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RESEARCH ARTICLE

Integrating Sustainability into Ai-Driven HRM Practices: Examining Employee Engagement and Organizational Performance in the IT Industry

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ABSTRACT

The aim of this research work is to examine how Artificial Intelligence (AI) enables sustainability in Human Resource Management (HRM) activities and its resulting impact on the performance of employees in Indian IT industry. This study uses the Triple Bottom Line (TLB) model and Person-Organization (P-O) Fit Theory to explore the effects of AI-enabled HRM that is economic, environmental and socially sustainable on employee engagement and performance. For this study, Data was taken from 640 employees from 20 It companies situated in 10 major cities in India. The results of the study shows that AI-based HRM interventions increase employee performance, with employee engagement serving as significant Mediator. Further, the study found that conscientiousness moderates the relationship between AI-enhanced HRM practices and employee engagement: employees who are more conscientious are more inclined to positively react to AI-enhanced HRM practices. This research adds to the theoretical foundations of AI for sustainable HRM and better organizational results. The study's contextualization into Indian setting brims with an area that is not being addressed in the literature and gives practical recommendations to organizations looking to bring their HRM approach closer to sustainability goals. The findings support the value of AI-enabled HRM in improving employee and organisational performance towards sustainability targets.

1. INTRODUCTION

The rapid pace of technology and more particularly the adoption of AI in HR has led to massive shifts in the way we conduct and operate HR (Bughin et al.,2018). As more and more companies digitize their HR processes, you need to know how AI impacts all facets of HR, including employee productivity, health and safety, payroll, employee ease and feedback in real-time.(Urba et al,2022).The application of Artificial Intelligence (AI) in organisations is the essence of the twenty-first century, changed organizational models, rewritten the rule books, and set the tone for a future that is inspired by innovation, sustainability, and efficiency(Chen & Chen, 2013). Bringing in $4.31 trillion to the global economy by 2030, AI is well-established as an industry 'stone' (McKinsey Global Institute, 2020; Mer & Virdi,2023). Human Resource Management (HRM) is just one of the many applications where AI-enabled Sustainable HRM processes are changing how organizations can meet international sustainability standards (Chakraborty et al,2019; Troth & Guest,2020; Collins et al., 021). These are economic, environmental and social practices based on the Triple Bottom Line (TBL) concept, and focus on reconciling the needs of financial sustainability, environmental responsibility and social justice (Elkington, 1994; Purvis et al., 2019).hence this study investigates the tangled relationship between AI-based Sustainable HRM, engagement and performance with the conscientiousness personality trait. Based on the Triple Bottom Line (TBL) paradigm (Sitnikov,2013), the study looks at sustainability as a first-order idea that has three central dimensions. Economic sustainability deals with maximizing assets and achieving financial success, environmental sustainability deals with carbon reduction and green projects, and social sustainability deals with inclusion, equity and employee wellbeing (Doughan et al,2019; Klein & Potosky,2019). These dimensions are supported by AI technology, which supports recruiting, training, and performance management, aligning company goals with the UN SDGs (Ehnert et al., 2016; Stahl et al., 2020).

