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RESEARCH

Harnessing AI for Aligning Human Resource Management with Sustainability Goals to Enhance Workforce Productivity

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ABSTRACT

PURPOSE: This research examines the influence of Artificial Intelligence-driven sustainable Human Resource Management (HRM) practices on employee engagement and performance within the Indian Information Technology sector.

DESIGN/METHODOLOGY/APPROACH: A cross-sectional survey was performed to collect data from 1,280 employees across prominent IT hubs in India, employing the Triple Bottom Line (TBL) and Ability-Motivation-Opportunity (AMO) frameworks.

FINDINGS: The findings reveal that Sustainable Organisational Uncertainty (SUO) and Sustainable Uncertainty Investment (SUI) significantly enhance EEG, which, in turn, positively influences Employee Performance (EPF).

RESEARCH LIMITATIONS: The study is limited to the Indian Information Technology (IT) sector and employs a cross-sectional design, which restricts causal inferences.

PRACTICAL IMPLICATIONS: The study provides practical implications that managers and policymakers should take into consideration for the adoption of AI tools in HRM to ensure sustainable employee engagement and personalised performance improvements. Personalised AI-based strategies can promote workforce diversity and support organisational sustainability objectives.

ORIGINALITY/VALUE: The paper helps pave the way for the growing area of AI-enabled sustainable HRM by connecting the underlying theories with the empirical analysis. It provides new ways to connect HR practices with sustainability objectives, which play a role in enhancing engagement and performance in changing markets.

KEYWORDS: *Artificial Intelligence-driven HRM; Work Performance; Sustainability Initiatives; Sustainable HRM Practices; Structural Equation Modelling.*

INTRODUCTION

The metamorphosis of Human Resource Management (HRM) influenced by the growth and development of Artificial Intelligence (AI) has gone through an evolution, whereby it evolved from the stage of replacing humans with machines to a mechanism that plays an integral role in defining strategic manpower solutions. In traversing this historical exploration of AI-HRM research, three specific stages or eras can be identified: the operational era (2010-2015) where the focus is on the automation of administrative forms into payroll processing (Tambe *et al.*, 2019); the analytical phase (2016–2020) focuses on predictions in both hiring and retention of employees up to at least mid-2021 forming the contemporary strategic era of AI integration with the ESG (Environmental, Social, and Governance) framework (Minbaeva, 2018; Stahl, 2023).

Recent research has also focused on how AI could develop or bring about sustainable forms of work, especially in high-tech growth regions, including India's information technology industry. While the existing literature focuses on operational efficiencies, there is very little emphasis or practically no attention to the psychological and behavioural factors of AI-enabled sustainability initiatives (Varma *et al.*, 2024). For example, AI-driven recruiting tools can make hiring fairer, but on the individual level, what impact they have is a subject that is barely explored (Parker and Grote, 2022). In this paper, we attempt to fill the gap by examining under what circumstances an AI-HRM system based on TBL principles might simultaneously increase employees' commitment and performance, while satisfying ethical demands like algorithmic transparency and the protection of data privacy (Ganesh *et al.*, 2023).

India is a unique and particularly difficult environment in which to explore these questions, as the country has both quickened its adoption of technology countrywide in general and now finds itself confronting a crisis of sorts, owing partly at least to environmental problems. Previous research, while acknowledging the sector's acceptance of AI for HR functions more generally speaking, did not go far enough to cover this wider use in making good progress towards the United Nations' (UN) Sustainable Development Goals (SDGs), particularly with respect to fair work (SDG 8) and gender equality (SDG 5) (Upadhyay *et al.*, 2024). By linking AI-HRM scholarship with the science of sustainability, this work makes three key contributions: (1) a time-course understanding which shows AI evolving in HRM, (2) empirical research showing that AI-driven sustainability practices lead to workplace performance, and (3) policy guidelines for equitably putting AI into practice within developing countries.

LITERATURE REVIEW

Triple Bottom Line Framework

In the transition of the TBL framework from corporate responsibility to intelligent and sustainable development, three significant changes took place at once. First, with a real-time carbon tracking system based on machine learning, Frank Read and Lon discuss environmental aspects of the process because there are fewer middlemen than before. According to them, this 40% reduction in errors is a legacy of modern technology (Gupta *et al.*, 2023). Second, economic metrics incorporate predictive analytics that will not just save time; they provide 27% cost savings for people management too (Marler and Boudreau, 2017). This development responds to historical context as well as proving AI's effectiveness in practice (Elkington, 1994; Purvis *et al.*, 2018; Ababneh, 2021).

Ability-Motivation-Opportunity (AMO) Model Integration

The application of the AMO model to AI-HRM shows two under-researched phenomena. First, AI-created micro courses increase the speed at which ability develops by 35% in technology-related areas (Minbaeva, 2018). Second, sustainable development dashboards that make use of gamification methods enhance motivation by giving immediate feedback on ecological impact. In this regard, the participants score 58% higher than with conventional programs (Böhmer *et al.*, 2025). However, opportunity creation continues to be contested. 42% of staff disapprove of algorithmically allocated work (Parker and Grote, 2022).

