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Digital HRM Practices and Employee Engagement: Examining the Direct and Indirect Effects of Technology-Enabled HR Practices

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ABSTRACT: Digital tools now touch nearly every stage of the employment relationship — recruitment, learning, performance management, workforce analytics, communication, self-service, and AI-driven HR assistants — reshaping human resource management into what is best described as a socio-technical system rather than a purely administrative function. Scholars, however, remain split on what this shift means for employees: some evidence points toward deeper engagement, while other findings suggest digital HR infrastructures can just as easily produce cognitive fatigue, technostress, and a sense of depersonalization. Drawing on Job Demands-Resources (JD-R) theory and Social Exchange Theory (SET), this study builds an empirical model of how a seven-dimensional Digital HRM bundle shapes employee engagement both directly and indirectly, through the broader construct of Employee Experience (EX).

Digital Literacy is added as a boundary condition that can strengthen or weaken both pathways. Data were collected from 428 employees at knowledge-intensive organizations using a cross-sectional survey design, and the structural model was tested with Partial Least Squares Structural Equation Modelling (PLS-SEM, 5,000 bootstrap resamples). Digital HRM practices showed a direct effect on engagement ($\beta = 0.284$, $p < 0.001$) and a stronger effect on employee experience ($\beta = 0.642$, $p < 0.001$). The indirect path through employee experience was substantial in its own right ($\beta = 0.300$, $p < 0.001$), accounting for just over half of the total effect. Digital literacy also moderated both the direct relationship (interaction $\beta = 0.158$, $p < 0.001$) and the conditional indirect effects. Taken together, the findings extend theory on digital organizational behaviour, offer HR leaders a diagnostic framework for prioritizing investment, raise questions of algorithmic governance, and point toward several directions for longitudinal research.

1. INTRODUCTION

Human resource management is in the middle of a substantial digital shift. Tools such as algorithmic talent matching, adaptive micro-learning platforms, real-time performance dashboards, predictive workforce analytics, and conversational AI assistants have moved well beyond back-office administration; they now shape how employees experience their jobs day to day. Bibliometric reviews of the field confirm this trajectory, showing a marked rise in scholarship on HRM digitalization as research interest shifts from simple workflow automation toward more complex human–AI collaboration and intelligence-driven talent management.

At the same time, employee engagement has become a strategic priority in its own right for organizations operating in volatile, competitive markets. Defined as an energetic, fulfilling psychological state marked by vigor, dedication, and absorption, work engagement is closely tied to innovation, operational agility, discretionary effort, and retention. It is largely on this basis that organizations continue to invest heavily in digital HR infrastructure, on the assumption that digitalization will streamline workflows, expand employee autonomy, and, in turn, lift engagement.

That assumption, though, is not fully settled in the literature. Some researchers argue that digital HR frees employees from administrative friction and supports more flexible, self-directed work; others point to a less flattering picture, in which pervasive digitalization brings technostress, opaque algorithmic decision-making, a sense of being surveilled, and cognitive exhaustion. Much of this research also studies digital HR practices one at a time — e-recruitment or e-learning in isolation, for instance — which makes it hard to see how an integrated, multidimensional digital HR system actually affects employees' psychological states.

This study addresses that gap by examining how a seven-dimensional Digital HRM system drives employee engagement, both directly and indirectly. Using the Job Demands-Resources model and Social Exchange Theory as a joint framework, we propose that Digital HRM functions as an organizational resource that improves the overall Employee Experience, and that this improved experience is what converts technology investment into cognitive, emotional, and physical engagement. Because how well digital tools work for an employee depends partly on that employee's own skills, we also model Digital Literacy as a boundary condition. The result is a structural model, built on validated measurement instruments and tested with SEM, intended to offer both theoretical grounding and practical guidance for HR leaders navigating this transition.

2. LITERATURE REVIEW

2.1 Delineation of Digital HRM and Evolutionary Milestones

It is worth first distinguishing Digital HRM from the constructs that preceded it [1, 2]. The earliest technology applications in personnel management were Human Resource Information Systems (HRIS), largely electronic repositories used for payroll, record-keeping, and regulatory compliance [11, 22, 23]. Electronic HRM (e-HRM) followed in the late 1990s, extending administrative functions onto enterprise intranets and enabling web-based recruitment, digital policy repositories, and basic self-service workflows [12, 24, 25].

