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SMART RECRUITMENT: USING DIGITAL HUMAN RESOURCE MANAGEMENT STRATEGIES TO ATTRACT AND ENGAGE TALENT

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ABSTRACT

To secure a lasting competitive edge, modern organisations increasingly integrate digital technologies into their human resource management (HRM) strategies. While prior research has demonstrated the performance benefits of digital HRM, the mechanisms through which such strategies translate into continuous learning and capability development remain insufficiently theorised. Addressing this gap, the present study examines how digital HRM strategies shape a continuous learning environment through the dual mediating pathways of talent acquisition and employee engagement. Drawing on an integrated socio-technical systems (STS) and resource-based view (RBV) framework alongside the Ability–Motivation–Opportunity (AMO) framework, survey data were collected from IT sector employees using purposive sampling and analysed using structural equation modeling (SmartPLS 4). The findings reveal that digital HRM strategies exert significant positive effects on both talent acquisition and employee engagement. However, employee engagement emerges as the dominant mediating mechanism linking digital HRM to continuous improvement and learning outcomes. This asymmetric mediation highlights that the strategic value of digital HRM lies not primarily in technological adoption or recruitment efficiency, but in its capacity to activate human-centred capabilities that are difficult to imitate. By empirically integrating STS and RBV, the study advances theory by demonstrating how digital HRM operates as a socio-technical capability-building system, thereby extending understanding of how digital transformation in HR contributes to sustained competitive advantage.

Keywords: *digital HRM strategies, continuous learning and improvement, employee engagement, IT industry, talent acquisition*

INTRODUCTION

In recent years, the transition in social contacts to the digital realm has been widely observed (Barba-Sánchez et al., 2024). This evolving environment significantly influences organisations, which must increasingly confront risks and possibilities arising from this technology-driven revolution (Costa Melo et al., 2023; Reis & Melão, 2023). Within this context, digital transformation in human resource management (HRM) is increasingly recognised as a critical enabler of organisational efficiency, strategic value creation, and sustained competitiveness in IT organisations, as digital transformation reshapes business processes and management practices to enhance organisational performance and adaptability (Kraus et al., 2022). The conceptualisation of digital HRM as a learning-oriented ecosystem for talent acquisition and engagement is supported by prior evidence which demonstrates that digital and IT-based capabilities create organisational value primarily through learning mechanisms, organisational adaptability, and human-centred capability development, rather than technological automation alone (Hoa et al., 2025).

The expanding role of digital HRM extends beyond administrative automation to include the implementation of digital HR platforms that enhance HR service delivery, the use of HR analytics and artificial intelligence to support data driven decision making and workforce performance, and the adoption of digital practices that improve organisational agility and employee adaptability in dynamic work environments (Theres & Strohmeier, 2023; Wirges & Neyer, 2023; Fenwick et al., 2024). Evidence indicates that digital analytics currently infiltrate various HRM areas, including compensation and benefits, succession planning, and diversity management, so augmenting organisational effectiveness and facilitating evidence-based HR practices (Bottesch et al., 2025).

Although prior research has demonstrated that digitally enabled HR practices improve talent acquisition, employer branding, proactive work behaviours, and employee engagement (e.g., Benitez et al., 2020; Stachová et al., 2024; Ruiz et al., 2024), this field of research remains primarily techno-centric, emphasising system adoption and efficiency outcomes rather than the integration of digital HRM strategies into continuous improvement and organisational learning through human-centred mechanisms. Engagement or recruitment outcomes are typically examined in isolation in existing studies (Shah et al., 2025; Dutta & Mishra, 2025), providing limited empirical insight into their relative explanatory power as mediating pathways. Moreover, there is a dearth of socio-technical research that elucidates learning-oriented outcomes by concurrently modelling internal engagement processes and external talent acquisition mechanisms, particularly in emerging economy contexts.

In order to address this lacuna, the current study employs a socio-technical perspective to investigate the differential mediating roles of employee engagement and talent acquisition in the conversion of digital HRM strategies into continuous improvement and learning capabilities.

Despite notable advancements in digital HRM, literature underscores significant ongoing barriers. Digital skill gaps, reluctance toward technology adoption, and infrastructural limitations can impede the full realisation of digital HRM's benefits, particularly in resource-constrained contexts (Frey & Osborne, 2017). Overcoming these challenges requires continuous learning cultures and knowledge sharing, which catalyse innovation, organisational resilience, and sustained employee engagement capabilities considered vital as digital transformation and Industry 4.0 trends increasingly redefine the workplace (Zhang, 2022).

To move beyond prevailing automation-oriented narratives, this study adopts a dual-theoretical perspective complemented by Ability–Motivation–Opportunity (AMO) framework that intentionally challenges techno-centric interpretations of HR digitalisation. Rather than viewing digital HRM as a primarily technological enhancement, the study conceptualises it as a system in which technological tools and human agency are inseparable and co-evolving. Drawing on socio-technical systems (STS) theory, the study departs from the assumption that advanced technologies such as AI-enabled recruitment and HR analytics generate value solely through efficiency gains. Instead, STS theory posits that such tools produce meaningful outcomes only when integrated into social structures that support trust, participation, and employee motivation (Trist & Bamforth, 1951; Cherns, 1987; Murugesan et al., 2023). This perspective enables the investigation to transcend adoption-focused explanations and examine how human-centred mechanisms transform digital HR investments into learning-oriented outcomes.

Simultaneously, the study extends digital HRM research grounded in the resource-based view (RBV), which emphasises that sustainable competitive advantage arises not from technology ownership alone, but from valuable, rare, and socially embedded resources such as employee capabilities, engagement, and organisational learning (Barney, 1991). However, given RBV's predominant focus on organisational-level resources and outcomes, the present study incorporates the AMO framework to underscore employees and to explain how digital HRM strategies shape individual-level outcomes. The AMO framework posits that organisational performance is enhanced when employees possess the necessary abilities, are sufficiently motivated, and are provided with opportunities to contribute effectively (Appelbaum et al., 2000). By integrating STS, RBV, and AMO, this investigation advances a more comprehensive interpretation of digital HRM as a socio-technical and capability-building mechanism that not only reconfigures technical systems and organisational resources but also enhances employee competencies, engagement, and continuous learning to support sustained organisational improvement in dynamic IT environments.

LITERATURE REVIEW

Digital HRM Strategies

The intricate requirements of the contemporary workforce require a reevaluation of conventional HRM strategies, which predominantly concentrated on administrative functions. Talent acquisition today utilises sophisticated algorithms to more efficiently align individuals' skills with job specifications (Black & van Esch, 2020). Similarly, employee engagement strategies increasingly rely on digital HR platforms to facilitate continuous communication, employee voice, and real-time feedback mechanisms, thereby strengthening employee involvement and organisational connectedness in digitally transforming workplaces (Stachová et al., 2024; Dutta et al., 2023). In digitally enabled workplaces, performance management systems increasingly employ real-time analytics and continuous feedback mechanisms, replacing conventional annual appraisal models with more adaptive and responsive performance evaluation approaches (Gal et al., 2020). These emerging HR paradigms increasingly emphasise organisational agility, strategic alignment, and the integration of digital technologies into workforce management, reflecting a broader theoretical transition toward digital HRM as a strategic organisational capability (Ruiz et al., 2024).

A recent study underscores the complex nature and increasing significance of digital transformation in HRM (Bondarouk & Brewster, 2016). Contributions in digital HRM research increasingly emphasise the role of digital HR technologies in improving HR service delivery and strengthening strategic HR functions through integrated systems and automation (Theres & Strohmeier, 2023; El Saeed et al., 2025). Furthermore, HR analytics has expanded organisations' capacity for data driven decision making by enabling evidence-based workforce planning and predictive insights into employee behaviour and performance (Wirges & Neyer, 2023). More recently, AI-enabled HR systems have provided deeper insights into employee performance, workforce productivity, and talent potential, allowing organisations to identify high-potential employees and design targeted development programmes (Fenwick et al., 2024).