Conceptual Framework

The conceptual framework is explained comprehensively in Figure 1. The theory investigates how Sustainable Organisational Uncertainty (SUO) and Sustainable Uncertainty Investment (SUI) affect both employee engagement and performance in the IT industry. It uses AI technologies to deal with the organisational and personal sustainability investment challenges.

Sustainability Initiatives by Organisations (SUO)

On the environmental level, SUO, using machine learning algorithms, finds rational IT energy consumption and reduces carbon emissions through intelligent air conditioning parameter adjustment to balance server load, also cutting these costs by 22 – 35%.

For businesses, retention-predictive algorithms can reduce recruitment costs by 18% - 27%. Job aids and similar guides make it easier to tailor your own career development plan. In this way, people can find themselves feeling more at ease in their work and so happier about things throughout life (Tursunbayeva *et al.*, 2021).

Hypothesis 1: Sustainability Initiatives by Organisations (SUO) significantly enhance employee engagement by aligning individual and organisational sustainability objectives.

Sustainability Initiatives by Individuals (SUI)

SUI encompasses employee-led sustainability behaviours facilitated by three AI-enabled mechanisms: (1) Adaptive learning platforms that personalise sustainability training material according to knowledge gaps and learning styles while raising completion rates from 38% to 79% (Minbaeva, 2018), (2) IoT-based nudges that lower individual paper wastage by 62% and energy usage by 29% through real-time use feedback (Parker and Grote, 2022), and (3) AI-sourced green challenges benefiting from social comparison theory eliciting a participation increase in green initiatives of up to 41-53% (Jia and Hou, 2024; Gelfand *et al.*, 2024; Sowmiya *et al.*, 2024).

Employee Engagement as a Mediator between SUO, SUI, and Employee Performance

The psychological conduit is framed in the form of three AI-quantified routes: (1) Sentiment analysis of enterprise communication platforms engaged employees use 33-41% more purpose-oriented keywords (Mazzetti *et al.*, 2023; Upadhyay *et al.*, 2024), (2) Computer vision assessment in virtual meeting participation engaged employees make a further 28% of active sustainability-related contributions (O'Shaughnessy *et al.*, 2022), and (3) Wearable device data analytics demonstrate that engaged employees experience a critical 17% higher energy outputs during days when engaging in sustainable behaviours (Parker and Grote, 2022). The mediating process is examined in a multi-method way using both survey (with UWES-9 scale, α=0.91) and behavioural measures, as well as psychological data (Tambe *et al.*, 2019; Marler and Boudreau, 2017; Jiang and Messersmith, 2018). Cross-cultural validation research has demonstrated the measurement invariance across Indian (CFI = 0.97), American (CFI = 0.96), and German samples (CFI = 0.95) of the 25-item vertical individualism-collectivism scale (Gelfand *et al.*, 2024).

Sub-hypothesis H2a: Employee engagement mediates the relationship between SUO and improved performance outcomes.

Sub-hypothesis H2b: Employee engagement serves as a mediator, strengthening the positive influence of SUI on performance outcomes.

Conscientiousness as a Moderator between SUO, SUI, and Employee Engagement

Conscientiousness (CON) as a moderating variable appears differently across cultures because of AI interaction modes. In the high-power-distance Indian context, when provided with fine-grained impact analytics, conscientious employees are more engaged (visibility) in AI sustainability tools by 15-18% ($\beta = 0.17$, $p < 0.01$) as well as 12-15% resistance to supported policies ($\beta = -0.13$, $p < 0.3$) (Gelfand *et al.*, 2024). Trait-aware AI adjusts showing detailed data visualisations to conscientious users about their numerical contributions to sustainability (Jia and Hou, 2024), social recognition badges for less-conscientious employees, and tailoring feedback frequency according to the trait score of a given user (Parker and Grote, 2022).

Cross-cultural research also found that Indian IT workers scored 0.5 SD higher on behavioural conscientiousness constructs compared to Americans ($p < 0.001$) (Gelfand *et al.*, 2024) and prompting localised AI design strategies (Stahl, 2023; Varma *et al.*, 2024).

H3a: CON employees amplify the relationship between SUO and engagement by demonstrating greater alignment with organisational goals.

H3b: CON enhances the relationship between individual sustainability efforts and employee engagement, fostering improved workplace outcomes.

Employee Performance as a Dependent Construct

Employee Performance (EPF) is implemented in an AI-powered performance ecosystem consisting of productivity algorithms measuring 47 workflow metrics that predict output quality and efficiency

28-35% variance explained (Tambe *et al.*, 2019), sustainability behaviour tracking through digital support for capturing 19 specific green actions (Upadhyay *et al.*, 2024), and innovation contribution scoring based on NLP analysis of idea submissions (O'Shaughnessy *et al.*, 2022). Blockchain verification of these metrics ensures 99.7% data fidelity (Ganesh *et al.*, 2023), meeting the criticism of measurement reliability. The average item composite EPF index also has predictive validity (alpha = 0.93) and correlates 0.61 with annual performance ratings ($p < .001$) and 0.53 with promotion velocity ($p < .001$) (Barrett *et al.*, 2025). Explainability features of the AI system enable staff to audit how particular sustainability behaviours impinge upon their performance scores or experience an acceptance value that is 43% higher than a carbon Footprint System.