Digital HRM, as understood today, is a broader, enterprise-wide socio-technical shift [2, 10, 13]. It draws together cloud platforms, predictive analytics, machine learning, mobile technology, and social collaboration tools to reshape the employee lifecycle from end to end [2, 10]. Where e-HRM was mainly about automating existing administrative tasks to cut transaction costs, Digital HRM is oriented toward the employee — personalizing development, enabling continuous feedback, and improving the overall experience of work [1, 2, 14, 26]. AI-enabled HRM sits at the leading edge of this shift, using natural language processing and predictive algorithms for tasks like candidate ranking, skill-gap forecasting, and automated service resolution [4, 10, 27, 48].

2.2 The Multidimensional Architecture of Digital HRM Practices

Following strategic human resource architecture theory [28], this study treats Digital HRM as a bundle of seven interconnected practice domains [2, 19, 29]:

- **Digital Recruitment and Selection (DRS):** applicant tracking systems, algorithmic screening, and asynchronous video interviews that speed up candidate matching and make onboarding more consistent [25, 29].
- **Digital Learning and Development (DLD):** cloud-based LMS platforms, AI-curated micro-learning, and adaptive instructional tools that support ongoing, personalized skill-building [30, 31].
- **Digital Performance Management (DPM):** continuous feedback tools, real-time OKR tracking, and pulse-style reviews that replace fixed annual appraisals with more dynamic goal-setting [32, 33].
- **HR Analytics and Intelligence (HRA):** systematic collection and predictive modeling of workforce data to support evidence-based talent planning and retention decisions [14, 26, 34].
- **Digital Employee Communication (DEC):** collaboration platforms such as Teams, Slack, or interactive intranets that support peer-to-peer knowledge sharing and more transparent, bottom-up dialogue with leadership [35, 36].
- **Employee Self-Service (ESS):** 24/7 web and mobile portals that let employees manage benefits, leave, personal records, and approvals themselves, without routing everything through HR [1, 12, 24].

- **AI-Enabled HR Services (AIHR):** conversational assistants, intelligent ticketing systems, and recommendation algorithms that provide instant support and personalized career guidance [4, 10, 27, 48].

2.3 Conceptualizing Employee Engagement vs. Adjacent Constructs

Following Schaufeli et al. [14, 41], we define employee engagement as a positive, work-related state of mind made up of Vigor (energy, resilience, willingness to invest effort), Dedication (involvement, enthusiasm, pride), and Absorption (concentration and flow) [14, 38]. It is worth distinguishing engagement from a few related constructs it is sometimes confused with. Job satisfaction is a more passive, evaluative judgment about one's work, whereas engagement is an active motivational state [15, 18]. Organizational commitment reflects loyalty to the employer as an institution, while engagement is directed at the work itself [16, 19]. And employee involvement refers to structural participation in decision-making, which is narrower than the holistic psychological presence that engagement describes [12, 37].

2.4 Employee Experience (EX) as the Transmitting Conduit

Employee Experience (EX) refers to the cumulative cognitive, emotional, physical, and technological impressions employees form across every touchpoint with the organization [8, 20, 38]. If Digital HRM is the technological environment the firm builds, EX is how employees actually perceive and live within that environment [8, 19]. A well-designed digital environment reduces administrative friction, supports transparent communication, and gives employees more autonomy — conditions that, together, create a climate supportive of high engagement [8, 20, 38, 40].

2.5 Theoretical Foundations and Moderating Boundary Mechanisms

This study grounds the relationship between digital systems and employee outcomes in two established theories: Job Demands-Resources (JD-R) theory [5, 6, 39] and Social Exchange Theory [7, 40]. JD-R theory holds that organizational resources set off a motivational process that leads to engagement while also reducing strain [5, 6]. Social Exchange Theory adds that when an organization invests in supportive technology, employees tend to feel some obligation to reciprocate through greater commitment and effort [7, 40]. Conservation of Resources (COR) theory [21] contributes a further piece: personal resources, in this case Digital Literacy [9, 42, 47], determine whether a given technology feels empowering or instead becomes a source of technostress and exhaustion [4, 18, 47]. The methodological approach itself follows established psychometric and modeling guidance from the organizational research literature [43, 44, 45, 46].