Digital technology, including e-commerce, digital marketing, and cloud solutions, provides distinct advantages for efficiency and competitiveness (Criveanu, 2025; Piwowar-Sulej et al., 2024) and enhances both operational efficiency and workforce adaptability, which are essential for firms striving to remain competitive

(Zhang & Chen, 2024). Consequently, firms must cultivate digital competencies and augment human resource capabilities, with strategic HRM being pivotal in workforce development and performance enhancement (Piwowar-Sulej et al., 2024). Similarly, Thite (2022) asserts that strategic HR planning is crucial for digital transformation, as it integrates human capital with technology advancements. Organisations can enhance performance and achieve enduring success in a digital-first economy (Connelly et al., 2021) by integrating strategic management with digital HR practices (Verhoef et al., 2021). However, prior research highlights that academics and HRM professionals express scepticism over the efficacy of digital recruiting tactics in enhancing organisational economic efficiency and sustainable growth. They contend that although these tactics may modify the recruiting process and techniques to some extent, the results are similar to those of conventional strategies, leading to the conclusion that digital recruitment strategies provide limited additional value (Priyono et al., 2020).

All in all, digital recruitment platforms like MileagePlus and BOSS Direct have emerged as essential avenues for companies to enhance recruitment efficiency through sophisticated data-matching technology (Francis et al., 2023), thereby streamlining the hiring process, lowering costs, and markedly improving hiring outcomes. Moreover, AI screening systems have transformed resume evaluation and preliminary assessment by automating the identification of qualified candidates, thereby substantially alleviating recruiters' workload, enhancing the efficiency of corporate human resource departments, and lowering recruitment expenses.

Digital HRM and Talent Acquisition

In contemporary organisations, digitalisation has become a critical driver of competitiveness, transforming HRM practices related to talent acquisition, workforce development, performance management, and employee retention (Verhoef et al., 2021). Within this transformation, digital HR strategy refers to the systematic integration and strategic alignment of digital technologies with HR processes to enhance workforce management efficiency, decision making quality, and organisational responsiveness (Ruiz et al., 2024; Theres & Strohmeier, 2023). Ruiz et al. (2024) emphasised its role in enhancing productivity, strengthening employer branding, and creating competitive advantages, factors that have intensified the global "war for talent" (Benitez et al., 2020). These developments have encouraged both scholars and practitioners to revisit traditional HRM practices and examine shifting workforce dynamics, acknowledging that only well-designed HR strategies can foster knowledge renewal and sustain success in knowledge-based competition (Connelly et al., 2021).

Digital HRM frequently conceptualised as the socio-technical outcome of HR digitalisation represents the strategic integration of digital data and electronic networking resources to execute HR practices, ranging from operational data management to transformational networking (Strohmeier, 2020). Early research recognised the growing importance of digital HRM solutions and their potential to improve HR efficiency, support performance evaluation, and enhance strategic HR contributions (Strohmeier, 2007). However, contemporary studies demonstrate that digital HRM has evolved beyond operational efficiency to become a strategic capability that enhances organisational agility, data driven decision making, talent optimisation, and sustained competitive advantage through the integration of AI, people analytics, and digital platforms (Ruiz et al., 2024; Theres & Strohmeier, 2023). Recent evidence further highlights the role of digital HR systems in aligning HR practices with broader organisational strategy by enabling real-time workforce insights, strategic talent management, and improved organisational responsiveness (Verhoef et al., 2021).

As per Ruiz et al. (2024), technology has become a primary force in HR, a field also marked by persistent talent acquisition competition (Benitez et al., 2020). For organisations to pioneer in the digitally driven market (Priyono et al., 2020), they need to adopt stringent cost-reduction and efficiency measures to remain viable in a challenging economic climate. Within this context, corporate HR departments face the pressing challenge of recruiting highly suitable candidates while minimising expenditures of both time and financial resources. Accordingly, digital recruiting solutions have increasingly been favoured by small and medium-sized Internet firms, enhancing recruitment efficiency and competitiveness in recent years (Priyono et al., 2020).

H1: Digital HRM strategies have a significant effect on talent acquisition.

Digital HRM and Employee Engagement

Innovative capabilities represent an emerging dimension of digital HRM practices, particularly when they are realised through the adoption of advanced technologies that streamline and enhance HR processes. However, the successful translation of such innovation into organisational outcomes is largely contingent upon employee engagement (Zhang, 2022). Engaged employees, motivated by enthusiasm for their roles and organisational commitment, actively cultivate competencies that contribute to organisational success. Conversely, disengaged employees tend to perform more poorly, ultimately undermining overall organisational effectiveness (Ben Moussa & El Arbi, 2020).

Beyond talent management, digital tools such as learning management systems, people analytics platforms, and AI-enabled decision-support systems have increasingly influenced multiple HR functions, including compensation, benefits administration, succession planning, and diversity management. For instance, compensation analytics empower organisations to develop transparent, equitable, and market-competitive pay structures by leveraging real-time workforce data and predictive insights, thereby improving employee satisfaction and minimising pay disparities (Minbaeva, 2021). Similarly, HR analytics facilitates the customisation and optimisation of employee benefits by aligning benefit packages with employees' diverse preferences, life stages, and utilisation patterns, which contributes to enhance employee well-being, satisfaction, and retention (Bottesch et al., 2025; Strohmeier, 2022). In succession planning, analytics yield insights into employee competencies, performance, and potential, enabling more focused talent development initiatives (Deloitte Insights, 2020). Additionally, analytics support diversity and inclusion efforts by enabling organisations to monitor representation, identify gaps, and design evidence-based strategies that promote inclusivity (Minbaeva, 2021).

At a broader strategic level, innovation-driven initiatives, particularly digital transformation, have emerged as fundamental catalysts of organisational change and long-term competitiveness. However, the effectiveness of such transformation extends beyond the mere adoption of digital technologies and requires substantial organisational adaptation, including strategic alignment, capability development, and employee involvement (Verhoef et al., 2021). In this regard, top management plays a critical role in driving digital transformation by establishing a clear strategic vision, allocating resources, and fostering an organisational culture that supports innovation and continuous renewal (Nadkarni & Prügl, 2021). Moreover, the successful implementation of digital transformation depends on the development of dynamic organisational capabilities that enable firms to continuously reconfigure resources and respond to evolving market demands, thereby enhancing organisational resilience and innovation outcomes (Warner & Wäger, 2019).

H2: Digital HRM strategies have a significant effect on employee engagement.

Contextual Challenges in Digital HRM Adoption

Despite ongoing advancements, many organisations continue to face challenges in integrating digital HRM due to inadequate digital capabilities, employee resistance to change, and limited organisational readiness. The effective implementation of digital transformation depends not only on technological adoption but also on employees' digital competencies and organisational preparedness to support new systems and processes (Nadkarni & Prügl, 2021). Similarly, the adoption of digital HRM is often hindered by insufficient digital skills, resistance to technology-enabled work practices, and limitations in supporting digital infrastructure (Strohmeier, 2020). These challenges are especially evident in Indonesian MSMEs, where inadequate digital literacy and limited technology infrastructure are significant obstacles (Priyono et al., 2020). In line with these concerns, Nadkarni and Prügl (2021) posit that as digital technologies evolve rapidly, organisations are increasingly required to adopt new strategic approaches and organisational capabilities rather than relying on conventional frameworks.

The process of digital transformation encompasses more than technological investments or routine digitisation; it also implicates substantial modifications in organisational structure, culture, and overall value creation (Montero Guerra et al., 2023). Successful transformation depends not only on technological implementation but also on strategic renewal, organisational adaptability, and employee acceptance of new digital practices (Nadkarni & Prügl, 2021; Warner & Wäger, 2019).

Talent acquisition and employee engagement: A way forward to gaining continuous improvement and learning

Employee engagement is widely understood as a positive and fulfilling work-related psychological state reflected in employees' enthusiasm, dedication, and active involvement in their work, contributing to improved well-being and organisational performance (Albrecht et al., 2021). Engagement extends beyond fulfilling job requirements to encompass proactive involvement that benefits both the individual and the organisation (Neuber et al., 2022). Given its importance, organisations increasingly rely on engagement-focused policies to encourage employees' willingness to contribute beyond expectations and to address competitive challenges (Zhang, 2022).

