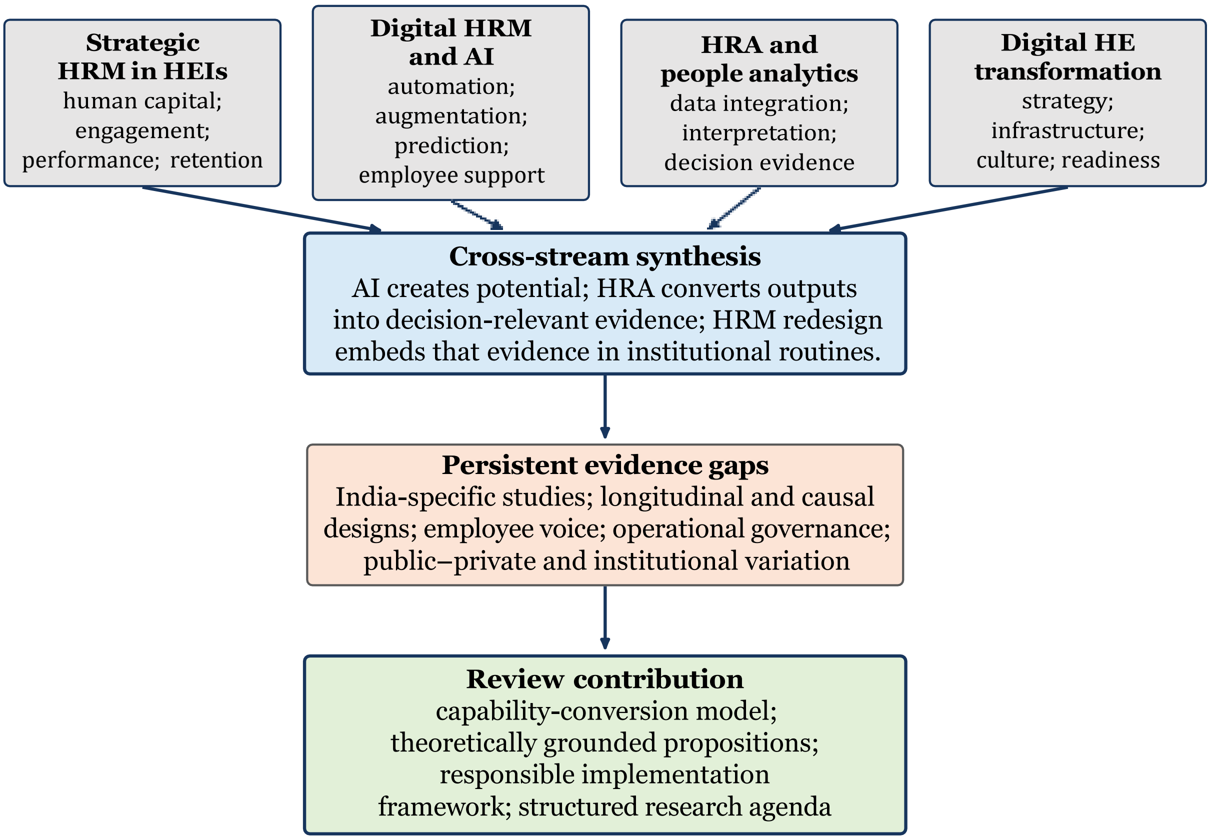

Figure 2: Literature synthesis framework

4.1 Strategic HRM in higher education

Strategic HRM scholarship broadly agrees that mutually reinforcing practices affect outcomes through employee skills, motivation, opportunity, and organizational processes (Becker & Huselid, 2006; Jiang et al., 2012; Wright & McMahan, 1992). In higher education, studies connect performance appraisal, rewards, development, and work engagement to organizational commitment (Aboramadan et al., 2020). Research on Indian academia similarly points to psychological climate and job crafting as antecedents of engagement (Kaur et al., 2025). This evidence supports investment in coherent HR systems rather than isolated practices.

The disagreement concerns what should count as performance and how tightly HR systems should control academic work. Talent-management research shows that seemingly merit-based systems can privilege narrow career templates and reproduce unequal access to advancement (van den Brink et al., 2013). Faculty engagement research also remains conceptually fragmented, with wide variation in outcomes, levels of analysis, and institutional context (Raina & Khatri, 2015). General HRM-performance evidence cannot be imported without considering professional autonomy, disciplinary diversity, contract status, and the different missions of universities and colleges.

Methodologically, much of the HEI evidence is cross-sectional and based on self-reported perceptions. Such designs can establish patterned associations but cannot demonstrate that HR practices cause institutional performance. They also underrepresent contingent faculty, non-teaching staff, and public-sector governance constraints.

The apparent consensus in favour of coherent HR systems therefore conceals an unresolved tension. Studies typically record employee commitment or engagement as desirable outcomes, whereas critical talent-management research asks who receives developmental opportunity, whose work becomes visible, and whether standardized criteria narrow legitimate academic careers. Positive average associations do not resolve distributional effects or establish that the same practice benefits different employee groups.

Synthesis. Strategic HRM is relevant to HEIs when it builds capability and employee support, but digitalization should not intensify reductive performance management. Any AI-HRA model must preserve plural definitions of academic contribution and include employee voice in the design of metrics.

4.2 AI-enabled HRM: automation versus augmentation

AI-HRM reviews identify applications across recruitment, selection, learning, performance manage-ment, workforce planning, and employee services (Gong et al., 2025; Tambe et al., 2019; Votto et al., 2021; Vrontis et al., 2022). The strongest recurring benefit is operational: AI can process large volumes of information, standardize routine tasks, and surface patterns that human decision-makers may not readily detect. India-based corporate evidence also associates AI applications with HR digitalization and readiness, although it does not concern universities (Murugesan et al., 2023).

The literature does not support a simple claim that AI eliminates bias or improves decisions. Histor-ical data can encode prior discrimination; proxy variables can reproduce protected characteristics; and opaque systems can reduce procedural justice even when predictive performance is acceptable (Hunkenschroer & Luetge, 2022; Leicht-Deobald et al., 2019; Naoum et al., 2026). Research on workers' reactions further distinguishes automation, in which systems replace judgment, from augmentation, in which systems inform accountable human decisions (Langer & Landers, 2021). The latter is more compatible with high-stakes academic employment decisions.

The methodological base remains immature. Many articles are conceptual or review-based, while empirical studies often measure perceptions of AI rather than audited decision quality. Positive findings commonly rely on managers or expert respondents and rarely compare algorithm-assisted decisions with appropriate human baselines. Few studies examine error distribution, disparate impact, appeals, or consequences over time.

