Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 4

ISSN: 1540-3270

Leveraging Green HRM Practices for Employee Performance: The Role of AI-Enabled HR Processes in Higher Education Institutions of India

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Abstract:

Incorporating environmental sustainability into people-management systems through Green Human Resource Management (GHRM) and digitising HR service delivery through Artificial Intelligence (AI)-enabled HR procedures are two revolutionary human resource agendas that organisations are pursuing concurrently. Few studies have looked at how these two dynamics work together to influence employee performance, despite the fact that each stream has produced a sizable and quickly growing body of literature. In this paper, a conceptual model is developed and empiricaly tested in which Green HRM practices are suggested to have a direct and indirect impact on employee performance through their association with AI-enabled HR processes in HEIs of Uttarakhand. The results portray partial medieting effect of AIHRP on the relation between GHRM practices and EP. The theoretical contributions, managerial implications for HR digitalisation and sustainability strategy, limits, and future research possibilities are discussed in the paper's conclusion.

Keywords: Green Human Resource Management (GHRM); AI-enabled HR Processes (AIHRP); Employee Performance (EP)

1. Introduction:

The human resource (HR) function is going through two concurrent, possibly related changes. The first is the shift to sustainability, in which through the integration of their commercial objectives and HR management procedures with eco-friendly sustainability goals, environmental issues have moved from the perimeter of corporate strategy to the core of HR policy, giving rise to the notion of Green HRM (Yong et al., 2020; Shahzad et al., 2023). The second is the digital shift, where AI-enabled HR processes (AIHRP) may support workforce planning and talent retention, improve candidate screening, personalise employee development, and offer real-time performance analytics (Safshekan et al., 2026). The nexus of these two concepts implies that through the use of digital and smart technological solutions, Green HRM helps organizations simplify their operations while cutting down on environmental harm, making it a key driver of sustainable business practices (Rahman et al., 2026).

AIHRP and GHRM are becoming more closely related since AI may improve the application and efficacy of ecologically friendly HR practices. According to research, AI capabilities enable more data-driven and ecologically mindful HR decisions, which support organisational sustainability through GHRM (Ali et al., 2025). According to Ajuluchukwu et al. (2026), employees' environmental awareness and sustainability results can be enhanced by AI-supported green training and eco-feedback systems. AI-enabled HR procedures can therefore serve as a technical enabler of GHRM, increasing the effectiveness, quantifiability, and strategic alignment of green HR practices with corporate sustainability goals.

Agarwal et al. (2024) argue that “Higher education Institutions” (HEIs) are critical building blocks for achieving long-term sustainable development. Academicians and institutional leaders, who are seen as the primary instructors, mould students, who are viewed as future leaders. Effective university leadership paired with sustainable practices is a major driver in cultivating environmental awareness and values among stakeholders (Aggarwal & Agarwala, 2026). Strohmeier (2007) notes that when HEIs digitalize their HR systems, it not only minimizes reliance on paper and physical materials but also improves operational efficiency and speeds up communication. Digital transformation is regarded as a competitive approach that creates new opportunities in the contemporary educational system (Rahman et al., 2026). AI-enabled digital transformation enables educational institutions to enhance operational agility, automate data processing, and personalise learning. In the

meantime, institutional objectives pertaining to environmental responsibility and quality assurance are supported by green HRM practices like digital hiring, paperless workflows, and sustainability training (Gautam and Mishra, 2025). Particularly in India, where educational institutions are embracing digital technologies through the National Education Policy 2020 and the Sustainable Development Goals (SDGs), integrating AI into HRM practices offers a chance to promote environmental sustainability through AI as well as improve HR administrative efficiency (Al-Sharafi et al., 2023).

A complex configuration of ability, motivation, and opportunity-enhancing HR policies shapes employee performance, which is defined as the extent to which an employee satisfies task, contextual, and adaptive role criteria (Bos-Nehles et al., 2023). In order to improve employee performance and promote institutional sustainability, HEIs are rapidly implementing AIHRP and GHRM practices. Although it hasn't been explicitly modelled in the literature, the question of whether green HR initiatives directly result in performance improvements or if this link is mediated through the organization's AI-enabled HR infrastructure has significant theoretical and practical implications.