A central dimension of engagement lies in disseminating and applying knowledge. Knowledge sharing enables employees to collectively strengthen organisational outcomes, supporting innovation and sustained success (Venkatesh, 2022). As Verhoef et al. (2021) argue, employees are critical drivers of performance, and their contributions can significantly amplify results when firms strategically invest in innovation and new practices. Social exchange theory (SET) (Homans, 1958) further explains this dynamic: employees evaluate the benefits of their relationship with the organisation, and when perceived rewards outweigh risks, they reciprocate through stronger engagement. Conversely, weak reciprocity reduces commitment and may lead to disengagement (Zhang, 2022).

Continuous Learning and Development

Continuous learning is an essential enabler of engagement and innovation. By fostering learning opportunities, organisations empower employees to adapt, develop competencies, and contribute to efficiency gains (Zhang, 2022). A culture of knowledge sharing thus supports access to critical information, enhances cooperation, and cultivates a positive work environment that sustains long-term engagement (Al Kurdi et al., 2020). With the ongoing transition toward Industry 4.0, automation and digitisation are increasingly displacing tasks traditionally performed by humans. A range of mega-trends such as the mobile revolution, edge computing, augmented reality, big data, cybersecurity, energy sustainability, cloud orchestration, artificial intelligence, smart machines, and interconnected products are reshaping organisational operations. Consequently, employment roles are evolving at an unprecedented pace, making continuous learning not merely an option but an imperative for sustaining industrial performance and competitiveness (Hiremath et al., 2021). Establishing a robust IT and digital learning infrastructure is critical for creating an effective digital learning ecosystem (Sarnok et al., 2020). Such systems provide access to online resources, support training on how to utilise these resources and foster an environment that promotes continuous organisational learning. In this regard, digital learning infrastructures enhance accessibility, adaptability, and knowledge sharing, thereby strengthening employees' continuous skill development in dynamic work settings (Nadkarni & Prügl, 2021). This transition guarantees that digital HRM methods function not merely as instruments, but as integral components of an ongoing learning environment that fosters enduring organisational performance. This perspective is reinforced by Sarnok et al. (2020), emphasising the pivotal role of digital learning ecosystems in enabling organisations to deliver comprehensive learning and development opportunities. Similarly, Yıldız et al. (2025) illustrate that a culture of knowledge sharing enhances organisational creativity by facilitating the exchange of explicit and tacit information among employees, especially in dynamic ICT settings.

Hiremath et al. (2021) emphasise the strategic importance of organisational learning for talent acquisition and retention, skill development, cultivation of a value-based culture, employer branding, and employee motivation. These capabilities are especially vital in the context of Industry 4.0, where the convergence of the digital and physical realms is transforming corporate operations across sectors.

Another important dimension is employee brand engagement, which extends the advantages of engagement to the broader organisational image. Employees who strongly identify with their company's brand naturally act as ambassadors, promoting the organisation much like marketers and thereby reinforcing its reputation both internally and externally (Yousf & Khurshid, 2024). This form of engagement fosters a virtuous cycle in which employee commitment strengthens organisational culture while simultaneously enhancing brand equity. In addition, Yıldız et al. (2025) illustrate that fostering a strong knowledge sharing culture significantly enhances an organisation's overall creativity. This interaction is predominantly facilitated by the exchange of tacit insights rooted in experience rather than the dissemination of formal, documented, explicit knowledge. The mediating function of tacit knowledge establishes a significant, statistically confirmed pathway that is especially vital in rapid information and communications technology settings. In these dynamic environments, innovative problem-solving depends significantly on individual, tacit knowledge rather than conventional, readily available databases.

H3: Talent acquisition positively affects continuous improvement and learning.

H4: Employee engagement positively affects continuous improvement and learning.

H5a: Talent acquisition mediates the effect of digital HRM strategies on continuous improvement and learning.

H5b: Employee engagement mediates the effect of digital HRM strategies on continuous improvement and learning.

Research Gap

While existing research recognises the potential of digital HRM to improve organisational efficiency and competitiveness (Zhang & Chen, 2024; Verhoef et al., 2021), previous research has been fragmented, concentrating on isolated practices such as e-recruitment, e-learning, or HR analytics while separately addressing implementation challenges related to change resistance, digital skills, and data governance (Maier et al., 2013; Galanaki et al., 2019). Socio-technical research underscores the need to integrate social and technical subsystems (Bostrom & Heinen, 1977; Ruiz et al., 2024), whereas RBV-oriented studies prioritise the strategic significance of employee engagement and capability development. Nevertheless, empirical research rarely incorporates these perspectives to elucidate how digital HRM simultaneously aligns technological systems with human processes and develops learning-oriented organisational capabilities. This absence of theoretical synthesis restricts comprehension of the mechanisms by which digital HRM results in sustainable competitive advantage and continuous improvement.

Theoretical Framework

This study specifically utilises STS theory and the RBV as its principal analytical frameworks, given their alignment with the study's objectives and outcome focus, despite the use of various theoretical perspectives in prior digital HRM and digital transformation research. In addition, the AMO framework is incorporated as a complementary perspective to support the employee-level unit of analysis adopted in this study.

The Technology Acceptance Model predominantly focuses on individual-level technology adoption, perceived usefulness, and ease of use (Davis, 1989). While this framework is useful for explaining the initial acceptance of HR technologies, it provides limited explanatory power for understanding how digital HRM strategies contribute to broader organisational learning, innovation capability, and talent management outcomes. Institutional theory emphasises external legitimacy pressures and is better suited to explaining why organisations adopt digital HR practices rather than how these practices foster internal capability development and performance variability (DiMaggio & Powell, 1983). Similarly, SET, while effective in explaining reciprocal employee attitudes and behaviours (Blau, 1964), offers limited consideration of the role of technological systems as active components in shaping organisational processes. STS theory distinctly captures the joint optimisation of social and technological subsystems, emphasising the interdependent relationship between employees and digital technologies in organisational settings.

RBV further provides an organisational-level explanation by highlighting how digitally enhanced human capabilities and learning competencies can serve as valuable organisational resources that contribute to sustained competitive advantage. However, because the present study relies on employee-level data, the AMO framework is incorporated to explain the mechanisms through which digital HRM practices enhance employees' abilities, motivation, and opportunities to contribute effectively. In this regard, AMO complements RBV by bridging the employee-level unit of analysis with broader organisational capability outcomes. Together, STS, RBV, and AMO provide a more suitable and comprehensive foundation for analysing digital HRM as a mechanism for organisational capability enhancement, employee development, and talent management, rather than solely as a technology adoption or compliance-driven phenomenon.

Proposed Conceptual Model

Utilising STS theory and the RBV, the proposed conceptual model (see Figure 1) elucidates how digital HRM solutions foster ongoing enhancement and learning via human-centred processes. The concept asserts that digital HRM techniques favourably affect talent acquisition and employee engagement, which serve as essential mediating routes connecting digital HRM to learning-oriented organisational outcomes. From an STS perspective, the model defines digital HRM as a socio-technical arrangement in which technology infrastructures and social processes are concurrently optimised. Digital HRM solutions are posited to influence recruiting and engagement results by aligning with employee-related social factors, rather than functioning as independent technological interventions. In addition to this perspective, the RBV positions talent acquisition and employee engagement as strategically significant human and social capital resources that empower organisations to cultivate learning capacities that are challenging to replicate. The approach enhances a capability-based understanding of digital HRM by merging STS and RBV, framing continuous improvement and learning as emergent results of linked socio-technical systems and resource development driven by participation.