Accordingly, the literature contains competing rather than cumulative claims. Efficiency-oriented studies treat standardization and prediction as improvements, while employee- and ethics-oriented studies show that the same features may reduce dignity, contextual judgment, or perceived fairness (Langer & Landers, 2021; Naoum et al., 2026). These positions cannot be reconciled by assuming that human oversight is automatically protective: reviewers may correct model errors, defer to them, or introduce different biases. The unresolved empirical question concerns which allocation of human and machine judgment performs better for a defined task and affected population.

Synthesis. AI should be treated as a portfolio of affordances, not a unitary independent variable. Its value depends on task characteristics, data provenance, human-AI role allocation, and the reversibility of decisions. High-stakes selection, appraisal, promotion, and contract renewal require explanation, contestability, and accountable human review.

4.3 HRA as a translation mechanism

HRA is commonly defined as the systematic use of workforce data and analytical methods to improve people-related decisions. Reviews agree that it can support workforce planning, retention analysis, capability mapping, and evaluation of HR interventions (Margherita, 2022; Marler & Boudreau, 2017; Tursunbayeva et al., 2018). Yet they also identify a persistent gap between technical analysis and managerial action. Data teams may produce sophisticated outputs that do not answer an institutional question, while HR units may lack the authority or expertise to translate findings into redesigned practices (Angrave et al., 2016; Edwards et al., 2024).

This distinction is central. A dashboard is an information product; HRA capability is a repeatable organizational capacity. It includes data definitions, integration, analytic expertise, HR domain knowledge, causal reasoning, communication, governance, and the ability to evaluate whether action improved an outcome. The adoption of analytics is therefore influenced by leadership, data culture, stakeholder relationships, and the organizational position of HR (Shet et al., 2021).

The evidence is inconsistent about where the principal bottleneck lies. Some accounts emphasize weak tools and fragmented data; others locate failure in HR's analytical competence, credibility, or access to strategic decisions (Angrave et al., 2016; Edwards et al., 2024; Marler & Boudreau, 2017). These explanations imply different remedies and may coexist. Better prediction is of limited value when the construct is poorly specified, while a valid analysis has little effect when decision-makers do not alter a rule, allocate resources, or evaluate implementation.

HRA also carries ethical risks independent of AI. Continuous monitoring can expand surveillance, weak proxies can pathologize normal variation, and easily measurable indicators can displace important but less quantifiable academic work. Responsible HRA requires purpose limitation, data minimization, access controls, bias testing, and a clear route for employees to correct data or challenge interpretations (Bankins, 2021; Bujold et al., 2024). In India, implementation must also be designed around the Digital Personal Data Protection Act 2023 and the staged commencement of the Digital Personal Data Protection Rules 2025 (Ministry of Electronics and Information Technology, Government of India, 2023, 2025).

Synthesis. HRA mediates the relationship between AI and HRM because it converts technological outputs into contextually interpreted evidence. Institutions create value not by maximizing data collection, but by improving the validity, legitimacy, and actionability of workforce decisions.

4.4 Digital transformation and organizational readiness in HEIs

Higher education digital transformation is broader than digitization. Reviews describe it as coordinated change involving strategy, people, processes, culture, governance, and technology (Castro Benavides et al., 2020; Fernandez et al., 2023). Common barriers include fragmented systems, legacy infrastructure, inadequate skills, unclear ownership, resource constraints, and resistance rooted in poorly managed change (Singun, 2025). These barriers are especially consequential for HRM because workforce data are often distributed across payroll, attendance, recruitment, research, learning-management, and appraisal systems.

Recent empirical studies in non-Indian HEIs offer emerging but qualified evidence. A UAE study of 215 respondents reports associations between AI-driven insights, decision enhancement, HRM process optimization, and sustainable HRM performance (Mahade et al., 2025). An Egyptian study of 346 users finds that performance expectancy, organizational support, risk perception, ease of use, and digital literacy shape continuance intention for AI-enabled HRM (Hammad & Alawad, 2026). Another Egyptian study of 300 academics finds that a supportive digital innovation climate strengthens the relationship between IT capability and sustainable innovation performance (Galal & El Morsy, 2026). These studies are useful, but cross-sectional self-reports and different national systems limit causal and Indian-context inference.

Their findings should not be read as three replications of a single effect. One study models perceived sustainable HRM performance, one models intention to continue using a system, and one models broader innovation performance rather than HRM. Their shared emphasis on organizational support is suggestive, but the constructs, respondents, and outcomes differ. This inconsistency helps explain why adoption, continued use, workflow change, and verified institutional benefit must remain separate stages in the proposed model.

Leadership and change management are recurring conditions rather than direct substitutes for capability. Leaders must clarify the problem being solved, allocate decision rights, protect time for learning, and respond to legitimate employee concerns. Change that is framed solely as efficiency improvement may generate resistance because employees anticipate work intensification or loss of discretion (Kotter, 1996; Rozman et al., 2023).

Synthesis. Digital readiness is a configuration of infrastructure, skills, leadership, culture, and governance. HEIs should not scale AI-HRM pilots until they can demonstrate reliable data, usable workflows, employee acceptance, and monitored consequences.

4.5 Responsible governance and employee agency

Responsible-AI scholarship converges on fairness, transparency, accountability, privacy, security, and human oversight, but disagrees on how these principles should be operationalized. A tech-nically explainable model may still be organizationally illegitimate if employees cannot contest the data, understand the purpose, or obtain meaningful review. Conversely, human involvement does not automatically make a system fair; human reviewers can defer uncritically to algorithmic recommendations (Bujold et al., 2024; Hunkenschroer & Luetge, 2022).

HEIs have additional responsibilities because they are knowledge institutions and public-interest actors. Recruitment and appraisal systems shape academic freedom, disciplinary diversity, and the careers of early-stage researchers. Responsible governance should therefore include an approved-use-case register, data lineage, pre-deployment impact assessment, subgroup performance testing, documentation of human override, appeal procedures, vendor accountability, and scheduled retire-ment or revalidation of models. Policy frameworks developed for teaching and learning reinforce the importance of institution-wide responsibility, literacy, and stakeholder participation (Chan, 2023).

Synthesis. Governance is not merely a moderator that reduces risk; it is a productive capability that makes experimentation legitimate. Employee agency, contestability, and documented account-ability are mechanisms through which HEIs can learn from errors without normalizing opaque or harmful systems.