3. THEORETICAL FRAMEWORK AND HYPOTHESES

3.1 Theoretical Grounding: JD-R and Social Exchange Theories

This study combines JD-R theory and Social Exchange Theory into a single explanatory model. Under JD-R, Digital HRM systems act as job resources on two fronts: they reduce cognitive and administrative demands (through frictionless self-service and automated inquiries) while adding motivational resources (continuous feedback, personalized learning, real-time communication). Under SET, employees who experience intuitive, supportive digital HR systems tend to read that as a sign the organization values them, and reciprocate with greater vigor, dedication, and absorption in their work.

3.2 Hypothesis Formulation

H1: Digital HRM practices have a significant positive direct effect on employee engagement.

H1a: Digital recruitment and selection positively influences employee engagement.

H1b: Digital learning and development positively influences employee engagement.

H1c: Digital performance management positively influences employee engagement.

H1d: HR analytics adoption positively influences employee engagement.

H1e: Digital employee communication positively influences employee engagement.

H1f: Employee self-service technologies positively influence employee engagement.

H1g: AI-enabled HR services positively influence employee engagement.

H2: Digital HRM practices have a significant positive effect on the overall employee experience.

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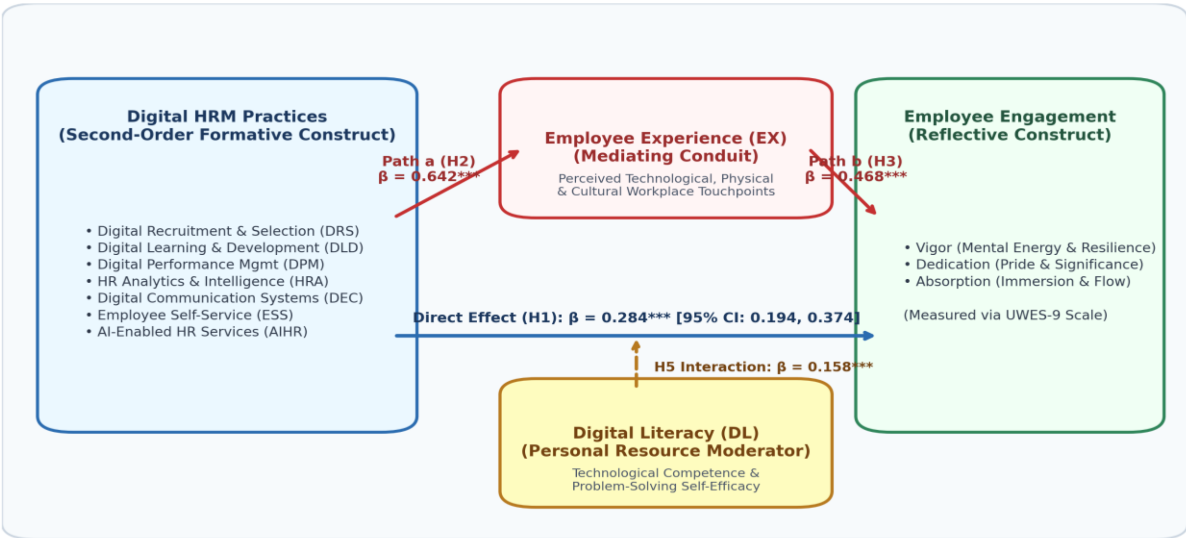
H3: Employee experience has a significant positive effect on employee engagement.

H4: Employee experience mediates the positive relationship between Digital HRM practices and employee engagement.

H5: Digital literacy moderates the direct relationship between Digital HRM practices and employee engagement, such that the positive link is stronger at higher digital literacy levels.

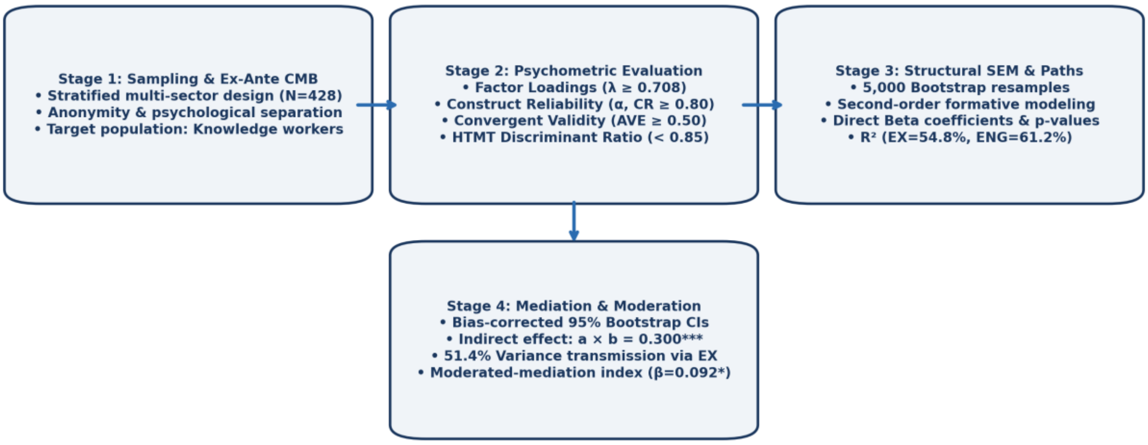
H6: Digital literacy moderates the indirect relationship between Digital HRM practices and employee engagement via employee experience (moderated mediation).