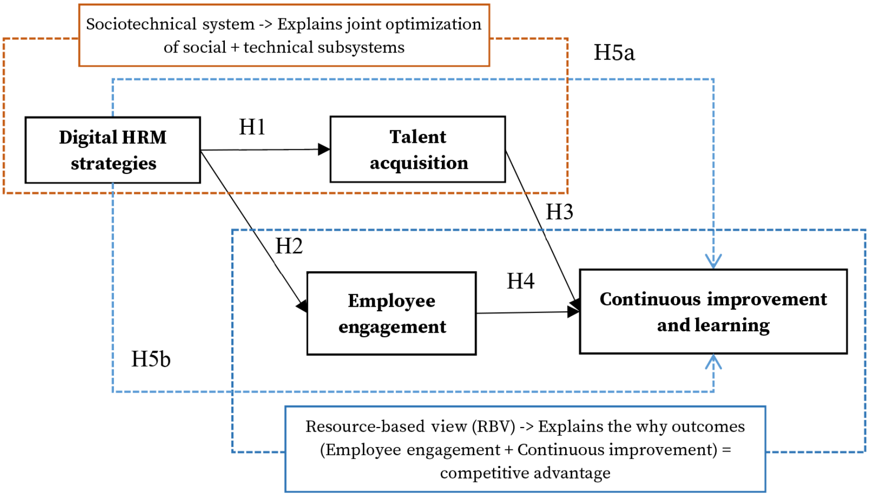

Figure 1. Proposed conceptual model

METHODOLOGY

Research Design

This study examines how digital HRM strategies influence talent acquisition and employee engagement in the Indian IT industry. Drawing on STS theory, the study posits that digital HRM strategies are most effective when technological systems and employee-related processes are jointly optimised. While the RBV explains how digitally enhanced human capabilities contribute to organisational advantage, the AMO framework supports the employee-level perspective by explaining how digital HRM practices enhance employees' abilities, motivation, and opportunities, thereby improving talent acquisition and engagement outcomes. This linkage not only improves immediate HR results but also cultivates uncommon and precious resources engaged people and a learning-oriented workforce, which represent dynamic capabilities (Teece et al., 1997) for ongoing enhancement, continuous development, and learning. This study employs a quantitative research design to investigate the relationship between the independent variable, digital HRM strategies, and the dependent variables, talent acquisition and employee engagement, while further evaluating their collective influence on the outcome variable, continuous learning and development.

Population and Sampling

In the context of the IT industry, the target population for this study comprises employees working in IT firms located across three major IT parks in Kerala: Techno Park, Info Park, and Cyber Park, representing approximately 1,154 companies (see Figure 2). Since the study focuses on employee-level perceptions of digital HRM strategies, employees rather than organisations constituted the primary unit of analysis.

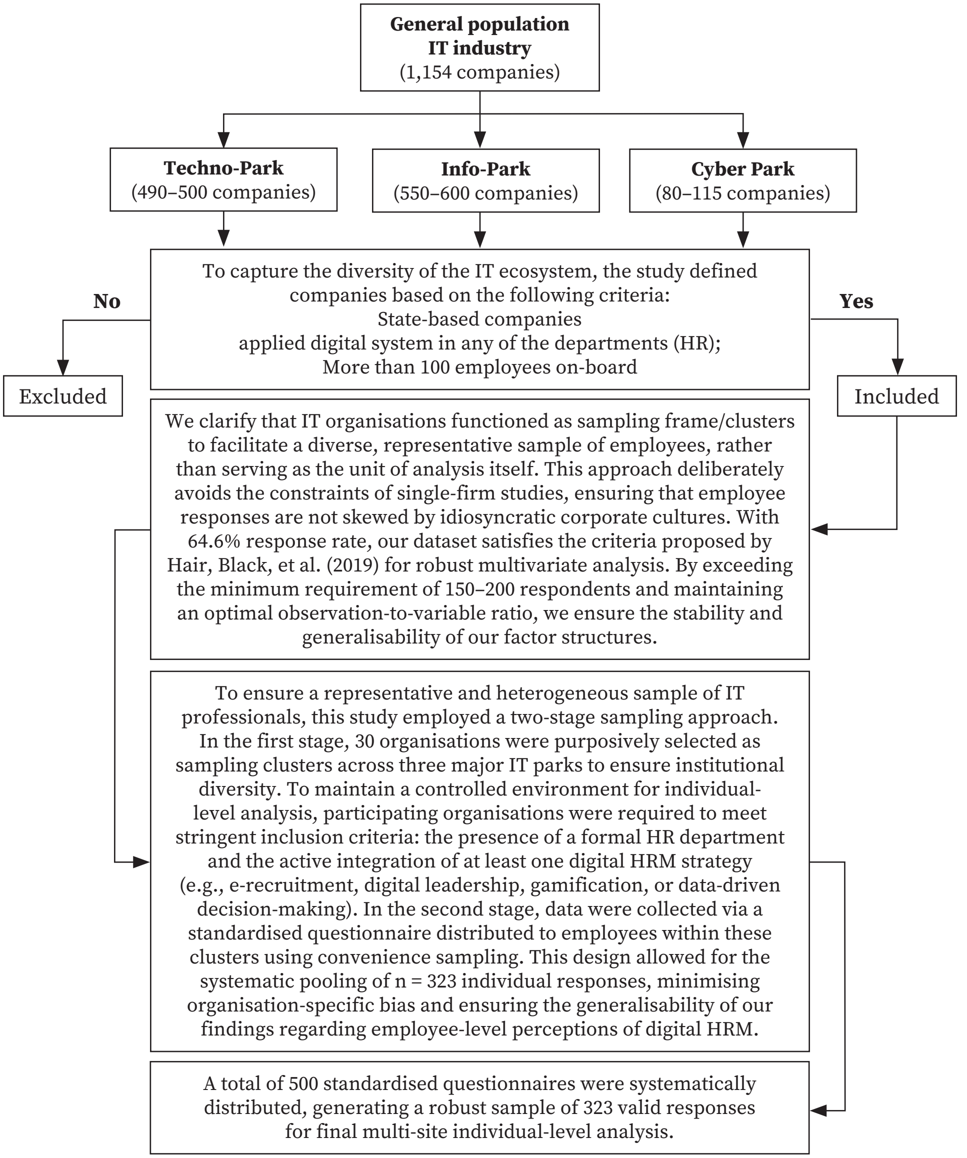

Figure 2. Population and sampling

A purposive sampling approach guided by predetermined criteria was employed to identify eligible employee respondents from organisations with relevant digital HRM practices. Purposive sampling enables the intentional selection of information-rich participants, particularly when a comprehensive sampling frame containing accurate employee-level information is unavailable (Palinkas et al., 2015). This non-probability sampling method is appropriate when participant inclusion is determined by clearly defined research-relevant criteria and is widely applied in organisational and management research under practical constraints (Memon et al., 2024). Accordingly, purposive sampling was considered methodologically appropriate for this study due to data accessibility limitations, explicit inclusion criteria, and the emphasis on employees' perceptions of digital HRM adoption and practices (Felix, 2021).

Data Collection

Data collection was conducted through a structured questionnaire survey. A total of 500 questionnaires were distributed among IT employees, out of which 323 valid responses were received, yielding a response rate of 64.6%, which is deemed robust for survey-based research, surpassing the widely recognised benchmark of 50%–60% for organisational and management studies (Baruch & Holtom, 2008), forming the basis for the subsequent analysis.

Measures

The survey instruments employed in this study were adapted from established sources and measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). All constructs demonstrated satisfactory levels of reliability (Cronbach's $\alpha > 0.70$), consistent with established methodological norms (Hair, Risher, et al., 2019).

The independent variable, digital HRM strategies, was operationalised through the following sub-constructs. Digital HRM Process (DHRMP) was measured using an 11-item scale (Wahyudi & Park, 2014; Davis, 1989; Thompson et al., 1991; Moore & Benbasat, 1991), yielding $\alpha = 0.918$. Digital inclusivity and diversity (DIN&DIV) was assessed using a 10-item scale (Anna Atta, 2024; Azrul et al., 2024), yielding $\alpha = 0.910$. Data driven decision making (DDDM) was measured using a 6-item scale (Korherr & Kanbach, 2023; Mikalef & Krogstie, 2020), yielding $\alpha = 0.871$. Digital leadership (DL) was evaluated using an 11-item scale (Azzam et al., 2023; Braojos et al., 2024; Roman et al., 2019; Van Wart et al., 2019; Wang et al., 2022), yielding $\alpha = 0.913$. Gamification (GAM) was evaluated using an 8-item scale (Azzam et al., 2023; Benitez et al., 2022; Eppmann et al., 2018), yielding $\alpha = 0.883$.