Table 2: Critical literature review matrix

Author/year	**Country/ context**	**Method and sample**	**Theory**	**Variables/focus**	**Major findings**	**Limitations and research gap**	**Ma tion**
Raina and Khatri (2015)	Global with India comparison	Narrative literature review	Engagement perspectives	Faculty engagement antecedents and outcomes	Faculty engagement is important but conceptually dispersed across disciplines and levels.	No causal test; limited integrated framework; predates recent AI-HRM developments.	Bui men than tiati
Marler and Boudreau (2017)	Cross-sector	Evidence-based review	Evidence-based management	HRA definitions, antecedents, and outcomes	HRA can improve decisions, but empirical evidence of organizational value is limited.	Heterogeneous definitions and few strong causal designs.	Lin to e eval
Tambe et al. (2019)	Cross-sector	Conceptual review	Strategic HRM and data science	AI applications, data constraints, fairness	AI offers scale and prediction but faces small samples, data quality, legal, and fairness problems in HR.	Primarily conceptual; limited HEI evidence.	Use tean able
Castro Benavides et al. (2020)	Global HEIs	Systematic literature review	Digital transformation	Strategy, technology, people, processes	HEI transformation requires coordinated organizational change, not isolated digitization.	Broad institutional focus; HRM is not the central unit of analysis.	Alig with stra
Shet et al. (2021)	Cross-sector	Framework development based on literature	Technology–organization–environment logic	Analytics adoption determinants	Successful HRA adoption depends on technological, organizational, environmental, and data factors.	Framework requires further contextual testing; not HEI-specific.	Ass pro owr cap
Votto et al. (2021)	Cross-sector	Systematic literature review	Human resource life cycle	Tactical AI applications across HR functions	AI research spans the HR life cycle, with ethics emerging as a distinct domain.	Evidence is application-focused and uneven in quality; strategic outcomes remain undertested.	Sele and nov
Vrontis et al. (2022)	Cross-sector	Systematic review	Multi-level HRM framework	AI, robotics, advanced technology, HR outcomes	Technology changes HR tasks and work relationships at individual, team, and organizational levels.	Fragmented methods; limited longitudinal and employee-centered evidence.	Ant and que tom

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Table 2 continued

Author/year context	**Country/**	**Method and sample**	**Theory**	**Variables/focus**	**Major findings**	**Limitations and research gap**	**Ma tio**
Fernandez et al. (2023)	Global HEIs	Multivocal review of academic and grey literature	Digital maturity	Transformation initiatives, processes, technologies	HEIs frequently pursue fragmented initiatives; strategy, people, and process integration are essential.	Grey literature varies in quality; HRM implications are indirect.	Cre roa sta
Rozman et al. (2023)	Slovenia	Survey of 437 medium and large firms; PLS-SEM and CB-SEM	Organizational culture and leadership	AI-supported culture, leadership, training, engagement	Supportive culture, leadership, and training are associated with engagement and team performance.	Corporate, single-country, cross-sectional design limits HEI inference.	Pai lea anc
Murugesan et al. (2023)	India; IT, manufacturing, and administration	Survey of 271 HR experts; SEM	HR readiness	AI applications, HR digitalization, readiness	AI application and readiness are associated with HR digitalization.	Corporate sectors; expert perceptions; no university sample or audited outcomes.	Do est to
Mahade et al. (2025)	UAE HEIs	Cross-sectional survey, n = 215; PLS-SEM	Capability and RBV-oriented model	AI insights, process optimization, decision enhancement, sustainable HRM	AI insights are associated with sustainable HRM; process and decision mechanisms mediate relationships.	Non-probability sampling, self-reports, single-country and cross-sectional design.	Pri red anc ado
Kaur et al. (2025)	India; 32 universities	Cross-sectional survey of 442 academics; PLS-SEM	Psychological climate/job crafting	Climate, job crafting, work engagement	Positive climate predicts engagement, partly through job crafting.	Does not study AI or HRA; common-method and cross-sectional limits.	Pro cra red
Hammad and Alawad (2026)	Egyptian private HEIs	Cross-sectional survey, n = 346; PLS-SEM	UTAUT and post-adoption theory	Support, ease of use, risk, expectancy, literacy, continuance	Organizational support and performance expectancy are strong predictors; digital literacy conditions continued use.	Private-sector, single-country, intention rather than objective performance.	Tre tin inv
Galal and El Morsy (2026)	Egyptian HEIs	Cross-sectional survey of 300 academics; SEM	Dynamic capabilities and organizational climate	IT determinants, innovation climate, sustainable innovation	IT capability predicts innovation, and supportive climate strengthens the relationship.	Perceptual measures and cross-sectional design; not specifically HRM.	Co tru cal tat
Naoum et al. (2026)	Global	Systematic review of 43 articles published 2016–2024	Responsible AI/DEI	AI-HRM effects on diversity, equity, and inclusion	AI can support or undermine inclusion depending on data, design, and governance.	Rapidly evolving field; limited longitudinal validation and context-sensitive auditing.	Re doc ing

4.6 Evidence quality and inferential boundaries

The evidence base is wider than it is deep. Recent HEI studies rely heavily on cross-sectional surveys, often analysed with structural equation models. Such designs are useful for examining theoretically specified associations, but temporal order remains uncertain and reciprocal relationships cannot be excluded. When respondents report both institutional capabilities and desirable outcomes in the same instrument, common-method variance, consistency motives, and social-desirability effects may inflate relationships. Statistical remedies cannot fully replace independent outcome data or temporal separation.

Self-reported measures also blur distinct stages of digital transformation. Awareness of a tool, intention to use it, perceived usefulness, continued use, workflow change, and verified benefit are not equivalent. Managerial or expert reports may overstate implementation maturity, while faculty perceptions may capture legitimacy and work experience without establishing technical accuracy. Few studies combine survey evidence with system logs, documents, algorithm audits, employee appeals, subgroup error rates, or independently recorded HR outcomes.

The literature provides little basis for causal inference. Longitudinal studies, comparison groups, natural experiments, bounded field trials, and interrupted time-series designs remain uncommon. The predominance of positive, publishable associations may also underrepresent abandoned pilots, null results, implementation failures, and harmful effects. Most importantly for this review, direct empirical evidence on AI-enabled HRA in Indian HEIs is scarce. Evidence from corporations and HEIs in other national systems can identify plausible mechanisms, but it cannot establish effect size, feasibility, legitimacy, or transferability across India's heterogeneous institutions.