In order to close this gap, this paper proposes and theoretically justifies a conceptual model (shown in Figure 1) in which green HRM practices are hypothesised to have an impact on EP both directly (H1) and indirectly through AIHRP, which serves as an antecedent of EP (H3), an outcome of green HR practices (H2), and ultimately as a mediating mechanism connecting the two (H4). This study addresses that gap by developing and empirically testing a model that connects these three variables to sustainability outcomes in Universities.

2. Theoretical foundation

This paper's conceptual model is based on three complimentary theoretical stances-

2.1 Resource-Based View (RBV)

Barney (1991) explains that firms can achieve sustained competitive advantage through the RBV by owning and deploying resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable. According to the current paradigm, RBV supports treating Green HRM practices as a strategic organisational capability that influences the organization's potential to create complementary capabilities, such AI-enabled HR infrastructure (H2), in addition to producing direct performance consequences (H1).

2.2 Ability-Motivation-Opportunity (AMO) Framework

The main micro-foundational logic for the model is provided by the AMO framework, which explains how AI-enabled HR procedures and GHRM practices could improve individual EP by fostering opportunity, ability, and motivation (Appelbaum et al., 2000; Bos-Nehles et al., 2023).

2.3 Social Exchange Theory (SET)

According to the SET, when companies give their workers valuable resources or preferential treatment, workers return the favour by adopting positive work attitudes and behaviours, such as improved performance (Blau, 1964). In addition to the more structural, capability-based reasoning provided by RBV and AMO, SET is employed here to support the reciprocal, attitudinal pathway linking Green HRM practices and AI-enabled HR processes to employee success.

3. Literature Review and Hypothesis development

3.1 GHRM Practices:

In general, GHRM involves embedding eco-conscious practices within an organization's HR policies and initiatives (Ren and Hussain 2022). GHRM is defined by Sharma and Gupta (2015) as applying HRM practices to increase organisational resource sustainability, which in turn helps to reinforce environmental sustainability, and raising employee cognizance of environmental performance. By embedding GHRM practices within their HRM strategies, organizations aim to foster positive attitudes, behaviors, and enhanced overall performance (Farrukh et al. 2022). GHRM is a possible catalyst for developing socially and ecologically conscious

organisational cultures because of its emphasis on incorporating environmental factors into human resource policy (Benevene and Buonomo 2020). Through their participation in the strategic application of HRM techniques, HRM and green HRM are uniting in the environmental movement to support organisational environmental sustainability. By encouraging employees to adopt green behaviours, green HRM practices assist organisations achieve their green performance goals (Shah & Soomro, 2023).

3.2 AI-Enabled HR Processes

The way businesses manage their human capital is changing as a result of the integration of artificial intelligence (AI) technologies into HRM. AI, which includes data analytics, machine learning, and natural language processing, has the potential to completely transform HR procedures (Kaushal et al., 2023). Islam et al. (2022) note that AI's ability to process vast amounts of data in real time supports more informed, data-driven decision-making, which can substantially improve both the accuracy of performance evaluations and the personalization of talent management strategies.

The application of machine learning, natural language processing, predictive analytics, and intelligent automation to fundamental HR tasks, such as hiring and candidate screening, onboarding, learning and development, performance management, workforce planning, and employee engagement monitoring, is known as AI-enabled HR processes (AIHRP) (Ncube, 2025).

Nawaz et al. (2024) observe that the rapid integration of AI into HRM processes has automated repetitive tasks such as resume screening and interview scheduling, freeing up HR personnel to focus on more strategic priorities. A range of popular AI tools illustrate the transformative shift resulting from AI's integration into HRM processes. To improve both the efficiency and effectiveness of HRM, these tools feature fully integrated AI capability models, ethical decision-making frameworks, and algorithmic applicant shortlisting (Madanchian et al., 2023). Despite this, a notable gap remains in the AI-HRM literature regarding how AI and related technologies can deliver effective HRM solutions, and how AI-enabled HRM practices link with broader operational tasks to drive improved organizational outcomes (Bujold et al., 2023; Zehir et al., 2019).