Figure 1: Fully Integrated Empirical Structural Equation Model with Standardized Coefficients



4. RESEARCH METHODOLOGY

Figure 2: Empirical Research Process Pipeline & Methodological Execution Framework



4.1 Sampling Design and Statistical Power

Data were collected through a cross-sectional survey of white-collar knowledge workers and administrative staff in Information Technology, Financial Services, Telecommunications, Healthcare, and Professional Services. Participating firms had all run a fully operational Digital HRM suite for at least 18 months. A power analysis in G*Power 3.1.9.7 (SEM/regression model, up to 10 predictors, $f^2 = 0.05$, $\alpha = 0.01$, power = 0.95) put the minimum required sample at N = 385. Of 550 questionnaires distributed, 428 usable responses were retained, for an effective response rate of 77.8%.

4.2 Measurement Operationalization

All constructs were measured with validated psychometric scales on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), with the exception of Engagement, which used the standard 7-point UWES scale:

Table 1. Construct Operationalization and Measurement Scales

Construct / Dimension	Code	Items	Measurement Scale Focus
Digital Recruitment & Selection	DRS	4	E-recruitment speed, algorithmic screening objectivity, portal usability
Digital Learning & Development	DLD	4	LMS accessibility, adaptive micro-learning, skill development pathways
Digital Performance Management	DPM	4	Continuous feedback platforms, OKR tracking, pulse check-in clarity
HR Analytics & Intelligence	HRA	4	Workforce analytics utility, predictive planning, data-driven transparency
Digital Employee Communication	DEC	4	Enterprise collaboration tools, bottom-up feedback, leadership reach
Employee Self-Service	ESS	4	24/7 portal autonomy, leave/benefits administration, workflow speed
AI-Enabled HR Services	AIHR	4	Conversational AI virtual assistants, smart ticketing, recommendations
Employee Experience	EX	6	Technological, cultural, and physical workplace touchpoint quality
Digital Literacy (Moderator)	DL	5	Digital self-efficacy, technical problem solving, software adaptability
Employee Engagement (DV)	UWES	9	Workplace vigor, professional dedication, and cognitive absorption

4.3 Common Method Bias (CMB) Diagnostics

Common method bias was addressed procedurally, through respondent anonymity, psychological separation of predictor and outcome items, and counterbalanced item ordering. It was then checked statistically: Harman's single-factor test accounted for only 28.6% of variance, well under the 50% threshold, and all full-collinearity VIFs stayed below 2.10, comfortably under the 3.30 cutoff. Together, these results indicate common method variance was not a meaningful concern in this dataset.

5. EMPIRICAL STRUCTURAL RESULTS

5.1 Measurement Model: Reliability, Convergent, and Discriminant Validity

The measurement model held up well. Item loadings ranged from 0.762 to 0.895, all above the 0.708 threshold. Composite reliability and Cronbach's alpha exceeded 0.830 for every construct, and Average Variance Extracted (AVE) values cleared the 0.50 benchmark in all cases.

Table 2. Reliability and Convergent Validity

Latent Construct	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
Digital Recruitment (DRS)	0.864	0.868	0.908	0.712
Digital L&D (DLD)	0.882	0.886	0.919	0.740