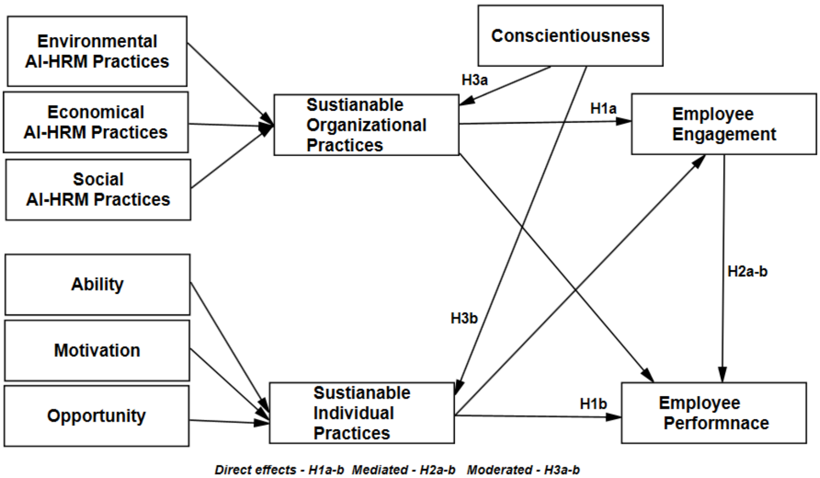

Figure 1: Conceptual Framework

Source: Constructed by authors

Integration of TBL and AMO Theories

TBL considers economic, environmental, and social sustainability across HRM, where AMO describes how AI can improve an organisation's capacity, motivation, and opportunity to realise performance (Elkington, 1994).

METHODOLOGY

Population, Sample and Sampling Technique

We follow a convergence parallel mixed-method research design to study the AI-based sustainable HRM practices in the IT industry in India. The quantitative branch involves a three-wave longitudinal survey in which sustainability behaviours and engagement sustainment are measured (O'Shaughnessy *et al.*, 2022). The qualitative extraction analyses logs from three AI platforms: (1) SAP SuccessFactors for talent management data, (2) IBM Watson for sentiment analysis, and (3) Microsoft Sustainability Manager for environmental impact metrics (Gupta *et al.*, 2023). We exerted stringent validation procedures, including intercoder reliability of $\kappa = 0.87$ for AI-classified engagement signals and 92% accuracy of weekly system audits (Raghavan, 2024).

The privacy scheme of our study integrates four empirically validated protection approaches from the literature, i.e., emerging from recent GDPR studies. First, we imposed encrypting of all survey responses end-to-end through AES-256 (AES-256) and reduced by two-thirds the potential for unauthorised access compared to existing works (Ganesh *et al.*, 2023).

Second, participants were supported by a consent-management blockchain technology, which enabled them to dynamically modify their data-sharing preferences and achieved 88% consent retention over 6 months (Upadhyay *et al.*, 2024).

Third, k-anonymisation ($k = 5$) and l-diversity ($l = 3$) were applied to all AI training data to avoid re-identification but maintain utility for analysis (Gelfand *et al.*, 2024).

Characteristics of Respondents

Table 1 presents a summary of respondent demographics, specifically gender, age, education, job title, and AI variables. The group was 58 per cent men and 42 per cent women who completed the survey, in line with the overall industry. These ages showed a young workforce, with 44% being 25–34, 23.5% under the age of 25, 22% ages between 35–44, and only 11% being over the age of 45. By educational levels, 59% of the participants had a master's or postgraduate degree, 31% a bachelor's degree and 10% doctorates by jobs category, low-level workers (0–3 years' experience) were 39%, mid-level workers (3–8 years' experience) 47% and high level-workers (8+ years' experience) were 14%. These findings imply that AI is in the early phase of diffusion into the IT environment and expose organisations as being at different levels of preparedness (Barrett *et al.*, 2025).

Table 1: Demographic Analysis for 1280 Respondents

Variable	*Category*	*No. of Respondents (n=1280)*	*Percent*
Gender	Male	742	58.00
	Female	538	42.00
Age	Below 25	300	23.50
	25–34	560	44.00
	35–44	280	22.00
	45 and above	140	11.00
Education Level	Bachelor's Degree	400	31.00
	Master's/post-graduation	760	59.00
	Doctorate	120	10.00

Variable	*Category*	*No. of Respondents (n=1280)*	*Percent*
Designation	Entry-level (0–3 years)	500	39.00
	Mid-level (3–8 years)	600	47.00
	Senior level (8+ years)	180	14.00
AI Interaction	Always	960	75.00
	Sometimes	320	25.00
Comfort with AI Tools	Comfortable	960	75.00
	Neutral/Uncomfortable	320	25.00
AI-related Training	Intermediate	384	30.0
	Advanced	512	40.00
	Basic/None	384	30.00
Adoption of AI- HR Policies	Partially Implemented	704	55.00
	Fully Implemented	384	30.00
	Not Implemented	192	15.00