3.3 Employee Performance

The traditional definition of employee performance (EP) is the degree to which a person fulfils the task, contextual, and adaptive requirements related to their organisational function (Bos-Nehles et al., 2023). According to Kloutsiniotis and Mihail (2020), an EP is determined by how much effort and behaviour they put in during a specific time period to fulfillll their given responsibilities. HR systems using AI capabilities can help people perform better at work, promote knowledge sharing, and enhance HR decision-making (Olan et al., 2024). Additionally, recent research suggests that AI-based performance feedback might boost learning motivation, which in turn enhances EP (Pei et al., 2024). Because academic and non-academic staff members directly contribute to teaching, research, administration, innovation, and institutional sustainability, EP is especially important at HEIs. According to recent research, supportive green environments and ecologically conscious HR practices can improve employee-related outcomes and encourage long-term university success (Akbar et al., 2024; Zahrani, 2024).

3.4 GHRM Practices & Employee performance

Faisal (2023) emphasizes that existing research on GHRM practices underscores the significant influence environmentally conscious HR approaches have on both employee-level and organization-level outcomes. According to earlier studies, EP and green HRM practices are positively correlated (Kim et al., 2019; Pham et al., 2019). However, more research is still required to fully understand the mechanisms underlying this link, particularly in the context of HEIs.

Both directly and through the mediating role of retaining young talent, GHRM methods positively and significantly affect EP, according to a study conducted on 400 young Indonesian hotel sector workers (Palupiningtyas et al., 2025). Additionally, current research indicates that GHRM methods that include green hiring, training, performance management, incentives, and employee involvement are favourably connected with

workers' workplace performance (Ramachandaran et al., 2024). According to a bibliometric analysis on the relationship between GHRM practices and EP by Trivedi and Bhatt (2025), there are still few empirical studies that directly link GHRM practices to employee performance, despite an increase in scholarly interest in GHRM. According to the Social Exchange Theory, workers who believe their company is making an investment in ecologically friendly HR practices are likely to return the favour by putting forth more effort and performing better (Kaur & Gupta, 2026). According to recent research, GHRM is linked to both green and non-green employee outcomes, including as work satisfaction and task performance (Tandon et al., 2023). From the aforementioned literature, the following hypothesis is put forth-

H1: GHRM practices are positively associated with EP

3.5 GHRM Practices & AI- enabled HR processes:

By fostering an organisational orientation toward sustainable, effective, and technology-supported HRM, GHRM practices can aid in the creation and implementation of AIHRP. Businesses should use AIHRP and technologies to manage and cut waste, involve environmentally conscious workers in their sustainability initiatives, and backing SDG targets with a competence that promotes distinction while taking risks like algorithmic bias and carbon costs into account (Kapruwan et al., 2026). According to recent studies, there is a growing convergence between AI and GHRM, whereby organisations can more methodically incorporate sustainability considerations into HR procedures thanks to technological capabilities (Khan et al., 2025). Additionally, recent research indicates that AIHRP can support environmentally sustainable hiring, training, performance management, and employee engagement strategies (Safshekan et al., 2026; Fenwick et al., 2024). A favourable correlation between GHRM practices and AIHRP is suggested by the likelihood that organisations pursuing GHRM practices will become more motivated and prepared to integrate AIHRP. Thus, this hypothesis is proposed-

H2: Green HRM practices are positively associated with the adoption of AI-enabled HR processes.