The mediating variables, talent acquisition (TA) (Durai & Viji, 2022; Mujtaba et al., 2022; Tessema & Soeters, 2006) and employee engagement (EE) (Mujtaba et al., 2022), were each measured using 10-item scales, with reliability coefficients of $\alpha = 0.912$ and $\alpha = 0.915$, respectively. Finally, continuous improvement and learning was assessed using a 9-item scale (Berg, 2017; Liu et al., 2006). Items representing both sub-dimensions were combined into a single latent construct for the PLS-structural equation modeling (SEM) analysis, given their demonstrated measurement validity ($\alpha = 0.89$). The measurement scales exhibited adequate internal consistency and were deemed suitable for empirical analysis.

Data Analysis

A multivariate analysis method, PLS-SEM, is used to examine the structural relationships among components. For the analysis of the research model, Smart PLS 4 was used (Ringle et al., 2024). SEM is a powerful analytical method that facilitates the concurrent analysis of intricate interactions between observable and latent variables. It promotes measurement accuracy, facilitates the examination of mediating and indirect impacts, and enriches both theoretical and practical understanding, rendering it particularly beneficial in management and business research (Memon et al., 2024). Furthermore, PLS-SEM is considered a suitable analytical approach for exploratory and prediction-oriented research (Hair et al., 2014). In addition, PLS-SEM is frequently employed to maximise the explained variance of endogenous constructs in structural models (Hair et al., 2017). The PLS-SEM approach involves two sequential stages of estimation. In the first stage, the measurement model establishes how latent constructs relate to their observed indicators, while in the second stage, the structural model captures the directional relationships between predictor and outcome constructs (Hair et al., 2022).

RESULTS

Demographic Profile

Table 1 presents the demographic characteristics of the respondents. A total of 323 valid responses were collected from employees in the IT sector. The sample was predominantly female (57.89%) and young, with the majority of respondents (74.61%) aged 20–30 years old. The education level was high, with a significant portion of the sample holding a graduate (61.30%) or postgraduate (27.55%) degree. In terms of professional background, the largest group of respondents were associates (67.80%) with 0–2 years of industry work experience (50.77%). The data indicates a notable finding regarding digital HRM awareness. A combined 80.18% of respondents reported either medium (51.70%) or low (28.48%) awareness of digital HRM, suggesting a potential knowledge gap within the surveyed population. This study adopts individual employees as the unit of analysis, focusing on their perceptions of digital HRM practices, talent management, and continuous learning and improvement within IT firms.

Table 1

Demographic profile of the respondents

Variables	Description	Count	%
Gender	Male	136	42.11
	Female	187	57.89
Age	20–30	241	74.61
	31–40	67	20.74
	41–50	13	4.02
	50+	2	0.62
Education level	Diploma	30	9.29
	Graduate	198	61.30
	Post graduate	89	27.55
	PhD	6	1.86
Designation	Associate	219	67.80
	Manager	79	24.46
	Senior manager	12	3.72
	Head	13	4.02
Work experience (Years in the industry)	0–2	164	50.77
	3–5	98	30.34
	6–10	39	12.07
	10+	22	6.81
Digital HRM awareness & usage	Low awareness	92	28.48
	Medium awareness	167	51.70
	High awareness	64	19.81
Grand total		323	100

Measurement Model Assessment

The measurement model was assessed through a two-stage approach (Sarstedt et al., 2019) utilising Smart PLS-SEM (Ringle et al., 2024). In the first stage, all sub-constructs of the higher order construct were modeled as separate lower-order components and linked to the dependent variables to evaluate the measurement properties. This stage focused on examining how well the observed indicators represent their respective constructs (see Figure 3). Specifically, indicator loadings, internal consistency reliability, convergent validity, and discriminant validity were assessed. The PLS algorithm was employed to obtain indicator loadings, ensuring the reliability and adequacy of the measurement items in capturing their underlying constructs. In the second stage, latent variable scores obtained from the first stage were used to model the higher order construct and assess structural relationships. This approach enabled a more accurate estimation of the structural model while addressing potential issues associated with hierarchical component modeling.

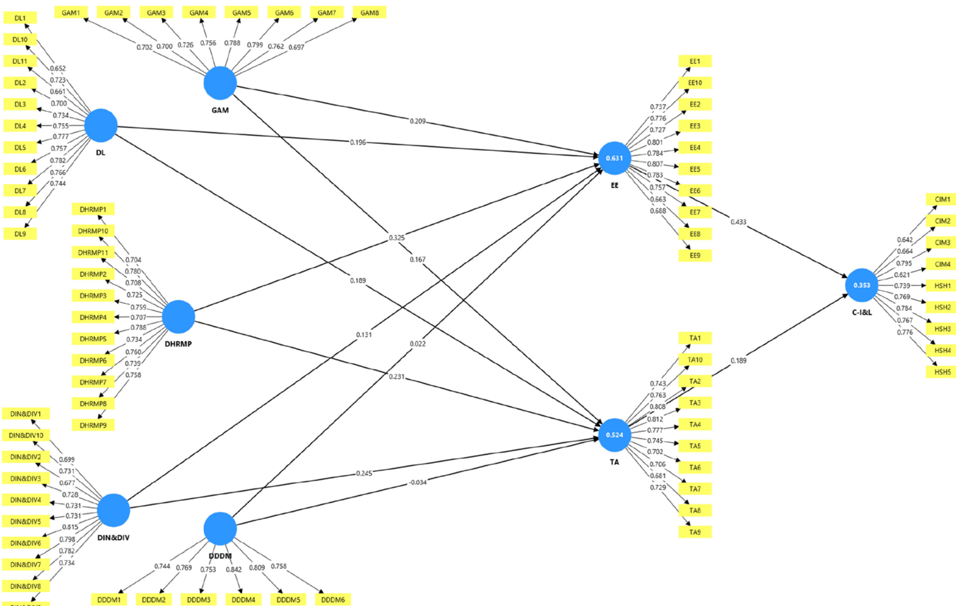

Figure 3. Measurement model

Construct Reliability (Cronbach's alpha)

The internal consistency and convergent validity of the constructs are well established. As presented in Table 2, all values of Cronbach's alpha range from 0.871 to 0.918, exceeding the recommended threshold of 0.70, thereby confirming satisfactory reliability. Similarly, composite reliability values (ρa and ρc) for all constructs are above 0.87 and 0.90, respectively, further supporting strong internal consistency across the measurement model. In addition, the average variance extracted (AVE) values range between 0.535 and 0.608, all surpassing the minimum criterion of 0.50. This indicates that each construct explains more than half of the variance of its indicators, thereby confirming adequate convergent validity. These results demonstrate that the measurement model exhibits robust reliability and satisfactory convergent validity, indicating that the indicators consistently and accurately represent their respective constructs (Fornell & Larcker, 1981; Hair et al., 2022).

Factor Loadings

Table 2 shows that the factor loadings for all items across each construct are uniformly robust, ranging from 0.621 to 0.842. Since all loadings surpass the suggested criterion of 0.50, with the majority exceeding the stricter 0.70 standard, this validates robust convergent validity (Hair et al., 2022). This signifies that each survey item reliably reflects its corresponding construct.

Variance Inflation Factor

The assessment of multicollinearity indicates no critical concerns within the model. All variance inflation factor (VIF) values range from 1.483 to 2.624, which are well below the conservative threshold of 5. This suggests that multicollinearity is not a significant issue among the predictor constructs. The relatively low VIF values confirm that the independent variables do not exhibit high intercorrelations, thereby allowing for reliable and unbiased estimation of the structural relationships (Hair et al., 2017).