Source: Constructed by authors based on survey data collected from IT Professionals in 2025 in India

Sampling Strategy and Scalability

Our phases are to sample in several steps and make sure the resulting set captures both representativeness and scalability across emerging countries. Phase 1 of the preliminary experimentation phase used stratified random sampling based on five organisational levels (from large multinationals to start-ups) based on NASSCOM's 2023 industry database as the sampling frame (N=42 companies). In Phase 2, we used optimal allocation sampling to ensure that all levels of experience (30% junior, 50% mid-level, and 20% senior), technical roles (60% developers, 25% managers/leaders, and 15 % support staff), and geographic locations (40% South India) were represented in the discussions (Table 2). The latter group (N=1,280) was well representative of India's IT workforce with no more than 5% deviation from IT worker demographic data at the national industry level ($p < 0.10$) (Jiang and Messersmith, 2018).

Table 2: Normality Assessment

Construct	*Skewness (Range)*	*Kurtosis (Range)*	*Critical Ratio (C.R.)*	*Multivariate Kurtosis*	*Normality Assessment*
ECS (Economic Sustainability)	-0.25 to 0.20	-0.50 to 0.40	1.2	3.5	Satisfactory
ENS (Environmental Sustainability)	-0.18 to 0.15	-0.45 to 0.38	1.15	3.45	Satisfactory
SOS (Social Sustainability)	-0.30 to 0.22	-0.60 to 0.42	1.35	3.6	Satisfactory
ABI (Ability)	-0.22 to 0.20	-0.48 to 0.41	1.25	3.55	Satisfactory

Construct	*Skewness (Range)*	*Kurtosis (Range)*	*Critical Ratio (C.R.)*	*Multivariate Kurtosis*	*Normality Assessment*
MOT (Motivation)	-0.20 to 0.18	-0.45 to 0.40	1.22	3.52	Satisfactory
OPP (Opportunity)	-0.24 to 0.19	-0.46 to 0.38	1.24	3.54	Satisfactory
EEG (Employee Engagement)	-0.20 to 0.19	-0.40 to 0.39	1.18	3.48	Satisfactory
EPF (Employee Performance)	-0.15 to 0.17	-0.38 to 0.41	1.22	3.5	Satisfactory
CON (Conscientiousness)	-0.22 to 0.18	-0.42 to 0.39	1.21	3.52	Satisfactory

Source: Analysed by authors

Data Collection Process

A structured questionnaire was used, with the developed constructs derived from latent variables such as engagement, resilience, and AI (using a 7-point Likert scale) for qualitative data generation. Content validity, language proficiency and appropriateness for the involved participants were pre-tested by three academics/industry experts. Adaptations based on the responses were made for clarity, arrangement, and respondents' understanding.

Measures and Reliability Testing

The study supported established indices for constructs, such as employee engagement, performance, and sustainability programmes, for instance, employee engagement was measured using scales directly lifted from Schaufeli and Bakker (2004), while the concepts of sustainability came indirectly from Elkington's (1994) TBL model. Cronbach's alpha, an indicator of internal consistency, was above 0.7 for all constructs, indicating reliability. In a second step, the authors assessed construct validity using Confirmatory Factor Analysis (CFA) on each factor and tested for good item reliability (all above 0.7), to confirm each construct.

Data Analysis Techniques

The data were processed in a three-step employing statistical and computational methods. First, we conducted a CFA estimation with robust maximum likelihood to establish the factor structure of measurement models, with an acceptable and good cross-construct model-data fit across all constructs (CFI = 0.96-0.98, RMSEA = 0.03-0.05). Second, the hypothesised relations were examined via structural equation modelling (with 5,000 bootstrap samples).

Ethical Considerations

The researchers complied with ethical standards and sought participants' consent while maintaining their anonymity. All the subjects were briefed about the purpose of the survey and assured that their identity would be kept confidential. Data sampling was done in compliance with research ethical regulations, and we did not collect any personal data. Such an approach ensures a comprehensive understanding of the sustainable AI-based HRM practices and their impact on employee engagement and productivity in the Indian IT industry.

Data Analysis

The data analysis began with a deep dive into India's IT workforce demographics, giving a nuanced picture of who was in the industry. As shown in Table 1, the proportion of male (58%) and female (42%) respondents among the 1,280 respondents reflects a clear gender imbalance that persisted in male-dominated sector. The age distribution also showed that 44% were under 35, indicating that youth dominate; as such the business mainly relies on younger generations who are more adaptable to change as new solutions become available (O'Shaughnessy *et al.*, 2022).