3.6 AI- enabled HR processes and employee performance

The actuality of AI in organisational HRM practices is still largely unexplored (Tambe et al., 2019). As a result, little research has been done on how the development of AI technologies can affect workplace performance and HRM procedures (Tambe et al., 2019; Troth & Guest, 2020). It is essential to consider employees' interests alongside concerns related to valuing individual expertise, employee trust, data protection, information-sharing policies, and business ethics in order to reduce obstacles and improve employees' performance using AI (Jayawickrama et al., 2017). A study investigating the impact of AIHRP and EP within the healthcare sector indicate that both AIHRP significantly contribute to improvements in leadership effectiveness and EP (Alwali and Alwali, 2026). According to Al Samman and Al Obaidly (2024), using AI-driven e-HRM has a statistically significant effect on raising EP at the research organization. Boosting employee productivity and cultivating a sense of belonging remain essential elements of incentive programs, notwithstanding advancements in our understanding of how AI-enabled HR analytics might improve employee performance (Arora et al., 2025). Drawing on survey data from 349 workers in Bandung, Indonesia's manufacturing sector, Bagis and Yulianeu (2024) provide empirical evidence of a strong beneficial link between AI-enabled HR analytics and employee performance, with the results offering actionable managerial insights for those seeking to boost sustainable performance through such analytics. From the aforementioned literature, the following hypothesis is proposed-

H3: AI- enabled HR processes positively influences employee performance

3.7 Mediating role of AI- enabled HR processes between GHRM Practices and employee performance

According to recent study, AIHRP serve as a key mediating factor in the conversion of GHRM practices into better EP and more comprehensive sustainability results. Organisations can improve the accuracy, personalisation, and measurability of GHRM initiatives by integrating AI into core HR functions like green recruitment, training, performance appraisal, and feedback systems. This strengthens employee engagement, digital literacy, and green behaviour, all of which improve performance. Dinh et al. (2026) offer direct empirical support for this approach, showing that AI mediates the relationship between employees' green talents and performance and has a favourable

impact on employee performance. Furthermore, AI serves as a crucial mediating mechanism through which GHRM promotes sustainable workplace outcomes, according to Mahat et al. (2025). The integration of AI with GHRM through AI-supported green training, eco-feedback, recruiting, and performance evaluation enhances sustainability-oriented organisational outcomes, according to recent research by Ajuluchukwu et al. (2026). Hence, it can be hypothesized that:

H4: AI- enabled HR processes positively mediates the relationship between GHRM practices and EP.

4. Postulated Model:

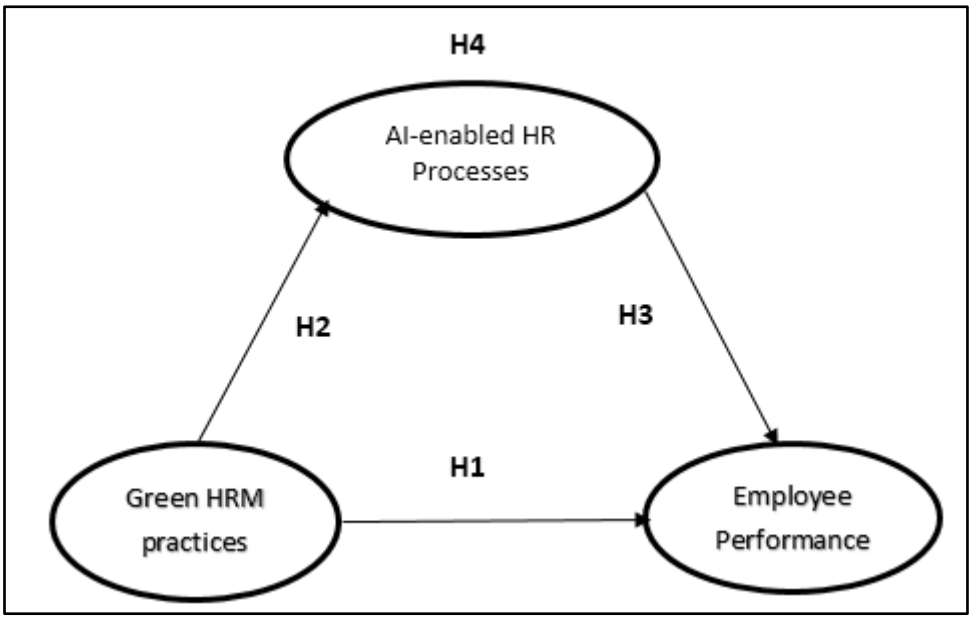


Figure 1: Postulated Model

5. Methodology

5.1 Research Design

The study scans the affiliation between EP and GHRM practices. It also aims to unravel how GHRM practices influences EP in academicians of Indian HEIs through AIHRP. While considering the research topics, the study uses a single cross-sectional descriptive research design.