Average Variance Extracted

The AVE values for all constructs meet the recommended threshold of 0.50. As presented in Table 2, the AVE values range from 0.535 to 0.608, indicating that each construct explains more than 50% of the variance in its respective indicators. Notably, none of the constructs fall below the minimum criterion, thereby providing strong evidence of convergent validity. These results confirm that the measurement items adequately represent their underlying constructs (Fornell & Larcker, 1981).

Table 2
Constructing reliability and validity

Construct	Items code	Factor loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
DDDM	DDDM1	0.744	0.871	0.872	0.903	0.608
	DDDM2	0.769				
	DDDM3	0.753				
	DDDM4	0.842				
	DDDM5	0.809				
	DDDM6	0.758				

(*continued*)

Table 2 *(continued)*

Construct	Items code	Factor loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
DHRMP	DHRMP1	0.704	0.918	0.920	0.931	0.551
	DHRMP10	0.780				
	DHRMP11	0.708				
	DHRMP2	0.725				
	DHRMP3	0.759				
	DHRMP4	0.707				
	DHRMP5	0.788				
	DHRMP6	0.734				
	DHRMP7	0.760				
	DHRMP8	0.739				
	DHRMP9	0.758				
DIN&DIV	DIN&DIV1	0.699	0.910	0.911	0.925	0.553
	DIN&DIV10	0.731				
	DIN&DIV2	0.677				
	DIN&DIV3	0.728				
	DIN&DIV4	0.731				
	DIN&DIV5	0.731				
	DIN&DIV6	0.815				
	DIN&DIV7	0.798				
	DIN&DIV8	0.782				
	DIN&DIV9	0.734				
DL	DL1	0.652	0.913	0.914	0.927	0.537
	DL10	0.723				
	DL11	0.661				
	DL2	0.700				
	DL3	0.734				
	DL4	0.755				
	DL5	0.777				
	DL6	0.757				
	DL7	0.782				
	DL8	0.766				
	DL9	0.744				

(continued)

Table 2 (*continued*)

Construct	Items code	Factor loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
GAM	GAM1	0.702	0.883	0.885	0.907	0.551
	GAM2	0.700				
	GAM3	0.726				
	GAM4	0.756				
	GAM5	0.788				
	GAM6	0.799				
	GAM7	0.762				
	GAM8	0.697				
EE	EE1	0.737	0.915	0.916	0.929	0.568
	EE10	0.776				
	EE2	0.727				
	EE3	0.801				
	EE4	0.784				
	EE5	0.807				
	EE6	0.783				
	EE7	0.757				
	EE8	0.663				
	EE9	0.688				
TA	TA1	0.743	0.912	0.916	0.927	0.559
	TA10	0.763				
	TA2	0.808				
	TA3	0.812				
	TA4	0.777				
	TA5	0.745				
	TA6	0.702				
	TA7	0.706				
	TA8	0.681				
	TA9	0.729				
Continuous Improvement and Learning (CIM)	CIM1	0.739	0.890	0.894	0.911	0.535
	CIM2	0.769				
	CIM3	0.784				
	CIM4	0.767				
	CIM5	0.776				
	CIM6	0.642				
	CIM7	0.664				
	CIM8	0.795				
	CIM9	0.621				

Final Assessment

The measurement model exhibits a strong and well-fitting structure. The robust factor loadings, elevated reliability coefficients, and satisfactory AVE values collectively affirm the validity and reliability of all constructs. This guarantees that the constructs are psychometrically valid and appropriate for subsequent analysis in a structural model to evaluate the proposed relationships.

The higher order constructs reliability and validity results indicate satisfactory measurement quality. All constructs, continuous improvement and learning (C-I&L), digital HRM strategies (DHRM-S), EE, and TA, demonstrate strong internal consistency reliability, as Cronbach's alpha values range from 0.890 to 0.939, exceeding the recommended threshold of 0.70. Similarly, composite reliability values (rho_a and rho_c) are above 0.70 for all constructs, confirming good reliability. Furthermore, the AVE values range from 0.535 to 0.804, surpassing the acceptable cutoff of 0.50, which indicates adequate convergent validity. The findings in Table 3 confirm that the measurement model possesses acceptable reliability and convergent validity.

Table 3

Reliability and validity - HOC

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
C-I&L	0.890	0.894	0.911	0.535
DHRM-S	0.939	0.940	0.953	0.804
EE	0.915	0.916	0.929	0.568
TA	0.912	0.917	0.927	0.559

Discriminant Validity-HTMT

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT) as recommended by Henseler et al. (2015). Following the two-stage approach, discriminant validity was first examined at the level of first-order constructs. The HTMT values for the lower-order constructs and other latent variables in Table 4 were below the conservative threshold of 0.90, indicating acceptable discriminant validity. However, a few construct pairs (e.g., DDDM–DL) approached the threshold, suggesting conceptual proximity but remaining within acceptable limits.

In the second stage in Table 5, the higher order construct was assessed using latent variable scores derived from its dimensions. According to Henseler et al. (2015), HTMT values should be below 0.85 (strict criterion) or 0.90 (liberal criterion) to confirm discriminant validity. The results indicate that all HTMT values fall within the acceptable threshold. Specifically, the HTMT value between DHRM-S and EE is 0.849, which is marginally below the conservative threshold, while the value between DHRM-S and TA is 0.766, demonstrating clear discriminant validity. Similarly, the HTMT value between EE and TA is 0.868, which, although relatively high, remains below the recommended upper limit of 0.90 as suggested by Hair et al (2022). These findings confirm that the constructs are empirically distinct from one another. The comparatively higher association between EE and TA reflects a meaningful theoretical relationship rather than a lack of discriminant validity.

Table 4

Discriminant validity – LOCs-other variables

Discriminant validity	C-I&L	DDDM	DHRMP	DIN&DIV	DL	EE	GAM	TA
C-I&L								
DDDM	0.716							
DHRMP	0.663	0.817						
DIN&DIV	0.677	0.886	0.894					
DL	0.754	0.900	0.787	0.841				
EE	0.644	0.749	0.796	0.786	0.775			
GAM	0.722	0.812	0.755	0.823	0.861	0.771		
TA	0.585	0.666	0.709	0.734	0.702	0.868	0.692	

Table 5

Discriminant validity-HOCs-other Variables

Discriminant validity	C-I&L	DHRM-S	EE	TA
C-I&L				
DHRM-S	0.771			
EE	0.644	0.849		
TA	0.585	0.766	0.868	

Assessment of the Structural Model

The final stage of the analysis involved the evaluation of the structural (inner) model, which examines the relationships among the study constructs. The structural model was assessed to determine its explanatory power and test the proposed research hypotheses. A bootstrapping procedure with 5,000 resamples was performed to evaluate the significance of the path coefficients (Hair et al., 2022). This analysis enabled examination of the relationships among the constructs in the proposed model and testing the study hypotheses. The findings, encompassing the path coefficients (β), t-statistics, and p-values, are provided to evaluate each hypothesis. The importance of the correlations is assessed by the t-statistics (which must exceed 1.96 for $p < 0.05$) and the p-values (which must be less than 0.05) (Hair et al., 2022).

The examination of the structural model verifies that all four proposed pathways are statistically significant. The findings indicate that DHRM-S have a significant, positive impact on both EE ($\beta = 0.788$, $p < 0.001$) and TA ($\beta = 0.716$, $p < 0.001$). EE was identified as a moderate positive predictor of C-I&L ($\beta = 0.433$, $p < 0.001$), whereas TA exhibited a lesser, although significant, positive effect on C-I&L ($\beta = 0.189$, $p = 0.015$) – (see Table 6). The results reframe digital TA as a supplementary, rather than primary, driver of learning and creativity.