5 Review Findings

5.1 Finding 1: Evidence supports a conversion chain, not a direct technology effect

Across the literature, the most defensible sequence is: AI affordances enable new forms of analysis; HRA capability converts outputs into contextual evidence; HRM redesign embeds evidence in decisions; and outcomes depend on how employees experience and respond to those decisions. This sequence explains why institutions with similar technologies can obtain different results. It also reveals the conceptual error in models that specify AI and HRA as parallel predictors of "innovative HRM" without defining their distinct roles.

5.2 Finding 2: Organizational readiness is multidimensional

Readiness includes interoperable data, analytical skill, HR domain expertise, leadership support, employee trust, change capacity, and governance. Technical infrastructure is necessary but insufficient. Conversely, a supportive culture cannot compensate for unreliable data or invalid models. Readiness should be assessed at the use-case level because a university may be ready for a low-risk HR service chatbot but not for algorithmic promotion recommendations.

5.3 Finding 3: Benefits are plausible, but causal claims remain premature

The reviewed evidence consistently reports associations with efficiency, decision support, engagement, or sustainable HRM. However, self-reported cross-sectional surveys dominate the recent HEI evidence. Few studies use longitudinal designs, comparison groups, objective outcome measures, or audits of error and fairness. The literature therefore supports cautiously worded expectations, not claims that AI and HRA *significantly improve* faculty productivity or institutional performance in Indian HEIs.

5.4 Finding 4: India is a consequential but under-evidenced context

Indian policy and sector scale make strategic workforce capability important, yet the direct evidence base remains insufficient. Corporate AI-HRM research and Indian faculty-engagement research pro-vide adjacent evidence, not validation of an AI–HRA–HRM causal model in universities. Institution type, state regulation, funding, contract mix, disciplinary profile, and digital maturity are likely to create substantial heterogeneity. This is the review's strongest contextual gap.

5.5 Finding 5: Governance and employee agency are value-creating conditions

Fairness, privacy, explainability, and contestability do more than reduce compliance risk. They improve data quality, surface contextual errors, and sustain use. Employee participation can reveal whether a proxy is misleading, whether a workload metric penalizes necessary service work, or whether a system changes behavior in unintended ways. Governance should therefore be integrated into capability building from the first diagnostic stage.

6 Proposed Research Model and Propositions

The model in figure 3 is proposed for future empirical testing; it is not presented as a tested result. It treats AI capability as the institution's ability to select and operate appropriate AI applications, HRA capability as the ability to produce decision-relevant workforce evidence, and strategic HRM redesign as actual change in recurring HR practices.

Table 3: Cross-theme synthesis of agreement, disagreement, and evidence gaps

Theme tension	Areas of agreement	Disagreement or	Priority evidence gap
AI in HRM	Useful for scale, pattern detection, and routine support.	Automation versus aug-mentation; efficiency ver-sus fairness and auton-omy.	Field experiments and audited decision outcomes in high-stakes HR tasks.
HRA	Can improve planning when analysis is tied to decisions.	Tool maturity versus organizational capability; prediction versus explanation.	Longitudinal studies tracing analytics use to changed practice and out-comes.
HEI transforma-tion	Strategy, culture, skills, and integration matter.	Central standardization versus academic and unit-level discretion.	Comparative pub-lic/private and univer-sity/college studies.
Employee out-comes	Supportive climate and development promote engagement.	Monitoring may enable support or intensify control and work pressure.	Employee-centered stud-ies including contingent faculty and non-teaching staff.
Responsible governance	Fairness, privacy, trans-parency, and oversight are necessary.	Principle statements versus operational metrics and enforceable account-ability.	Evaluations of impact assessment, appeals, audits, and human override.
Indian context	NEP and system scale create a strong strategic need.	Whether global evidence transfers across diverse Indian institutions.	Multi-level, multi-state, mixed-method, and longi-tudinal research.

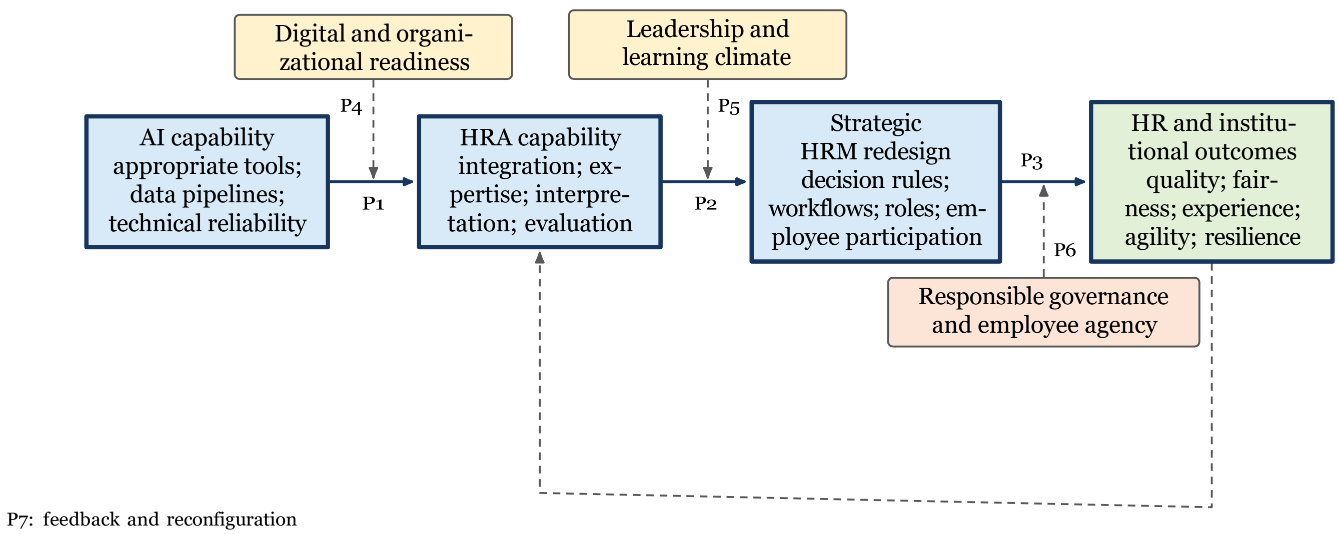

Figure 3: Proposed research model for future empirical testing

P1. AI capability will be positively associated with HRA capability when AI applications are technically reliable and aligned with defined workforce questions.

P2. HRA capability will be positively associated with strategic HRM redesign because analytics creates value only when insights alter decision rules, workflows, or resource allocation.

P3. Strategic HRM redesign will mediate the relationship between HRA capability and human resource and institutional outcomes.

P4. Data interoperability, digital skills, and organizational readiness will strengthen the relationship between AI capability and HRA capability.