5.2 Respondents and instrument design

Respondents embrace academicians employed in HEIs of Garhwal range of Uttarakhand region. Only academicians who could be reached through professional networks (LinkedIn, organisational contacts, alumni associations) and organisations that agreed to take part in our sampling frame were included. To guarantee adequate variance on all three constructs, data was gathered from full-time employees associated with Institutes that have formally implemented both green HR practices and AI-enabled HR systems. “Non-probability convenience sampling” technique was employed to choose the responders. A survey questionnaire served as the primary instrument for data collection. It comprises of four sections viz. (i) Demographic profile (ii) GHRM (iii) EP and (iv) AIHRP. GHRM practices was calculated with a 14-item scale devised by Tang et al. (2018). AIHRP were measured using a 15-item scale adapted from the conceptualisation of algorithmic and AI-assisted HRM proposed in prior literature (Meijerink et al., 2021; Vrontis et al., 2022). EP was assessed using a 10-item instrument adapted from the Individual Work Performance Questionnaire (IWPQ) developed by Koopmans et al. (2012). Item responses were captured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

5.3 Data Acquisition

The data set was compiled from acaemicians working in HEIs from Garhwal province of Uttarakhand state, India. Sample collection tenure is from January 2026 to May 2026. 339 personnels partaken in study. The response rate meets the required cut point criteria (Baruch, 1999). **Table 1** renders the personnels demographic abridgment.

Table 1: Demographic Outline

Demographic Outline of Respondent			
		Frequency	Percent
Gender	Male	121	35.7
	Female	218	64.3
Age	Up to 25 years	32	9.4
	25-35 Years	129	38.1
	35-45 Years	112	33.0
	Above 45 years	66	19.5
Qualification	Graduate	44	13
	Post Graduate	240	70.8
	Doctorate	55	16.2
Designation	Professor	31	9.1
	Associate Professor	122	36
	Assistant Professor	186	54.9
	TOTAL	**339**	**100**

6. Results:

6.1 Data Analysis:

As a preliminary step, the study variables were summarized through their means, standard deviations, and Pearson correlation coefficients. Variance inflation factor (VIF) measure for multicollinearity has also been checked. Thereafter, CFA was employed to verify the psychometric soundness of the constructs, and the measurement model was assessed for convergent and discriminant validity using established statistical benchmarks. Finally, the fit of the hypothesized structural model was evaluated, followed by hypothesis testing. For endorsing the model fit, "chi-square/degree of freedom" ($\chi 2/df$), "Goodness of fit index" (GFI), "Comparative fit index" (CFI), "Standardized root mean square residual" (SRMR), and "Root mean square error of approximation" (RMSEA) were castoff. Model adequacy was judged against established benchmarks: a χ^2/df ratio ranging from 1 to 3, and SRMR and RMSEA estimates below 0.10 (Bentler & Bonett, 1980). Correspondingly, GFI and CFI values exceeding 0.90 were deemed acceptable (Scott & Bruce, 1994).

6.2 Descriptive Analysis:

The descriptive statistics of the focal variables are summarized in Table 2. Mean values fell between 2.547 and 2.703 on the five-point scale, while standard deviations ranged from 0.723 to 0.803, reflecting moderate dispersion around the means. Furthermore, the inter-construct correlations remained below the 0.70 benchmark, which

reduces the likelihood of multicollinearity among the variables. The correlation between GHRM and AIHRP (0.432, $p < 0.001$), AIHRP and EP (0.342, $p < 0.001$) and GHRM and EP (0.487, $p<0.001$) were found positive, as expected. The VIF value for AIHRP and GHRM were below 5, substantiating that multicollinearity does not compromise the estimates (Hair et al., 2010).