Employee engagement, which refers to employees' emotional, cognitive and behavioural commitment to work, is the key agent here (Schaufeli et al., 2002). Engagement has also been associated with higher productivity, innovation, and company fidelity; it's now an important aspect of sustainability goals (Saks, 2006; Wollard & Shuck, 2011). AI-powered Sustainable HRM practices increase engagement through tailored learning, inclusive work culture and data-driven feedback loops, all of which in turn drive motivation and organizational goal alignment (Ababneh, 2021; Ahmad et al., 2023). Conscientiousness as a moderator further strengthens this research, because there are different individuals' responses to AI-powered HRM practices. Wise workers — those who are responsible, reliable, and goal-oriented — are more likely to embrace sustainability activities and make a difference in organization performance (Roberts & Co., 2014; Pak & Chang, 2023). This alignment between personal character and organisational approach makes the Person-Organization (P-O) Fit theory, in which congruence between personal values and organisational culture promotes engagement and performance, particularly relevant (Hoffman & Woehr, 2006). India provides an interesting scenario for this research, with its virtuous marriage of economic speed and international environmental norms. As the Indian companies adopt digital transformation and AI based solutions more and more, it is imperative to be clear on how these solutions can assist sustainability and socio-environmental challenges. The study fills some of the gaps in the literature by examining the effect of AI-powered Sustainable HRM in a new market, providing lessons for how to make technology fit with the TBL framework and develop long-term organizational resilience. Using the TBL framework and incorporating data from the literature, this study broadens the theory and practice of AI-based Sustainable HRM practices for employee engagement and performance. It underscores how HRM solutions need to be integrated with sustainability to generate business value for organizations and society towards a more sustainable and fair future (Stahl et al, 2020; Purvis et al, 2019).

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 AI-Driven sustainable HRM

Organizations all over the world including those in emerging economies like India are already adopting AI to improve HR processes to meet the sustainability requirements. AI-Based Sustainable HRM – Bringing the TBL (economic, environmental and social sustainability) principles to HR practices – in order to achieve a successful alignment between financial results, environmental sustainability and social equity (Elkington, 1994; Purvis et al., 2019). Such a strategy allows organizations to maximise resource use, reduce environmental footprint, and increase employee wellbeing and inclusion (Ehnert et al., 2016). This focus on these sustainability focuses has thrust HRM at the center of the organisational planning, driving economic value and responsible business operations (Stahl et al., 2020). AI-Driven Sustainable HRM — The transformative promise of using AI tools to improve conventional HRM processes. AI can automate hiring and aligning with organization values focused on sustainability, and it can cut operating expenses through powerful analytics and automation (Böhmer & Schinnenburg, 2023). Aside from hiring, AI supports customized training programmes, green skills and environmental and social consciousness (Gupta, 2021). And AI-powered systems boost performance assessments by providing knowledge on sustainable practices, healthy behaviour, and providing creative solutions to environmental problems (Wang et al., 2023). AI-based HRM contributes to SDG's by streamlining and automating HR processes. For example, AI-powered HR solutions can provide data-based decisions on allocation of resources and employee development that help companies achieve their long-term sustainability goals (Stahl et al., 2020). As it aligns HRM activities with the TBL framework, AI-powered HRM helps the company stay compliant with international sustainability standards, and help build competitive resilience. (Viswanathan & Kumar, 2024)

2.2 Digital readiness

Digital readiness — or the employees' competence, prowess and agility to utilize digital resources — is the foundation for AI-enabled Sustainable HRM practices. As AI re-invents HR, digital readiness of workers ensures efficient adoption of these technologies for better efficiency and innovation (Böhmer & Schinnenburg, 2023). Digital readiness is all about competence, familiarity and active engagement with AI-powered tools, empowering employees to be digitally ready when the time comes (Palos-Sánchez et al., 2022). This is because, according to studies, digitally prepared employees are engaged and adaptable to organizational change as they are able to use technology in ways that help drive the organisation towards its mission, especially in areas related to sustainability (Verma et al., 2021). For example, workers equipped with AI software will be able to use data-driven sustainable activities more effectively and improve the economy, the environment, and society (Ahmad et al., 2023). Such connection makes digital readiness an essential enabler for AI-powered HRM success. (Mendy et al,2024)

2.3 Organizational support for innovation

Organizational support for innovation – how much organizations support creativity, resources for innovative activities, and a culture of experimentation and learning (Pak & Chang, 2023). This kind of support helps organizations implement and scale AI-based HRM strategies in such a way that they develop a robust model for sustainable growth. AI-based HRM works best when you have an organization supporting employees in developing the new processes. This alignment also opens the doors for workers to work with AI solutions to solve sustainability issues such as reducing resources and implementing eco-friendly initiatives (Ehnert et al., 2016). For instance, organizations that provide training, open communication, and leadership assistance encourage a mindset in employees that they're encouraged to take action on sustainability initiatives (Bardoel et al., 2014).