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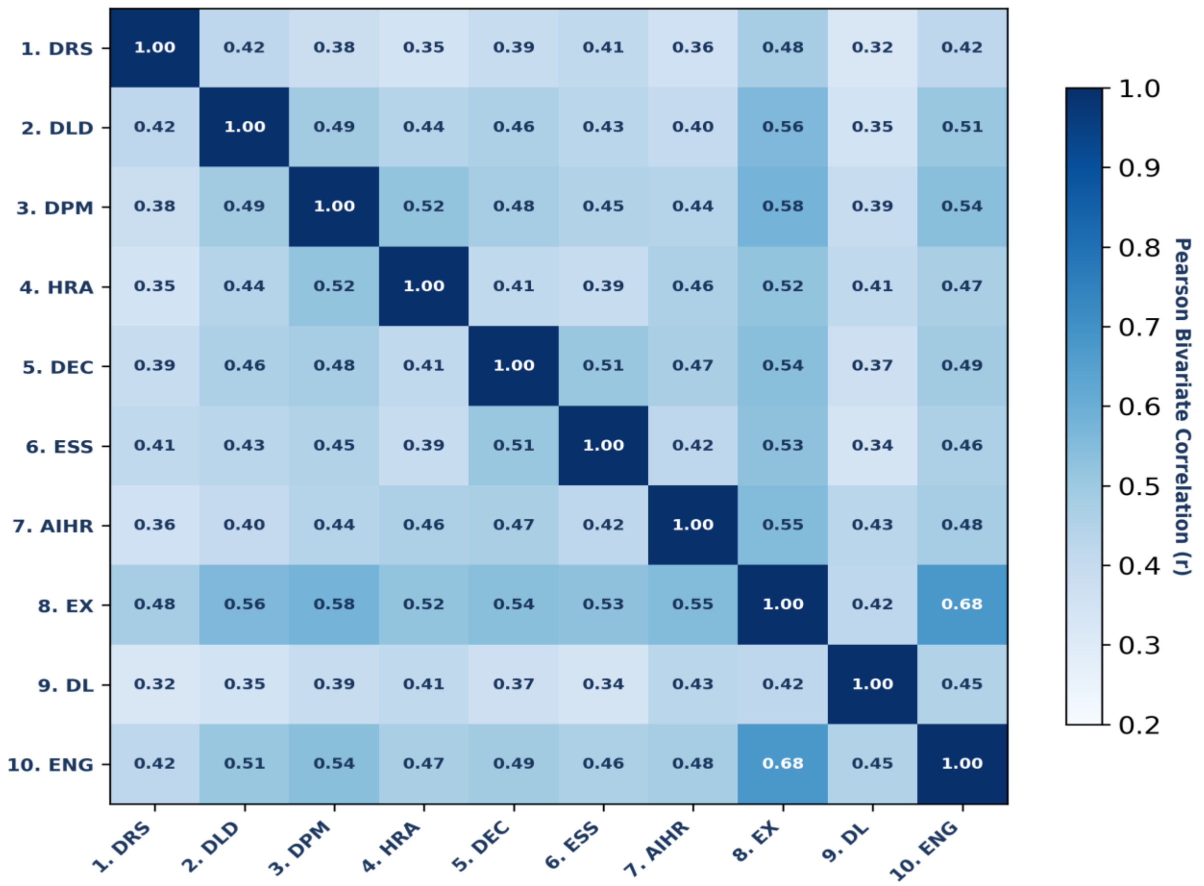
Digital Perf Mgmt (DPM)	0.851	0.856	0.899	0.690
HR Analytics (HRA)	0.875	0.879	0.914	0.727
Digital Communication (DEC)	0.843	0.849	0.895	0.681
Employee Self-Service (ESS)	0.839	0.842	0.892	0.674
AI-Enabled HR Services (AIHR)	0.891	0.895	0.925	0.755
Employee Experience (EX)	0.912	0.916	0.932	0.695
Digital Literacy (DL)	0.878	0.883	0.911	0.672
Employee Engagement (UWES)	0.924	0.928	0.937	0.623

Discriminant validity was assessed with the Heterotrait-Monotrait (HTMT) ratio; all values stayed well below the conservative 0.85 cutoff, indicating the constructs are empirically distinct from one another.