P5. Leadership support and a learning-oriented climate will strengthen the relationship between HRA capability and strategic HRM redesign.

P6. Responsible governance and employee agency will strengthen positive outcomes and reduce adverse outcomes by improving legitimacy, error detection, and accountable use.

P7. Outcome monitoring and employee feedback will support continuing reconfiguration of HRA capability, producing a learning loop rather than a one-time adoption effect.

7 Proposed HRM Digital Transformation Framework

The framework in figure 4 translates dynamic capabilities into a staged implementation process. Stages are sequential for governance, but learning can return an institution to an earlier stage. A failed pilot may reveal that the original problem was poorly framed or that the data are not fit for purpose.

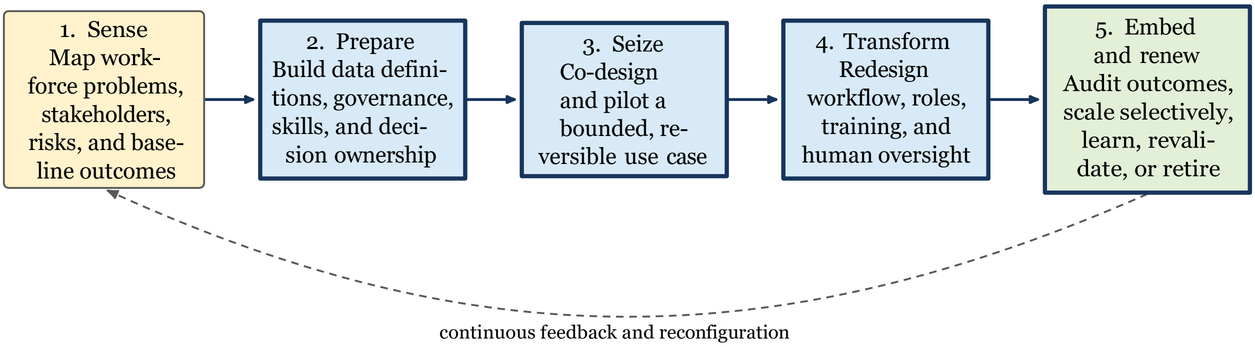

Figure 4: Proposed HRM digital transformation framework

Table 4: Construct clarification and future operationalization

Construct	Definition in this review	Illustrative indicators for future research
AI capability	Ability to select, integrate, validate, and maintain AI applications appropriate to HR tasks.	Use-case fit; model relia-bility; data-pipeline stabil-ity; vendor transparency; human-AI role clarity.
HRA capability	Ability to integrate workforce data and convert analysis into credible, relevant, and evaluable deci-sion support.	Data quality; analyst and HR expertise; causal rea-soning; insight use; evalua-tion routines.
Strategic HRM redesign	Observable change in recurring HR processes and decision rights.	Revised workflows; deci-sion criteria; role changes; participation; resource re-allocation; documented overrides.
Responsible gover-nance	Formal and enacted controls that protect rights and ensure accountability.	Impact assessment; privacy controls; subgroup testing; explanation; appeal; audit; incident response.
Employee agency	Employees' meaningful ability to understand, influ-ence, correct, and contest data-driven HR decisions.	Consultation quality; access to information; correction rights; appeal use; per-ceived voice and procedural justice.
Outcomes	Multi-level consequences rather than a single perfor-mance score.	Decision quality, time/cost, diversity, engagement, well-being, retention, re-search/teaching support, institutional agility.

7.1 Stage 1: Sense the institutional problem

Institutions should begin with a workforce decision, not a product. Appropriate questions include where vacancy delays arise, which skills will be needed for new programmes, whether development opportunities are equitably allocated, or why particular employee groups leave. Baseline measures and affected stakeholders should be specified before any AI claim is entertained.

7.2 Stage 2: Prepare data, governance, and capability

Preparation includes a shared data dictionary, lawful purpose, data minimization, access controls, retention schedules, named decision owners, and an assessment of data quality and representativeness. It also requires multidisciplinary competence spanning HR, institutional research, IT, law/ethics, faculty governance, and employee representation.

7.3 Stage 3: Seize through bounded co-designed pilots

Early pilots should be low-risk, reversible, and measurable. Examples include forecasting recruit-ment workload, identifying aggregate development needs, or supporting employee-service triage. Automated final decisions about hiring, appraisal, promotion, disciplinary action, or contract re-newal should not be an entry-level use case. Pilot success criteria should include fairness, usability, employee experience, and error handling alongside efficiency.

7.4 Stage 4: Transform HR routines

A successful model is not yet a transformed practice. Institutions must define how the output enters a decision, who may override it, what explanation is provided, how employees correct data, and how professional judgment is documented. Training should address both use and non-use: staff must recognize when evidence is insufficient or the system is outside its validated context.

7.5 Stage 5: Embed, audit, renew, or retire

Scaled systems need drift monitoring, subgroup outcome analysis, privacy and security review, employee feedback, and scheduled revalidation. An institution should be willing to retire a system whose benefits are not demonstrated or whose adverse effects cannot be corrected. This stage closes the dynamic-capability loop by feeding evidence back into sensing and reconfiguration.

Table 5: Implementation roadmap for Indian HEIs

Stage	Key deliverable gate	Minimum governance	Illustrative mea-sure
Sense base-line	Problem statement and	Named stakeholders; no solu-tion pre-selected	Vacancy cycle time, workload variation, development access, turnover pattern
Prepare readiness assessment	Data and capability	Lawful purpose, data map, access control, decision owner	Missingness, repre-sentativeness, skill coverage, data lineage Accuracy, false-
Pilot eval-uation plan	Bounded prototype and	Human review, reversal, inci-dent route, employee consul-tation	positive distribution, usability, perceived fairness Decision time and quality, override rate, appeal
Transform sion rights	Revised workflow and deci-	Explanation, correction, ap-peal, override documentation	outcomes Subgroup outcomes, privacy incidents, adoption quality, veri-fied
Embed/renew	Monitoring and revalidation record	Periodic audit, drift test, benefit review, retirement criteria	benefit

8 AI–HRA–HRM Relationship

Figure 5 clarifies the distinct roles of AI, HRA, and HRM. AI techniques operate on data to generate classifications, forecasts, recommendations, or interactions. HRA combines those outputs with contextual data, theory, and domain judgment to produce an interpretable claim. HRM is the organizational site where a decision is made and experienced. Outcome evidence then returns to the data and evaluation layer. Collapsing these layers obscures accountability: when a decision fails, the cause may be the model, the data, the interpretation, the HR rule, or the implementation context.