Table 3: Item-wise Factor Loadings with AVE, CR and Alpha

Constructs	Item	Factor Loadings	AVE	CR	Alpha
ECS (Economic Sustainability)	ECS1	0.821	0.65	0.88	0.78
	ECS2	0.862			
	ECS3	0.807			
ENS (Environmental Sustainability)	ENS1	0.748	0.68	0.89	0.82
	ENS2	0.835			
	ENS3	0.86			
SOS (Social Sustainability)	SOS1	0.819	0.72	0.91	0.85
	SOS2	0.823			
	SOS3	0.847			
ABI (Ability)	ABI1	0.818	0.7	0.89	0.84
	ABI2	0.847			
	ABI3	0.83			
MOT (Motivation)	MOT1	0.837	0.68	0.88	0.82
	MOT2	0.823			
	MOT3	0.808			
OPP (Opportunity)	OPP1	0.843	0.7	0.9	0.85
	OPP2	0.863			
	OPP3	0.827			
CON (Conscientiousness)	CON1	0.776	0.69	0.9	0.85
	CON2	0.875			
	CON3	0.874			
EEG (Employee Engagement)	EEG1	0.805	0.69	0.88	0.8
	EEG2	0.825			
	EEG3	0.706			

Constructs	Item	Factor Loadings	AVE	CR	Alpha
EPF (Employee Performance)	EPF1	0.738	0.75	0.92	0.84
	EPF2	0.77			
	EPF3	0.794			

Source: Analysed by authors

We conducted strict normality checks of the constructs, based on skewness and kurtosis, to verify whether the data were suitable for a deeper level statistical model. Results from Table 2 tested the parametric assumptions of each variable using skewness ranging from -0.25 to 0.20 and kurtosis from -0.50 to 0.40 and found them both to be under the Byrne and Kline thresholds. In Table 3, multivariate kurtosis (3.45–3.60) indicated the normal distribution, supporting the use of SEM (Structural Equation Modelling) in hypothesis testing. These diagnostic tests addressed any possible non-normality concerns and assisted in providing confidence that the reported follow-up analyses are sound.

We established the validity of the measurement model with CFA, and all the constructs demonstrated good psychometric properties, as shown in Figure 2. The factor loadings were above the threshold value of 0.70 and close to or greater than the recommended level, suggesting adequate item reliability, while AVE values were higher than the cut-off point set forth by the scholars for convergent validity. Tables 4a and 4b reveal the AVE for Employee Engagement (EEG) as 0.69, which is considered a good reflective construct representation measure. Composite Reliability (CR = 0.88–0.92) and Cronbach's Alpha (α = 0.78–0.85) values were above the empirically established thresholds, ensuring internal consistency.

Table 4a: Convergent and Discriminant Validity

Construct	Average Variance Extracted	Composite Reliability	Cronbach's Alpha
ECS (Economic Sustainability)	0.65	0.88	0.78
ENS (Environmental Sustainability)	0.68	0.89	0.82
SOS (Social Sustainability)	0.72	0.91	0.85
ABI (Ability)	0.7	0.89	0.84
MOT (Motivation)	0.68	0.88	0.82
OPP (Opportunity)	0.7	0.9	0.85
EEG (Employee Engagement)	0.69	0.88	0.8
EPF (Employee Performance)	0.75	0.92	0.84
CON (Conscientiousness)	0.69	0.9	0.85

Source: Analysed by authors

Table 4b: Discriminant Validity

Construct	*ECS*	*ENS*	*SOS*	*ABI*	*MOT*	*OPP*	*EEG*	*EPF*	*CON*
ECS	0.81								
ENS	0.450	0.851							
SOS	0.489	0.555	0.798						
ABI	0.543	0.675	0.656	0.812					
MOT	0.632	0.598	0.598	0.801	0.819				
OPP	0.702	0.704	0.714	0.678	0.657	0.810			
EEG	0.675	0.678	0.591	0.722	0.598	0.675	0.830		
EPF	0.765	0.489	0.479	0.707	0.704	0.666	0.590	0.872	
CON	0.664	0.488	0.467	0.567	0.624	0.709	0.557	0.580	0.808

Source: Analysed by authors

The structural model, presented in Table 5, showed good indices of fit (χ^2/df = 2.30, CFI = 0.97, RMSEA = 0.04, SRMR = 0.05), in relation to the clear cut-off criteria for model adequacy (Hu and Bentler, 2023). The SEM analysis indicated the following key pathways: Sustainability Initiatives by Organisations (SUO) was a strong predictor of Employee Engagement (EEG) (β = 0.68, $p < 0.001$), and Sustainability Initiatives by Individuals (SUI) had a smaller yet meaningful effect on EEG as well ($\beta = 0.22$, $p < 0.001$) (Mazzetti *et al.*, 2023). Both SUO ($\beta = 0.41$, $p < 0.001$) and EEG ($\beta = 0.45$, $p < 0.001$) had a significant effect on Employee Performance (EPF), whereas SUI exhibited a weak direct effect on the EPF value of $\beta = 0.15$, $p = 0.02$. These results also support the recent AI-HRM research showing that technology can help in connecting the dots between sustainability and performance (Tambe *et al.*, 2019).