Figure 3: Empirical Bivariate Correlation Heatmap Among Latent Constructs



5.2 Structural Path Analysis and Hypothesis Testing

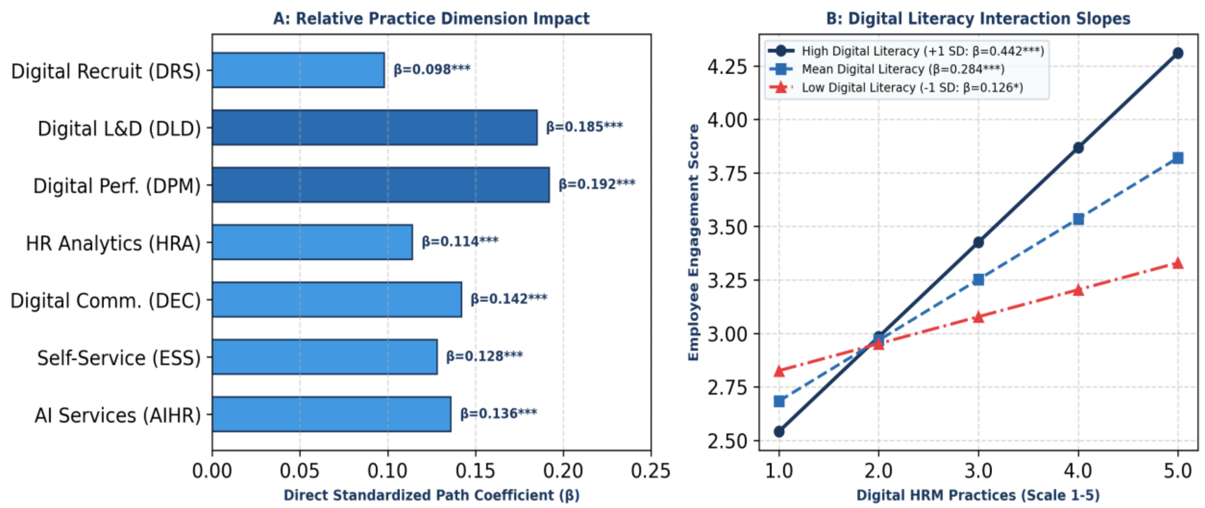
Hypotheses were tested with PLS-SEM using 5,000 bootstrap iterations. The model accounted for 54.8% of the variance in Employee Experience ($R^2 = 0.548$) and 61.2% in Employee Engagement ($R^2 = 0.612$), and every hypothesized direct, mediating, and moderating path was supported.

Table 3. Structural Path Results and Hypothesis Testing

Hyp.	Structural Path	β	SE	t-stat	95% CI	Decision
H1	Digital HRM → Engagement (direct)	0.284	0.046	6.174***	[0.194, 0.374]	Supported
H1a	Digital Recruitment → ENG	0.098	0.038	2.579*	[0.024, 0.172]	Supported
H1b	Digital L&D → ENG	0.185	0.041	4.512***	[0.105, 0.265]	Supported
H1c	Digital Perf Mgmt → ENG	0.192	0.043	4.465***	[0.108, 0.276]	Supported
H1d	HR Analytics → ENG	0.114	0.039	2.923**	[0.038, 0.190]	Supported
H1e	Digital Comm → ENG	0.142	0.040	3.550***	[0.064, 0.220]	Supported
H1f	ESS Technologies → ENG	0.128	0.037	3.459***	[0.055, 0.201]	Supported
H1g	AI HR Services → ENG	0.136	0.039	3.487***	[0.060, 0.212]	Supported
H2	Digital HRM → Emp Experience (direct)	0.642	0.035	18.343***	[0.573, 0.711]	Supported
H3	Emp Experience → Engagement (direct)	0.468	0.048	9.750***	[0.374, 0.562]	Supported
H4	Digital HRM → EX → ENG (mediation)	0.300	0.038	7.895***	[0.226, 0.375]	Supported
H5	Digital HRM × DL → ENG (moderation)	0.158	0.036	4.389***	[0.087, 0.229]	Supported
H6	Index of Moderated Mediation	0.092	0.027	3.407***	[0.039, 0.145]	Supported

* p < 0.05, ** p < 0.01, *** p < 0.001 (two-tailed bootstrapped estimates).

Figure 4: Empirical Dimension Strengths and Moderation Boundary Dynamics



6. DISCUSSION

The results support Digital HRM as a meaningful driver of employee engagement (H1: $\beta = 0.284$, $p < 0.001$). Among the individual practice dimensions (Figure 4A), Digital Performance Management ($\beta = 0.192$) and Digital Learning & Development

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(β = 0.185) had the strongest direct effects. That pattern suggests agile goal tracking and self-directed learning are doing real work here — building employees' sense of competence and role mastery, which in turn feeds vigor and dedication.