Table 6

Hypothesis testing results and direct effect

Hypothesis		β	M	ST.DEV	t-statistics (|O/STDEV|)	*p*-values	Results
H1	DHRM-S → TA	0.716	0.719	0.027	26.431	0.001	Supported
H2	DHRM-S → EE	0.788	0.788	0.026	30.214	0.001	Supported
H3	TA → C-I&L	0.189	0.195	0.077	2.444	0.015	Supported
H4	EE → C-I&L	0.433	0.432	0.080	5.387	0.001	Supported

Note: Sample mean = M

Direct and Indirect Effect

The results presented in Table 7 support the presence of complementary partial mediation. DHRM-S influences C-I&L through multiple significant indirect pathways alongside its direct effect. Specifically, the indirect effect via EE is strong and highly significant ($\beta = 0.341$, $p < 0.001$), indicating that EE serves as a key mediating mechanism in the relationship. In comparison, the indirect effect through TA is smaller but remains statistically significant ($\beta = 0.135$, $p = 0.017$), suggesting a secondary yet meaningful mediation pathway. Additionally, the total effects indicate that DHRM-S has a substantial influence on both mediators, EE ($\beta = 0.788$, $p < 0.001$) and TA ($\beta = 0.716$, $p < 0.001$). In turn, both EE ($\beta = 0.433$, $p < 0.001$), and TA ($\beta = 0.189$, $p = 0.015$) significantly impact C-I&L.

Table 7

Indirect effect

Specific indirect effect					
	β	M	ST.DEV	t-statistics (|O/STDEV|)	*p*-values
DHRM-S → TA → C-I&L	0.135	0.140	0.057	2.387	0.017
DHRM-S → EE → C-I&L	0.341	0.341	0.069	4.917	0.001
Total Effect (Direct effect + Indirect effect)					
DHRM-S → EE	0.788	0.788	0.026	30.214	0.001
DHRM-S → TA	0.716	0.719	0.027	26.431	0.001
EE → C-I&L	0.433	0.432	0.080	5.387	0.001
TA → C-I&L	0.189	0.195	0.077	2.444	0.015

The analysis reveals a distinct disparity between the two mediating processes. EE serves as the primary mechanism by which digital HRM methods impact C-I&L, demonstrating a significantly greater indirect effect than TA. This discovery corresponds with previous studies underscoring the pivotal role of engagement in converting HR systems into performance and learning results (Albrecht et al., 2015; Parry et al., 2021), and is additionally corroborated by evidence from Asian organisational settings that identify engagement as a crucial mediating factor between HR practices and employee outcomes (Karatepe & Aga, 2016). This study experimentally demonstrates that engagement surpasses recruitment-oriented methods in transforming digital HRM investments into learning-oriented outcomes.

While digital TA is prominently recognised as a strategic result of HR digitalisation (Theurer et al., 2018; Lievens & Slaughter, 2016), the relatively diminished mediating effect identified in this study reinforces the notion that talent inflows are inadequate without robust internal engagement and development mechanisms (Collings et al., 2019). Moreover, the presence of partial mediating mechanisms suggests that digital HRM methods continue to have a significant direct impact on C-I&L, even when engagement and TA are taken into account. This pattern indicates that digital HRM functions as a hybrid system, in which technological frameworks and human-centred processes collaboratively influence organisational learning outcomes (Strohmeier, 2020; Leonardi, 2011), underscoring the significance of human-centric principles in digitally facilitated HR systems, see Figure 4.

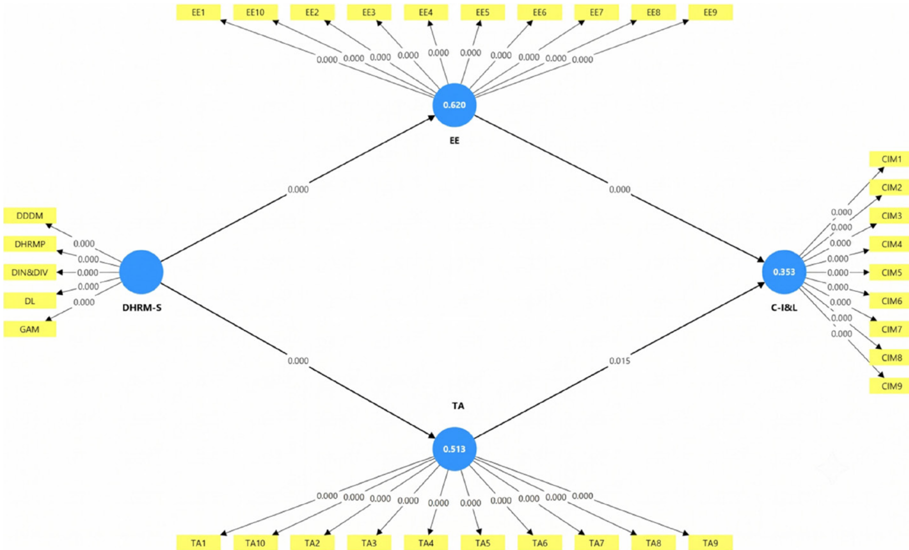

Figure 4. Structural model

Confidence Interval

Table 8 shows that the significance of the structural relationships was assessed using bias-corrected bootstrapped confidence intervals. As all reported confidence intervals do not include zero, the results indicate that both direct and indirect effects are statistically significant.

Table 8

Confidence interval

Confidence intervals bias-corrected	β	M	Bias	LL	UL	Decision
DHRM-S → C-I&L	0.476	0.481	0.005	0.375	0.571	Supported
DHRM-S → EE	0.788	0.788	0.001	0.732	0.835	Supported
DHRM-S → TA	0.716	0.719	0.003	0.654	0.762	Supported
EE → C-I&L	0.433	0.432	−0.002	0.280	0.591	Supported
TA → C-I&L	0.189	0.195	0.006	0.016	0.324	Supported
Indirect Effect						
DHRM-S → TA → C-I&L	0.135	0.140	0.005	0.011	0.236	Supported
DHRM-S → EE → C-I&L	0.341	0.341	0.001	0.211	0.482	Supported

Note: LL = lower limit ; UL = upper limit

Effect Size (f^2)

The f^2 results in Table 9 indicate that most relationships in the model have small to negligible effect sizes, based on the thresholds suggested by Cohen (1988). Relatively higher effects are observed for DHRMP → EE (0.086) and EE → C-I&L (0.106), though these remain in the small range. Several paths, such as DDDM → EE (0.001) and DDDM → TA (0.001), show negligible effects, indicating minimal practical contribution.

Table 9

Effect size

Relationship/path	f^2
DDDM → EE	0.001
DDDM → TA	0.001
DHRMP → EE	0.086
DHRMP → TA	0.034
DIN&DIV → EE	0.011
DIN&DIV → TA	0.029
DL → EE	0.027
DL → TA	0.019
EE → C-I&L	0.106
GAM → EE	0.041
GAM → TA	0.020
TA → C-I&L	0.020

PLSpredict MV Summary (Q^2)

The assessment of predictive relevance using Q^2 predict depicted in Table 10 indicates that all indicator values are above zero, ranging from 0.144 to 0.279. This confirms that the model demonstrates adequate out-of-sample predictive relevance for all endogenous constructs. Also, a comparison between PLS-SEM and linear model (LM) prediction errors shows that all PLS-SEM root mean square error (RMSE) values are lower than their corresponding LM RMSE values, as reflected by the consistently negative differences (PLS-SEM–LM).

Table 10
PLS predict (Q^2)

	Q^2 predict	PLS-SEM_RMSE	LM_RMSE	PLS-SEM(−)LM
CIM1	0.181	0.686	0.743	−0.057
CIM2	0.184	0.697	0.775	−0.078
CIM3	0.244	0.636	0.665	−0.029
CIM4	0.144	0.664	0.801	−0.137
CIM5	0.266	0.684	0.764	−0.080
CIM6	0.279	0.658	0.693	−0.035
CIM7	0.271	0.694	0.741	−0.047
CIM8	0.256	0.655	0.730	−0.075
CIM9	0.264	0.676	0.712	−0.037

RESULTS AND DISCUSSION

The integration of modern technology into HRM has become a critical driver of organisational performance. A prominent example is the growing use of HR analytics, which enables organisations to predict workforce trends, evaluate employee performance more effectively, and personalise employee development initiatives through DDDM (Minbaeva, 2021; Strohmeier, 2020). This technological shift, however, demands a new, broader skill set from HRM professionals, who must now balance technological proficiency with essential interpersonal skills (Aguinis et al., 2024).