Table 2: Descriptive Analysis

Variable	Descriptive Statistics		Pearson Correlation		
	Mean	Std. Deviation	EP	AIHRP	GHRM
EP	2.703	0.723	1		
AIHRP	2.547	0.744	.342**	1	
GHRM	2.635	0.803	.487**	.432**	1

Note: **p< 0.001

6.3 Assessment of "Measurement model":

CFA was carried out in AMOS (version 21) to validate the measurement structure. The model met all the prescribed criteria for good fit (CFI = 0.968, $\chi^2/df = 1.323$, PClose = 1.00, RMSEA = 0.034, SRMR = 0.042), in line with the benchmarks recommended by Gaskin and Lim (2017), which attests to its adequate fit. Table 3 presents the CFA results. Standardized factor loadings for all items were above 0.70, signifying robust item reliability (Hair et al., 2010), while Cronbach's alpha values for all constructs exceeded 0.70, corroborating the internal consistency of the scales.

Table 3: Factor loading and Master validity

Variable N=339	Cronbach's alpha	Factor Loading Range
AIHRP	0.836	0.725 – 0.866
EP	0.871	0.731 – 0.891
GHRM	0.855	0.763 – 0.832

6.4 Assessment of reliability and validity of construct:

The AVE estimates for GHRM (0.556), AIHRP (0.593), and EP (0.587) surpassed the cut-off of 0.50, while the CR coefficients, which ranged between 0.852 and 0.883, comfortably exceeded the 0.70 benchmark. These results substantiate the “Convergent validity” of the constructs (Hair et al., 2010). The bold diagonal values in **Table 4** denote the “Square roots” of the respective AVEs. Since the MSV for each construct falls below its AVE, discriminant validity is established (Hair et al., 2010). Collectively, the findings indicate that the constructs are both convergently and discriminantly valid.

Table 4: "Reliability and validity of construct"

Construct	CR	AVE	MSV	GHRM	EP	AIHRP
GHRM	0.864	0.556	0.468	0.745		
EP	0.883	0.587	0.437	0.495***	0.766	
AIHRP	0.852	0.593	0.372	0.445***	0.361***	0.770

Note: ***p< 0.001

6.5 Structural Model Appraisal:

Table 5: Model Fit Indices of the Hypothesized Model

Fit Index	Obtained Value	Recommended Threshold	Interpretation
GFI	0.924	≥ 0.90	Acceptable fit
CFI	0.968	≥ 0.95	Excellent fit
χ^2/df	1.323	< 3.00	Excellent fit
RMSEA	0.034	< 0.06	Excellent fit
SRMR	0.042	< 0.08	Excellent fit

Note. Threshold values are based on Hu and Bentler (1999) and Hair et al. (2010).

As presented in Table 5, all fit indices satisfy their recommended cut-off criteria, indicating that the hypothesized model fits the observed data well. The model is therefore considered suitable for subsequent path analysis.

6.6 Hypothesis Testing:

Table 6 substantiates the first hypothesis, revealing that GHRM practices exert a significant positive influence on EP among academicians in HEIs ($\beta = 0.511$, $t = 41.151$, $p < 0.001$). Accordingly, H1 is supported. The second hypothesis stated that GHRM practices is significant and positively related to AIHRP in academicians of HEIs and according to Table 5, GHRM is significant and positively related to AIHRP as ($\beta = 0.457$, $t = 8.965$, $p < 0.001$), thus H2 is accepted. The third hypothesis stated that AIHRP are significant and positively related to EP in academicians of HEIs, according to Table 6, AIHRP are significant and positively related to EP as ($\beta = 0.373$, $t= 12.674$, $p < 0.001$), thus H3 is acknowledged.

To ascertain the intervening role of AIHRP in the link between GHRM practices and EP, a mediation analysis was performed using the PROCESS macro for SPSS (Hayes, 2015). The fourth hypothesis posited that AIHRP substantially mediates the relationship between GHRM practices and EP among academic staff in HEIs. The bootstrapped estimates in Table 6 (5,000 resamples; 95% confidence level) reveal an indirect effect of .227, while the direct effect of GHRM on EP persisted at a significant level (.262) despite the inclusion of AIHRP. These results substantiate a partial mediation.