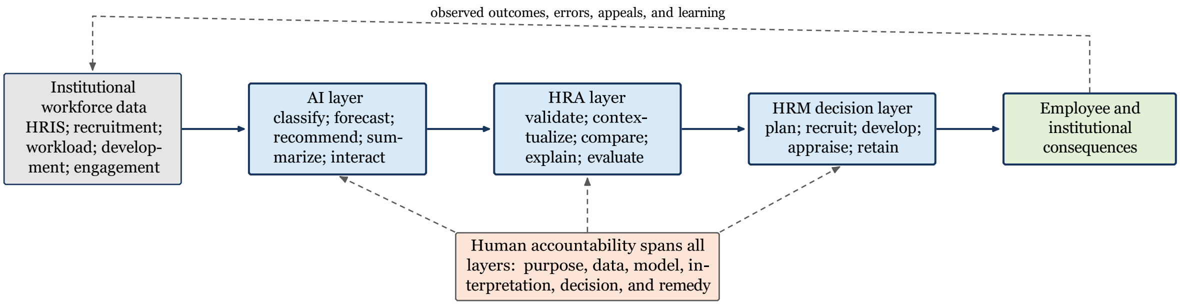

Figure 5: AI–HRA–HRM relationship and accountability diagram

9 Discussion

9.1 Theoretical implications

The review advances strategic HRM research by locating digital value in a conversion process. The resource-based view explains the importance of valuable human and analytical resources, but dynamic capabilities explain why some HEIs can repeatedly reconfigure those resources while others remain at the pilot stage. AI capability is an enabling lower-order capability; HRA is a bridging capability; strategic HRM redesign is the transformation mechanism; and governance/employee agency shapes whether the resulting routines are legitimate and sustainable.

The model also qualifies universalistic claims in HRM. A practice is not “best” because it is data-driven. Its value depends on institutional mission, task uncertainty, data validity, workforce composition, and the consequences of error. In professional organizations, employee agency is not merely a climate variable; it is a source of contextual knowledge and error correction.

9.2 Methodological implications

Future studies should avoid measuring AI adoption with a few broad Likert items and then regressing it on equally broad performance perceptions. Multi-source designs should distinguish technical capability, actual system use, analytics quality, workflow change, and outcomes. Longitudinal implementation studies can observe how capability develops and how resistance, overrides, or errors alter design. Where feasible, stepped-wedge pilots, matched comparisons, interrupted time series, and field experiments can strengthen causal inference.

Measurement should include potential harms as well as benefits. Relevant outcomes include time and cost, but also decision consistency, subgroup errors, procedural justice, employee well-being, appeal patterns, privacy incidents, and displacement of professional discretion. Qualitative work is needed to understand how faculty, HR staff, administrators, and contingent employees interpret data-driven management.

9.3 Practical implications

The implications differ by stakeholder and by authority over the system. Table 6 converts the review findings into role-specific priorities.

Table 6: Stakeholder-specific recommendations

Stakeholder before scaling	Priority recommendations	Minimum evidence or safeguard
University management	Govern a portfolio of defined workforce problems rather than purchasing a general AI solution; assign decision owners; fund data stewardship and staff learning; require employee participation and periodic benefit–harm review.	Documented problem and baseline, accountable governance body, lawful purpose, resources for evaluation, and authority to stop or retire an ineffec-tive system.
HR departments	Build a shared workforce-data dictionary; develop staff who can connect HR knowledge with data reasoning; separate descriptive, predictive, and causal claims; redesign the decision process rather than merely adding a dashboard.	Reliable data lineage, validated mea-sures, documented workflow and hu-man override, correction and appeal routes, and outcome monitoring be-yond time or cost.
Faculty members and employee representatives	Participate in problem definition, metric design, pilot evaluation, and governance; identify missing con-textual information; use correction and appeal mechanisms; report work-intensification, autonomy, or fairness concerns.	Timely explanation of purpose and data use, meaningful consultation, pro-tection against retaliation, accessible correction and review, and feedback on how concerns were resolved.
Policymakers and sector bodies	Issue proportionate standards that distinguish low-risk decision support from high-stakes employment decisions; support shared infrastructure and capability building for smaller HEIs; clarify audit, documentation, procurement, and accountability expectations.	Alignment with data-protection obli-gations, minimum impact-assessment and record-keeping standards, indepen-dent oversight options, and sector-level learning from incidents and failed pi-lots.
Technology ven-dors	Provide data and model documenta-tion, validation evidence, subgroup performance where applicable, security controls, audit logs, interoperability, deletion and portability mechanisms, and contractually meaningful access for institutional audit.	Disclosure of intended and excluded uses, evidence from a comparable con-text, change notification, limits on secondary data use, incident support, and an exit plan that preserves institu-tional records and employee rights.

10 Limitations

This article is a critical narrative review and is not exhaustive. Google Scholar offers broad interdisciplinary discovery but has opaque and changing coverage, ranking, and citation-linking practices. Searches performed by another reviewer or at another date may therefore return a different ordering or set of records. The review did not use subscription-database exports, independent dual screening, a registered protocol, or meta-analysis. Selection and interpretation consequently retain an element of reviewer judgment despite the stated criteria and source accounting.

Publication bias may favour positive or novel accounts of AI adoption, while null results, discontinued pilots, vendor failures, and organizational harms remain unpublished. Restriction to English-language sources creates language bias and may omit relevant regional scholarship. Backward and forward citation searching can introduce citation bias by favouring established, highly cited, and well-connected work. Google Scholar may index multiple versions unevenly, omit some publications, or surface non-peer-reviewed material that requires careful source checking. Unpublished theses, internal evaluations, procurement records, and institutional incident reports may therefore have been missed.

The corpus also spans sectors, countries, technologies, and outcome definitions, which limits direct comparison. Recent studies from UAE and Egyptian HEIs improve contextual relevance but do not establish transferability to India. Much of the empirical evidence uses cross-sectional, self-reported measures, leaving temporal ordering, common-method bias, and causal inference unresolved. The pace of AI development and Indian data-protection implementation means that governance requirements and technical practices will continue to evolve.

These limitations are partly addressed through explicit search strings, eligibility criteria, source ac-counting, design-sensitive appraisal, careful separation of evidence from propositions, and restrained causal language. They cannot be eliminated by reporting alone. The proposed framework should therefore be treated as a theoretically grounded synthesis and research agenda requiring empirical validation.

11 Future Research Agenda

Future research should prioritize designs that can distinguish adoption from capability, perception from observed practice, and association from causation. Table 7 sets out a structured agenda.