These findings unequivocally illustrate the importance of incorporating digital HRM solutions to attain enhanced personnel management and continuous organisational growth. Digital HRM practices exert a substantial positive influence on TA, as studies show that digital recruitment platforms and AI-driven screening technologies optimise hiring processes, reduce costs, and improve the ability to attract high-calibre candidates (Ruiz et al., 2024; Benitez et al., 2020). This suggests that firms utilise digitally enabled TA as a vital factor in enhancing competitiveness in technology-intensive sectors. Furthermore, a strong relationship exists between digital HRM practices and EE, as digital tools increasingly facilitate real-time communication, employee voice, knowledge sharing, and flexible work arrangements. Recent studies highlight that E-HRM tools and AI-enabled HR technologies enhance EE by improving participation, feedback mechanisms, and employee experiences within digitally enabled workplaces (Stachová et al., 2024; Dutta et al., 2023). Additionally, people analytics and algorithmic HR systems contribute to engagement by supporting more responsive and informed workforce management practices (Gal et al., 2020). The analysis revealed that

EE is the most effective pathway for fostering continuous learning and growth. This finding underscores the critical importance of an engaged workforce in promoting innovation, adaptability, and sustained organisational development, consistent with SET and empirical evidence emphasising the role of organisational resources and engagement climate in enhancing EE (Albrecht et al., 2018). Hence, the mediation analysis reveals that digital HRM strategies foster continuous improvement and learning both directly and indirectly through TA and EE. This dual pathway empirically validates the integration of STS theory, enhancing social-technical synergy and the RBV, leveraging engaged talent as a strategic asset for renewal and flexibility as robust foundations for digital HR transformation.

This study not only corroborates the theoretical perspectives of the RBV and STS but also extends them through empirical insights from the results. Specifically, digital HRM strategies alone do not directly generate competitive advantage; their value emerges only when they are transformed into human and social capital through TA and EE. This aligns with the RBV emphasis on resource orchestration rather than standalone digital tools fulfilling the valuable, rare, inimitable, and non-substitutable (VRIN) criteria for sustained competitive advantage (Barney, 1991). Furthermore, the findings advance STS by shifting from conceptual alignment to a validated mediation pathway that confirms the joint optimisation of social and technological subsystems (Trist & Bamforth, 1951). In doing so, the study challenges techno-centric digital transformation narratives (Singh & Shweta, 2025) by emphasising the human-centred dimension of digital transformation, reinforcing the socio-technical perspective that effective digital transformation depends on the dynamic interaction between technological systems and employees in contemporary organisational contexts (Nadkarni & Prügl, 2021). Overall, these contributions deepen understanding of how integrated digital HRM enables organisations to attract, engage, and retain talent, and cultivate learning cultures essential for innovation and sustained competitive advantage in dynamic environments.

Thus, prior studies endorse the perspective that attaining a sustainable competitive advantage transcends mere technology adoption; it necessitates the strategic integration of technology inside HRM to fit with overarching organisational objectives (Thite, 2022; Verhoef et al., 2021). This integrated approach is strongly supported by established theoretical frameworks. For instance, the STS paradigm posits that organisational success hinges on the co-optimisation of its social (human) and technical elements (Ruiz et al., 2024; Bostrom & Heinen, 1977). Similarly, foundational research in Information Systems emphasises that long-term viability depends on the strategic alignment of IT with broader business objectives (Wei et al., 2023).

Implications of the Study

This study provides important theoretical and practical implications by empirically demonstrating how digital HRM strategies (DHRM-S) contribute to continuous improvement and learning through TA and EE. The findings reveal that DHRM strategies significantly influence both TA ($\beta = 0.716$, $p < 0.001$) and EE ($\beta = 0.788$, $p < 0.001$), which subsequently enhance continuous improvement and learning within organisations. The mediation results further indicate that EE exerts a stronger indirect influence ($\beta = 0.341$, $p = 0.001$) compared to TA ($\beta = 0.135$, $p = 0.017$), highlighting engagement as a more influential mechanism through which digital HRM strategies foster organisational learning and improvement. From a theoretical perspective, the study extends the understanding of digital HRM by demonstrating that organisational outcomes are not generated solely through technological implementation but through people-centred mechanisms facilitated by digital systems. By integrating the perspectives of STS theory and the RBV, the findings emphasise that digital HRM creates value when technological capabilities are aligned with strategic TA and EE practices. Moreover, the study contributes to the digital HRM literature by clarifying the mediating pathways through which DHRM strategies influence continuous improvement and learning, particularly within the IT sector context.

Managerial Implications

From a managerial standpoint, the results indicate that organisations ought to transcend the perception of digital HRM as solely an efficiency-oriented automation tool, a view that has been shown to constrain its strategic significance (Strohmeier, 2020). Digital HRM initiatives should be strategically crafted to improve EE and promote continuous learning, as recent studies indicate that digital HRM enhances organisational capabilities mainly through human-centred approaches rather than technology alone (Parry et al., 2021). Consequently, managers ought to assess digital HR investments not solely in terms of process efficiency but also in relation to engagement levels, learning participation, and knowledge sharing behaviours (Kane, 2019).

The findings suggest that digital TA systems should be used to enhance employer branding and the candidate experience, which are essential for attracting talent aligned with an organisation's values and learning-oriented culture (Theurer et al., 2018). The significant mediating role of EE underscores the need for inclusive leadership, participatory digital platforms, and gamified HR practices to sustain employee motivation and commitment in digitally transformed work environments (Raisch & Krakowski, 2021).

Limitations of the Study

This study, while providing significant insights, has numerous drawbacks. The research uses a cross-sectional survey design, which limits the ability to demonstrate causal links among digital HRM methods, TA, EE, and continuous learning outcomes. Future research should employ longitudinal designs to investigate the evolution of digital HRM practices over time and their long-term impact on organisational learning.

The study focuses on personnel from specific IT enterprises located in three IT parks, using purposive and convenience sampling methods. This may restrict the applicability of the findings to other sectors or geographical locations. Subsequent research should broaden the examination to other industries, organisational scales, and global contexts to further validate the robustness of the model.

The model analyses TA and EE as mediating variables, excluding other pertinent factors. Factors such as organisational culture, DL competencies, and employees' digital skills may further elucidate how digital HRM fosters learning-oriented outcomes. Future research may integrate additional data sources, such as HR analytics and qualitative insights, to yield a more comprehensive understanding of the effects of digital HRM.

CONCLUSION

The strategic deployment of digital technologies has become an essential component of modern organisational operations. Nevertheless, this study shows that sustainable competitive advantage is not derived solely from digital adoption but rather from integrating digital HRM strategies into human-centred organisational systems. The results indicate that digital HRM generates value primarily through engagement-driven learning and continuous improvement processes, rather than through technological sophistication or recruitment efficiency alone, by analysing the dual mediating roles of TA and EE.

The study offers a coherent explanation of the operation of digital HRM as a socio-technical capability-building mechanism, integrating STS theory and the RBV. The findings emphasise the importance of aligning technological infrastructure with social systems, including employee motivation, participation, and learning orientation, in order to transform digital HR investments into enduring organisational capabilities. In this regard, the study expands upon current digital HRM research by transcending adoption- and efficiency-focused explanations and providing empirical evidence regarding the relative significance of internal human-centred mechanisms in digitally enabled HR systems.

As a result, the research emphasises that digital HRM should be regarded as a developing organisational capability rather than a solitary technological intervention. The research establishes a more nuanced foundation for future research on human-centred digital transformation and the conditions under which digital HR strategies generate lasting strategic value by elucidating the mechanisms through which digital HRM contributes to continuous learning and sustained performance.

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