Figure 3: Structural Model

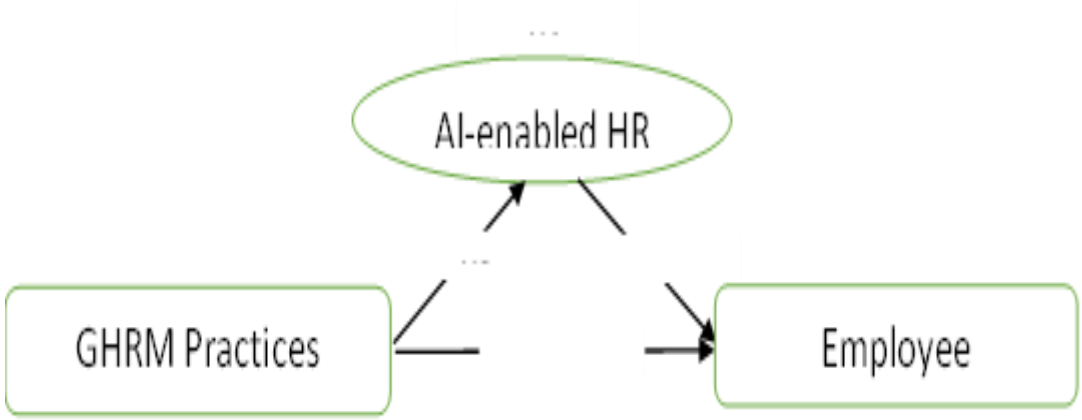


Table 6 Synopsis of Hypothesis Testing Outcomes

Hypothesis	Path	Direct Effect	Indirect Effect	Total effect	Conclusion
H1	GHRM → EP	.511***	NA	.511***	**H1 Accepted**
H2	GHRM → AIHRP	.457***	NA	.457***	**H2 Accepted**
H3	AIHRP → EP	.373***	NA	.373***	**H3 Accepted**
H4	GHRM → AIHRP → EP	.262***	.227***	.489***	**H4 Accepted (Partial Mediation)**

7. Discussion

The current study has three important variables named GHRM practices, AIHRP, and EP. The nested association between GHRM practices, AIHRP, and EP among academicians employed in HEIs, India is our objective. There is a significant and positive correlation between the adoption of GHRM practices and EP among faculty members working at HEIs, India according to the empirical data supporting the first premise, which implies when the Institutions make investment in ecologically friendly HR practices, academicians are likely to return the favour by putting forth more effort and performing better. This finding corroborates earlier studies conducted across other occupational sectors by Faisal (2023), Kim et al. (2019), Pham et al. (2019), Palupiningtyas et al. (2025), Ramchandaran et al. (2024), Tandon et al. (2023), which says that GHRM practices in the workplace have a relation with EP.

The empirical findings pertaining to the second hypothesis demonstrate a favourable linkage between the implementation of GHRM practices and AIHRP among academicians of HEI in India which means organisations pursuing GHRM practices will become more motivated and prepared to integrate AIHRP. This result is compatible with the preceding research performed by Kapruwan et al. (2026), Khan et al. (2025), Safshekan et al. (2026), Fenwick et al. (2024) in different professions.

The result further publicized a significantly positive and direct effect of AIHRP on EP of academicians staffed at HEI, India statistically, meaning EP of academicians would be amplified with improvements in AIHRP at the workplace. This finding corroborates earlier studies conducted across other occupational sectors by Jayawickrama et al. (2017), Alwali and Alwali (2026), Al Samman and Al Obaidly (2024) and Arora et al. (2024).

The study further witnessed the partial mediating effect of AIHRP between the above two variables which means academicians experience AIHRP play a decisive mediating part in the conversion of GHRM practices into better

EP and more comprehensive sustainability results. This finding is consistent with earlier research of Dinh et al. (2025), Mahat et al. (2025), and Ajuluchukwu et al. (2026).