Table 7: Structured future research agenda

Research gap	Suggested future study	Suggested methodology	Expected contribution
Unknown prevalence and maturity in India	Establish a baseline of formal, experimental, and informal AI/HRA use across public, private, deemed, autonomous, affiliating, and standalone HEIs.	Stratified multi-institution mixed-method study combining survey, document review, system inventory, and interviews.	Distinguish adoption claims from operational capability and identify institutional patterns in readiness, use cases, and governance.
Unobserved capability-conversion process	Follow bounded use cases from problem definition through preparation, pilot, workflow integration, evaluation, and renewal or retirement.	Comparative longitudi-nal case studies using interviews, observation, decision documents, system logs, and process tracing.	Test the sensing–seizing–transforming mechanism and explain why similar technologies produce different outcomes.
Weak causal evi-dence of benefit	Evaluate a clearly defined, reversible decision-support intervention against an appropriate baseline.	Stepped-wedge trial, matched comparison, interrupted time series, or difference-in-differences design where feasible and ethical.	Estimate whether observed changes follow the intervention rather than prior trends, selec-tion, or optimistic perceptions.
Limited employee-centred evidence	Examine faculty, contractual staff, and non-teaching employ-ees' experiences of monitoring, autonomy, workload, dignity, correction, and appeal.	Longitudinal qualitative study or explanatory sequential mixed methods with purposive inclusion of less powerful employee groups.	Extend evaluation beyond effi-ciency and reveal mechanisms affecting trust, well-being, resis-tance, and professional discretion.
Unverified fairness and accountability	Audit high-stakes recruitment, appraisal, promotion, or retention support for errors, subgroup effects, overrides, and appeals.	Socio-technical algo-rithm audit combining quantitative error analysis, data and model documentation, work-flow observation, and procedural-justice interviews.	Operationalize responsible gov-ernance and show whether safe-guards work in practice rather than only on paper.
Institutional het-erogeneity and transferability	Compare how governance, funding, employment arrangements, state context, discipline mix, and digital maturity alter implementation.	Multi-level comparative design across institution types and states, with contextual variables specified before analysis.	Identify boundary conditions and prevent inappropriate trans-fer of corporate or non-Indian findings.
Untested proposed model	Evaluate the relationships in figure 3 without relying on a single respondent or measurement occasion.	Multi-source, time-separated design using HR, IT, governance, faculty and staff reports; documents; system logs; and administrative outcomes.	Test mediation, moderation, and feedback while separating tech-nical capability, analytics qual-ity, workflow change, employee response, and institutional out-comes.
Vendor opacity and dependence	Examine procurement claims, contractual accountability, model changes, secondary data use, interoperability, and exit arrangements.	Comparative contract and documentation anal-ysis supplemented by interviews with HEIs, vendors, legal staff, and affected employees.	Develop evidence-based procure-ment standards and clarify the distribution of responsibility across institutions and suppliers.

12 Conclusion

AI and HRA can support strategic HRM in Indian higher education, but neither is a shortcut around institutional capability. The literature supports a conditional conclusion: AI creates potential, HRA converts that potential into evidence, HRM redesign embeds evidence in practice, and governance plus employee agency determines whether the result is legitimate and sustainable. Direct Indian HEI evidence remains too limited for claims of established performance effects.

The practical implication is a shift from technology procurement to capability building. Institutions should begin with bounded workforce problems, prepare reliable and lawful data, co-design reversible pilots, redesign decision processes, and scale only after benefits and harms have been evaluated. This sequence aligns digital transformation with the distinctive mission and governance of higher education while creating an empirically testable agenda for future research.

Declarations

Data availability. No new empirical dataset was created. The review is based on the sources listed in the reference section.

Ethics approval. Not applicable; the article does not report research involving human participants or identifiable personal data.

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References

Aboramadan, M., Albashiti, B., Alharazin, H., & Dahleez, K. A. (2020). Human resources man-agement practices and organizational commitment in higher education: The mediating role of work engagement. *International Journal of Educational Management*, *34* (1), 154–174. https://doi.org/10.1108/IJEM-04-2019-0160

Altbach, P. G., Reisberg, L., & de Wit, H. (2017). *Responding to massification: Differentiation in postsecondary education worldwide*. Sense Publishers. https://doi.org/10.1007/978-94-6351-083-7

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal*, *26* (1), 1–11. https://doi.org/10.1111/1748-8583.12090

Armstrong, M., & Taylor, S. (2023). *Armstrong's handbook of human resource management practice* (16th ed.). Kogan Page.

Baethge, C., Goldbeck-Wood, S., & Mertens, S. (2019). SANRA—a scale for the quality assessment of narrative review articles. *Research Integrity and Peer Review*, *4*, Article 5. https://doi. org/10.1186/s41073-019-0064-8

Bankins, S. (2021). The ethical use of artificial intelligence in human resource management: A decision-making framework. *Ethics and Information Technology*, *23*, 841–854. https://doi. org/10.1007/s10676-021-09619-6

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

Becker, B. E., & Huselid, M. A. (2006). Strategic human resources management: Where do we go from here? *Journal of Management*, *32* (6), 898–925. https://doi.org/10.1177/0149206306293668 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

Boxall, P., & Purcell, J. (2016). *Strategy and human resource management* (4th ed.). Palgrave Macmillan.

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

Bujold, A., Roberge-Maltais, I., Parent-Rocheleau, X., Boasen, J., Senecal, S., & Leger, P.-M. (2024). Responsible artificial intelligence in human resources management: A review of the empirical literature. *AI and Ethics*, *4* (4), 1185–1200. https://doi.org/10.1007/s43681-023-00325-1

Castro Benavides, L. M., Tamayo Arias, J. A., Arango Serna, M. D., Branch Bedoya, J. W., & Burgos, D. (2020). Digital transformation in higher education institutions: A systematic literature review. *Sensors*, *20* (11), Article 3291. https://doi.org/10.3390/s20113291

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*, Article 38. https://doi.org/10.1186/s41239-023-00408-3

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 manage-ment through an AI capability framework. *Human Resource Management Review*, *33* (1), Article 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Department of Higher Education, Ministry of Education, Government of India. (2026). *All india survey on higher education (AISHE) 2023–24*. Government of India. Retrieved August 5, 2026, from https://aishe.gov.in/aishe-final-report/

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., . . . 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*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edwards, M. R., Charlwood, A., Guenole, N., & Marler, J. (2024). HR analytics: An emerging field finding its place in the world alongside simmering ethical challenges. *Human Resource Management Journal*, *34* (2), 326–336. https://doi.org/10.1111/1748-8583.12435