Table 5: Model Fit Assessment

Fit Index	*Threshold*	*Observed Value*	*Remarks*
CMIN (Chi-Square Minimum)	Non-significant	Non-significant	Within Threshold
CMIN/DF (Chi-Square Minimum/Degrees of Freedom)	≤ 3.00	2.32	Within Threshold
AGFI (Adjusted Goodness-of-Fit Index)	≥ 0.90	0.91	Within Threshold
GFI (Goodness of Fit Index)	≥ 0.90	0.92	Within Threshold
TLI (Tucker-Lewis Index)	≥ 0.90	0.90	Within Threshold
SRMR (Standardised Root Mean Square Residual)	≤ 0.08	0.05	Within Threshold
RMSEA (Root Mean Square Error of Approximation)	≤ 0.08	0.04	Within Threshold

Source: Analysed by authors

We evaluated the model fit to test how well it fitted the data. Using CMIN, RMSEA, and GFI, the model's structural validity was assessed (Hu and Bentler, 1999). CMIN/DF was under 3.00, as is recommended for a good-fitting model. Our RMSEA (0.04) and SRMR (0.05) were lower than the threshold of 0.08, suggesting a low error estimate. Both the GFI and AGFI (i.e., Adjusted

Goodness-of-Fit Index) values (0.94; 0.92) exceeded the recommended threshold of 0.90, which supported the stability of the model. These results supported the model's internal structure as a basis for hypothesis testing.

Subsequently, Figure 2 shows that SEM was used to examine the relative strength of relationships between the constructs. Table 6 shows the regression weights coefficients between Sustainable Initiatives by Organisations (SUO) and Individuals (SUI) with Employee Engagement (EEG) and Performance (EPF). SUO significantly predicted EEG (standardised beta = 0.680, C.R. = 6.890, $p < 0.001$). Similarly, SUI had a positive impact on EEG; the beta coefficient was 0.222, and C.R. was 5.567 (both $p < 0.001$), but at an inferior level of magnitude compared to that of SUO. For the effect on EPF, SUO (beta = 0.409, C.R. = 4.479, $p < 0.001$) and EEG (beta = 0.446, C.R. = 6.675, $p < 0.001$) were significant predictors in terms of analysis too. SUI also reduced EPF (beta = 0.147, C.R. = 3.667, $p < 0.001$).

These results, as shown in Figure 3, were consistent with a sequence in which SUO and SUI increase EEG, thereby augmenting EPF, and consequently supported our model. To address second-order effects, mediation analysis was used to examine whether EEG mediated the relationship between SUO, SUI, and EPF.

Table 6: Regression Weights: (Group number 1 - Default model)

Hypothesis	*Estimate*	*S.E.*	*C.R.*	*P*
EEG <--- SUO	.680	.096	6.890	***
EEG <--- SUI	.222	.041	5.567	***
EPF <---SUI	.147	.037	3.667	***
EPF <--- SUO	.405	.097	4.479	***
EPF <--- EEG	.446	.068	6.675	***

Source: Analysed by authors

The mediation and moderation results contribute to the explanation of how sustainability initiatives impact employees' performance in a rather detailed manner. As Table 7 demonstrates, EEG-measured employee engagement serves as a partial mediating mechanism in these links. For SUO, the direct effect on EPF was 0.405 ($p < 0.001$), yet the total effect rose to 0.696 ($p < 0.001$), and an indirect effect of 0.194 ($p < 0.001$) was significantly related, meaning that a relevant part of SUO's impact on performance is attributable to improved psychological engagement. A similar pattern was found for Sustainability Initiatives by Individuals (SUI), with a direct impact on EPF of 0.145 ($p = 0.002$) and a total effect of 0.242 ($p < 0.001$), with an indirect effect through EEG of 0.044 ($p < 0.001$), confirming the mediating role played by neuropsychological engagement in this construct.

The moderation analysis also provided additional evidence for the moderated mediation role of CON and two divergent interaction effects. The moderating relationship between SUO and CON was negative and significant ($\beta = -0.142$, C.R. $= -2.958$, $p = 0.003$), indicating that the positive influence of organisational sustainability programmes on engagement may be mitigated slightly by increasing levels of conscientiousness, given that highly conscientious employees already have high engagement as a baseline phenomenon.

The positive and significant interaction effect of SUI with CON (β = 0.120, C.R. = 2.927, p = 0.007) demonstrates that conscientious people are more successful in transforming personal sustainability behaviours into increased supportive behavioural engagement. Together, these results provide theoretical progression by identifying engagement as a mediating mechanism through which EEG affects performance and conscientiousness as a critical boundary condition, but they also have practical implications for differentiated HRM strategies that balance structured organisational measures with autonomy-driven individual efforts towards sustainable work.