8. Implications of the study

8.1 Theoretical Implications

Three main theoretical contributions are made in this study. In order to address recent calls in the literature for research that looks at how sustainability-oriented and digitally enabled HR practices jointly shape employee outcomes, it first unifies two largely parallel research streams—GHRM and AI-enabled HRM—into a single, testable nomological network (Nadin et al., 2025); Ajuluchukwu et al., 2026). Second, the study expands the GHRM-performance literature beyond the well-known mediators of green behaviour, green innovation, and organisational culture (Hosain et al., 2026; Shahzad et al., 2023) to include a technological mediating mechanism that represents the modern digitalised HR environment by explicitly modelling AI-enabled HR processes as a mediating mechanism (H4). Third, the paper presents a multi-theoretical integration of RBV, AMO, and SET that links individual-level motivational and relational mechanisms with organizational-level capability logic, offering a more comprehensive theoretical explanation of how HR practice bundles translate into EP than any one theory can provide on its own.

8.2 Practical Implications

The suggested paradigm advises HR professionals and organisational executives to pursue green HR strategy and AI-enabled HR strategy as complementary and mutually reinforcing investments rather than as separate digital and sustainability objectives. Consistent with evidence that such AI-enabled green practices are associated with stronger sustainability and performance outcomes than non-digitized green HR practices alone, organisations looking to maximise the performance returns of their sustainability-oriented HR practices should think about purposefully integrating AI-enabled tools, such as AI-guided eco-feedback, AI-supported green training content, and AI-enabled green performance dashboards, into their green HR delivery infrastructure (Ajuluchukwu et al., 2026). In order to protect the reciprocal, trust-based employee relationship that SET identifies as essential to the performance-enhancing effect of both green and AI-enabled HR practices, organisations should pair AI-enabled HR deployment with transparent governance, employee communication, and human oversight of algorithmic decisions. This is because the ethical and organizational-readiness risks associated with AI in HR are well documented, including concerns about algorithmic bias, data privacy, and employee trust (Ncube, 2025; Úbeda-García et al., 2025).

9. Limits & upcoming research advices

There are several limits to this work that also provide fruitful directions for further investigation. First, the model has not yet undergone empirical testing; given that both GHRM and AI-HRM effects have been demonstrated to differ by institutional and cultural context, the hypotheses developed here (H1-H4) require validation using the survey-based approach, ideally across multiple industries and national contexts (Najam Shaikh et al., 2025; Nadin et al., 2025). Second, the model treats AIHRP as a single mediating construct; in order to determine which particular AI-enabled HR sub-processes have the strongest mediating effect, future research could break down this construct into distinct AI applications (such as AI-enabled learning, AI-enabled performance appraisal, and AI-enabled recruitment). In line with recent research demonstrating that organisational culture moderates AI-GHRM relationships (Najam Shaikh et al., 2025) and that AI moderates GHRM-innovation relationships (Housheya & Atikbay, 2025), potential boundary conditions, such as employees' AI literacy, algorithmic trust, and organisational AI-readiness, could be included as moderators of the H2 and H3 paths, extending the model beyond simple mediation. Lastly, longitudinal designs would enable researchers to investigate whether the proposed links become stronger over time as AI-enabled green HR systems advance and employees grow more accustomed to and confident in these systems.

10. Conclusion

In this research, a conceptual model that links GHRM practices to EP directly and through the mediating mechanism of AIHRP has been created and empirically justified. The paper presents four hypotheses (H1–H4) that collectively position AIHRP not just as a parallel digital HR trend but as a substantive contrivance through which sustainability-oriented HR practices are converted into EP outcomes. It does this by synthesising recent literature on green HRM, AI in HRM, and EP and grounding the model in the Resource-Based View, the AMO framework, and SET. Understanding how these two dynamics interact to create EP will become increasingly important both theoretically and practically as organisations continue to pursue sustainability and digitalisation objectives concurrently. For the empirical study required to evaluate, improve, and expand this understanding, the suggested model and related research methodology provide a solid basis.

Declarations

Each author affirms that they have no competing interests.

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