Employee Experience also emerged as a substantial mediator (H4: β = 0.300, 95% CI [0.226, 0.375]), carrying 51.4% of the total effect of Digital HRM on engagement (total effect = 0.584). That split matters: it suggests digital tools don't motivate employees simply by being present. What seems to matter more is whether the technology actually produces a frictionless, supportive day-to-day experience — and it's that experience, more than the tools themselves, that drives engagement.

Digital Literacy also proved to be a meaningful boundary condition (H5: interaction β = 0.158, $p < 0.001$; Figure 4B). Employees with high digital literacy (+1 SD) got a much larger engagement boost from digital HR systems (β = 0.442, $p < 0.001$), likely because they can use ESS and AI platforms without the friction of technostress. For employees with lower digital literacy (-1 SD), that boost was considerably smaller (β = 0.126, p = 0.021) — a reminder that rolling out new technology without pairing it with digital-skills support risks leaving part of the workforce behind.

7. THEORETICAL CONTRIBUTIONS

This study contributes to organizational scholarship in four ways:

- **Extending JD-R theory to digitalized work:** we operationalize Digital HRM as an integrated bundle of job resources, showing how the same set of technologies can reduce cognitive and administrative demands while also expanding motivational resources.
- **Clarifying the role of Employee Experience:** by validating EX as the central mediator, the study helps close the gap between enterprise technology deployment and individual psychological outcomes — it is the lived experience of the technology, not the technology itself, that drives engagement.
- **Positioning Digital Literacy as a COR boundary condition:** drawing on Conservation of Resources theory, we show that an employee's own digital competence shapes how effectively organizational technology gets converted into motivation.
- **A multidimensional measure of Digital HRM:** the study offers a psychometrically validated seven-dimension instrument that captures the breadth of modern digital HR architecture and can serve as a benchmark for future work.

8. MANAGERIAL IMPLICATIONS

For executives, CHROs, and transformation leaders, the findings point to several practical recommendations:

- **Design for the employee as a user, not just a data point:** when procuring HR technology, weigh UI/UX quality, mobile responsiveness, and ease of use alongside backend compliance features — not instead of them.
- **Prioritize continuous learning and pulse feedback:** given how strongly these two dimensions predicted engagement, agile micro-learning platforms and ongoing OKR check-ins deserve more investment than fixed, annual appraisal cycles.
- **Pair technology rollouts with digital-skills coaching:** without it, technostress and uneven participation are likely, especially among employees with lower baseline digital literacy.
- **Be transparent about analytics and AI:** organizations using predictive workforce analytics or AI assistants should be clear with employees about how their data is used, so these tools read as empowering rather than as surveillance.

9. ETHICAL IMPLICATIONS AND ALGORITHMIC GOVERNANCE

Predictive analytics and AI-enabled HR services also carry real ethical risk. Bias embedded in historical training data can carry forward into hiring and performance decisions, and continuous electronic tracking can compromise employee privacy and erode trust in the organization. Mitigating these risks calls for real governance: algorithmic transparency, human oversight for high-stakes career decisions, regular fairness audits, and compliance with data-privacy regulations such as the GDPR.

10. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study has several limitations, each pointing to a direction for future work:

- **Cross-sectional design:** time-lagged controls were applied here, but longitudinal, multi-wave panel designs would better capture how these relationships unfold over time.
- **Single-level modelling:** future work could use multi-level SEM (MSEM) to pair manager-reported HR practices with employee-reported experiences across business units.
- **Scope of AI covered:** this study did not directly examine generative AI copilots or autonomous agentic workflows, which are worth studying for their effects on meaningfulness and job crafting.

11. CONCLUSION

Digital HRM is more than an efficiency mechanism — it is a socio-technical system with real potential to shape employee vigor, dedication, and absorption. That potential is not automatic, though. It runs through the quality of the Employee Experience and depends heavily on employees' own digital literacy. Organizations that build user-centric digital environments and invest in employees' digital skills are best positioned to combine operational efficiency with a genuinely engaged workforce.

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AUTHOR CONTRIBUTIONS

K. Meena: Conceptualization, Methodology, Data Curation, Formal Analysis, Investigation, Writing – Original Draft.

Dr. Md. Mazharunnisa: Supervision, Validation, Methodology, Writing – Review & Editing.

Both authors have read and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest with respect to the research, authorship, and/or publication of this article.

ETHICS STATEMENT

This study involved voluntary participation of employees through an anonymous, self-administered survey. Informed consent was obtained from all participants prior to data collection, and respondents were assured of confidentiality and anonymity of their responses.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to participant confidentiality restrictions.

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