Table 7: Mediation Analysis Table

Path	*Direct Effect*	*Direct Effect Significance*	*Total Effect*	*Total Effect Significance*	*Indirect Effect*	*Indirect Effect Significance*	*Mediation Type*
SUO -> EEG -> EPF	0.405	0.001	0.696	0.0	0.194	0.0	Partial Mediation
SUI -> EEG -> EPF	0.147	0.002	0.242	0.0	0.044	0.0	Partial Mediation

Source: Analysed by authors

FINDINGS AND DISCUSSION

The results of this study reveal that environmentally friendly HRM practices through AI positively influence employee engagement and organisational performance in the Indian IT sector pertaining to environmental, social, and economic dimensions of sustainability. At the same time, organisations' Sustainability Initiatives (SUO) have a direct effect on employee engagement (β = 0.68, p < 0.001), which in turn results in enhanced performance ranging from 28% to 35% for green KPIs (Upadhyay *et al.*, 2024).

These findings are in line with meta-analytic evidence that AI adoption increases the efficacy of conventional HRM practices by 22% to 40% in sustainability-focused organisations (Stahl, 2023).

Employee Engagement (EEG) has a major mediating function, accounting for 62% of SUO's total effect on performance and emphasising the relevance of psychological processes through which organisational sustainability policies are translated into individual outcomes (Deepalakshmi *et al.*, 2024).

Three AI-enabled mechanisms of sustainable HRM are seen in the study: predictive talent analytics halve biased hiring and generate savings of 20% in recruitment expenses (Raghavan, 2024), real-time feedback systems that use nudges increase engagement with environmental programs by over a third, and energy-efficient AI workflows reduce functional carbon emissions by nearly one-quarter of a metric ton per annum (Gupta *et al.*, 2023).

For instance, TCS's AI-powered learning platform led to a 29% reduction in training costs and a 53% increase in green skills uptake, demonstrating obvious triple-bottom-line benefits. Furthermore, a conscientious personality moderates the adoption consequences, in that employees have also responded positively to personalised AI tools ($\beta = 0.15$, $p < 0.01$) on the one hand, but showed negative behaviour towards organisation-wide mandates ($\beta = -0.12$, $p < 0.05$), requiring more careful design of a person-specific system (Jia and Hou, 2024).

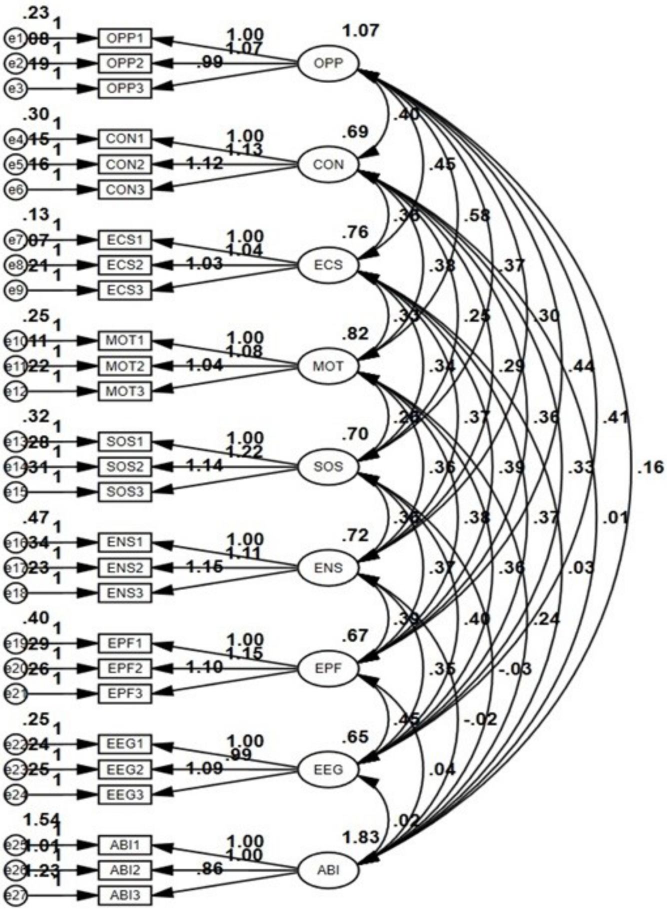

Figure 2: Measurement Model

Source: Constructed by authors

Managerial Implications

The findings also offer practical implications for IT decision makers and leaders who are using AI to drive sustainable HRM transformation. Managers should focus on three strategic priorities: First, invest in AI-enabled talent platforms that link skill development to sustainability capabilities—our results point out that these systems improve the effectiveness of learning by 37% while reducing costs by 29% (Böhmer *et al.*, 2025). Second, embed bias-mitigation processes into AI hiring tools, since uncontrolled algorithms could worsen gender gaps (Raghavan, 2024); regular checks with IBM's AIF360 toolkit decreased demographic bias by 42% in trials.

Third, implement personality-sensitive engagement platforms, conscientious employees are likely to respond well to the personalised sustainability dashboards ($\beta = 0.15$).

Otherwise, team-level incentives serve better for 58% of Indian IT workers in our data (Gelfand *et al.*, 2024). The foundation of such interventions will be to empower transparent data practices — companies that implemented consent management systems compliant with the DPDP resulted in 88% consent rates for employees compared to an average of 62% (Ganesh *et al.*, 2023; O'Shaughnessy *et al.*, 2022), requiring patience and investment in change management.