Fernandez, A., Gomez, B., Binjaku, K., & Mece, E. K. (2023). Digital transformation initiatives in higher education institutions: A multivocal literature review. *Education and Information Technologies*, *28* (10), 12351–12382. https://doi.org/10.1007/s10639-022-11544-0

Galal, H. M., & El Morsy, R. M. (2026). Synergizing dynamic capabilities and organizational climate to enhance sustainable innovation performance in higher education institutions. *Discover Education*, *5*, Article 437. https://doi.org/10.1007/s44217-026-01618-3

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

Guest, D. E. (2017). Human resource management and employee well-being: Towards a new analytic framework. *Human Resource Management Journal*, *27* (1), 22–38. https://doi.org/10.1111/ 1748-8583.12139

Hammad, M., & Alawad, N. (2026). Determinants of continuance intention in AI-enabled HRM: An application of the UTAUT model in the egyptian higher education sector. *Future Business Journal*, *12*, Article 181. https://doi.org/10.1186/s43093-026-00889-4

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, *178* (4), 977–1007. https://doi.org/10.1007/ s10551-022-05049-6

Jiang, K., Lepak, D. P., Hu, J., & Baer, J. C. (2012). How does human resource management influence organizational outcomes? a meta-analytic investigation of mediating mechanisms. *Academy of Management Journal*, *55* (6), 1264–1294. https://doi.org/10.5465/amj.2011.0088

Kaur, K., Ahuja, S., Kumar, P., & Saini, H. (2025). Psychological climate and work engagement in academia: The mediating role of job crafting. *Prabandhan: Indian Journal of Management*, *18* (8), 8–32. https://doi.org/10.17010/pijom/2025/v18i8/173917

Kotter, J. P. (1996). *Leading change*. Harvard Business School Press.

Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior*, *123*, Article 106878. https: //doi.org/10.1016/j.chb.2021.106878

Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I., & Kasper, G. (2019). The challenges of algorithm-based HR decision-making for personal integrity. *Journal of Business Ethics*, *160* (2), 377–392. https://doi.org/10.1007/s10551-019-04204-w

Mahade, A., Elmahi, A., Alomari, K. M., & Abdalla, A. A. (2025). Leveraging AI-driven insights to enhance sustainable human resource management performance: Moderated mediation model—evidence from UAE higher education. *Discover Sustainability*, *6*, Article 267. https: //doi.org/10.1007/s43621-025-01114-y

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, *32* (2), Article 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

Ministry of Education, Government of India. (2020). *National education policy 2020*. Government of India. Retrieved August 5, 2026, from https://www.education.gov.in/sites/upload_files/ mhrd/files/NEP_Final_English_0.pdf

Ministry of Electronics and Information Technology, Government of India. (2023). *The digital personal data protection act, 2023 (no. 22 of 2023)*. Government of India. Retrieved August 5, 2026, from https://www.meity.gov.in/content/digital-personal-data-protection-act-2023 Ministry of Electronics and Information Technology, Government of India. (2025). *Digital personal data protection rules, 2025*. Government of India. Retrieved August 5, 2026, from https: //www.meity.gov.in/documents/act-and-policies/digital-personal-data-protection-rules-2025-gDOxUjMtQWa

Murugesan, U., Subramanian, P., Srivastava, S., & Dwivedi, A. (2023). A study of artificial intelligence impacts on human resource digitalization in industry 4.0. *Decision Analytics Journal*, *7*, Article 100249. https://doi.org/10.1016/j.dajour.2023.100249

Naoum, R. F., Szakadati, T., & Balogh, G. (2026). Artificial intelligence (AI) in human resource management (HRM): A systematic review of its dual impact on diversity, equity, and inclusion (DEI). *Management Review Quarterly*. https://doi.org/10.1007/s11301-025-00580-y

Paauwe, J., & Boselie, P. (2005). HRM and performance: What's next? *Human Resource Management Journal*, *15* (4), 68–83. https://doi.org/10.1111/j.1748-8583.2005.tb00296.x

Raina, K., & Khatri, P. (2015). Faculty engagement in higher education: Prospects and areas of research. *On the Horizon*, *23* (4), 285–308. https://doi.org/10.1108/OTH-03-2015-0011

Rozman, M., Tominc, P., & Milfelner, B. (2023). Maximizing employee engagement through artificial intelligent organizational culture in the context of leadership and training of employees: Testing linear and non-linear relationships. *Cogent Business & Management*, *10* (2), Article 2248732. https://doi.org/10.1080/23311975.2023.2248732

Shet, S. V., Poddar, T., Wamba, S. F., & Dwivedi, Y. K. (2021). Examining the determinants of successful adoption of data analytics in human resource management—a framework for implications. *Journal of Business Research*, *131*, 311–326. https://doi.org/10.1016/j.jbusres. 2021.03.054

Singun, A. J. (2025). Unveiling the barriers to digital transformation in higher education institutions: A systematic literature review. *Discover Education*, *4*, Article 37. https://doi.org/10.1007/ s44217-025-00430-9

Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management*, *34* (3), 345–365. https : / / doi . org / 10 . 1177/ 2397002220921131

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. https://doi.org/10.1177/0008125619867910

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sus-tainable) enterprise performance. *Strategic Management Journal*, *28* (13), 1319–1350. https: //doi.org/10.1002/smj.640

Tursunbayeva, A., Di Lauro, S., & Pagliari, C. (2018). People analytics—a scoping review of concep-tual boundaries and value propositions. *International Journal of Information Management*, *43*, 224–247. https://doi.org/10.1016/j.ijinfomgt.2018.08.002

van den Brink, M., Fruytier, B., & Thunnissen, M. (2013). Talent management in academia: Performance systems and HRM policies. *Human Resource Management Journal*, *23* (2), 180–195. https://doi.org/10.1111/j.1748-8583.2012.00196.x

Votto, A. M., Valecha, R., Najafirad, P., & Rao, H. R. (2021). Artificial intelligence in tactical human resource management: A systematic literature review. *International Journal of Information Management Data Insights*, *1* (2), Article 100047. https://doi.org/10.1016/j.jjimei.2021.100047

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

Warner, K. S. R., & Wager, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52* (3), 326–349. https: //doi.org/10.1016/j.lrp.2018.12.001

Wright, P. M., & McMahan, G. C. (1992). Theoretical perspectives for strategic human re-source management. *Journal of Management*, *18* (2), 295–320. https://doi.org/10.1177/014920639201800205