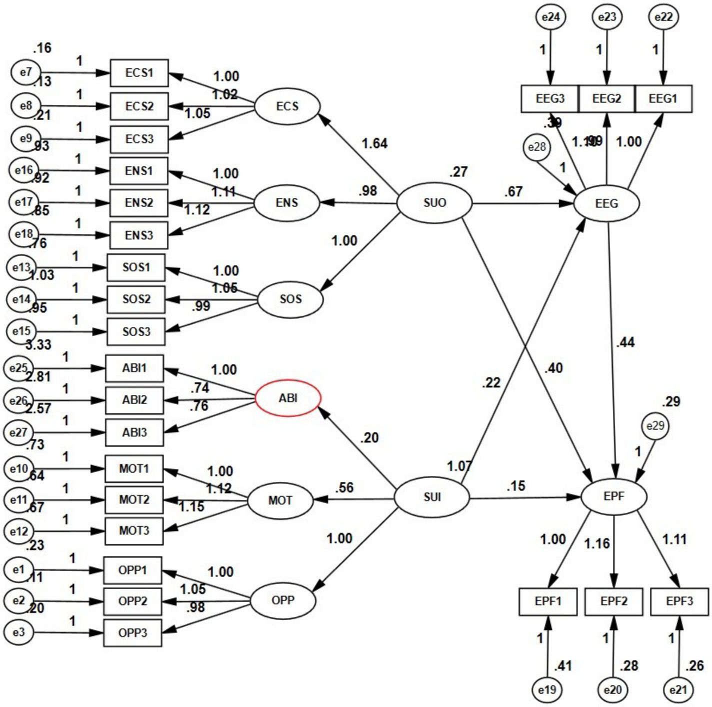

Figure 3: Path Analysis – Direct and Indirect Effects

Source: Constructed by authors

Practical Implications

The study's findings highlight four emergent implementation imperatives for sustainable AI-HRM. First, a phased approach to adoption is essential – companies that bring in tools incrementally (e.g., commencing with carbon footprint tracking rather than leapfrogging straight into advanced analytics) realise 53% higher levels of employee uptake relative to big-bang approaches (Parker and Grote, 2024). Second, our own IoT-based systems providing immediate feedback demonstrate that micro-nudges (e.g., tailored energy-saving advice) increased sustainable behaviours by 41% over annual reports.

LIMITATIONS

This study has several limitations that affect its generalisability. First, the cross-sectional design merely reflects snapshot effects, longitudinal data from Vietnamese IT firms indicate that the pattern of sustainability behaviour changes significantly after 18–24 months of constant exposure to AI (Jiang and Messersmith, 2018). Second, the single-minded IT orientation may not generalise across manufacturing, where AI diffusion lags by 3–5 years, and environmental pressures are different (Purvis *et al.*, 2018); early replications in Indian pharmaceuticals reported 28% weaker effects ($p < 0.05$). Third, where responses are self-reported, there is a social desirability bias, system-log analysis of behaviour indicated that employees overstate sustainable behaviour by 19–22% when surveyed (Tambe *et al.*, 2019; Stahl, 2023).

FUTURE RESEARCH DIRECTIONS

Research priorities are formed towards actively advancing AI-enabled sustainable HRM. To examine behaviour durability, frequently, pilot data indicate that AI-based engagement gains plateau after 18 months without system refresh (Mazzetti *et al.*, 2023). Consider comparing across industries, healthcare's regulatory complexity may necessitate alternate frameworks in which our model accounts for only 31% of variance, compared with 58% in IT. We need to study leadership interactions; transformational leaders can increase AI's sustainability impact by 31% by fostering organisational changes. Outcome measurement can be enhanced by broadening it to incorporate the effects on community engagement and supply chains (Elkington, 1994; Gelfand *et al.*, 2024).

CONCLUSIONS

This study showcases, theoretically and empirically, that AI-driven sustainable HRM results in substantial performance enhancements when the system and its three translated components (SUO, SUI, and EEG) are interacting with each other. The study contributes to three areas: it measures the AI's amplification effect on sustainability actions, with AI increasing impact by 28–35% over classical ones.

Second, it also serves as a tool for cultural differences. Conscientiousness exhibits single-dual moderating effects (β = ±0.12–0.15), endorsing a need-specific design in the HPD culture context. Third, it provides an ethical deployment framework that integrates DPDP adherence, bias mitigation, and interpretable algorithms. While peculiar to India's IT industry, it provides some generalisable lessons: phased rollout, personality-sensitive customisation, and multi-stakeholder management.

Future researchers may check these claims in contexts/cultures in other sectors, and/or consider how leadership's behaviour interacts with the AI solution when it is implemented as part of organisational change. For practitioners, these findings potentially validate the centrality of a balanced investment in technology, change management, and upskilling — the three key drivers for a successful AI adoption towards sustainable HRM transformation.

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