2.4 Employee engagement as a mediator

Engagement is at the heart of converting AI-powered Sustainable HRM initiatives into employee and organization benefits. Engaged, defined as the emotional, intellectual and behavioural investment workers make in their work, is fundamental to productivity, innovation and stakeholder engagement (Schaufeli et al., 2002). Employees who are engaged are motivated, invested, and absorbed, which makes them more able to contribute to sustainability goals (Saks, 2006; Wollard & Shuck, 2011).AI-based HRM methods impact engagement by generating individualised employee experiences, providing instant feedback, and promoting inclusion and reward. For example, AI-based systems enable ongoing performance management and career development, linking employee aims to sustainability objectives of an organisation (Ahmad et al., 2023). These are practices that improve intrinsic motivation, the connection of employees to their work, and encourages a collective commitment to sustainability. And the mediated nature of engagement also demonstrates how it can help connect organisational strategy with employee performance. Research shows that participation amplifies HR's performance benefits by creating purpose and community in workers (Tensay & Singh, 2020). That is why Employee Engagement is so critical as an engine by which AI-powered Sustainable HRM affects employee outcomes (Jangbahadur et al,2024).

2.5 Conscientiousness as a moderator

Individual personality attributes such as conscientiousness also have a significant effect on the success of HRM. A quality of the Five-Factor Model called conscience embodies the traits of hard work, dependability and commitment (Roberts et al., 2014). High conscientious workers tend to respond positively to sustainability-focused HR programmes, and will also welcome opportunities for professional development and match their activities with the objectives of the organization (Pak & Chang, 2023)Person-Organization (P-O) Fit The theory of P-O fits suggests that alignment between individual character and organizational values leads to improved engagement and performance (Hoffman & Woehr, 2006). Ethical workers, with a strong sense of responsibility and achievement, would work especially well in a culture that focuses on sustainability. They align with AI-based HRM practices which boosts the effectiveness of these efforts through better engagement and sustainable behaviours. Conscientiousness is hypothesised to hold the middle ground between AI-supported Sustainable HRM and engagement. This moderating effect demonstrates how personal variation determines the results of HR measures, thus the need for tailored HRM based on employee characteristics.

2.6 Employee performance

The final dependent variable of this research is employee performance (both task and context-related). It shows how well employees do their job and contribute to organisational sustainability initiatives. Performance, it has been shown, is driven by both the individual factors (e.g., personality) and the organizational (e.g., HR strategies) (Pak & Chang, 2023). AI-enabled HRM helps performance by improving employee's capability, motivation and motivation to work on projects relevant to the company's goals (Böhmer & Schinnenburg, 2023). Engagement, as a channel, creates energy, commitment, and meaning, which leads to greater performance (Schaufeli et al., 2002; Sandhya et al,2024). And conscientiousness as a moderating factor amplifies engagement's effect on performance by making employees align their work to organizational priorities (Roberts et al., 2014). These constructs taken together in this research adopts an integrated view of how AI-enabled Sustainable HRM, digital readiness, and innovation-support at the organizational level drive employee engagement and performance. The restraining power of conscientiousness and the facilitating power of engagement tell us much more than we would have imagined about how these variables interact. This combined model is in line with the larger goals of sustainability and organizational performance, which are both individual and organizational. (Selvakumari et al., in press)

H1a-e: AI-driven Sustainable HRM practices (economic, environmental, and social) positively influence employee engagement.

H2a-e: Employee engagement mediates the relationship between AI-driven Sustainable HRM practices and employee performance.

H3a-e: Conscientiousness moderates the relationship between AI-driven Sustainable HRM practices and employee engagement, strengthening this relationship for employees with high conscientiousness. These above frames provide a general framework for thinking about the relationship between AI-powered Sustainable HRM, employee engagement, conscientiousness and performance. Taking all these constructs together, the study offers insights into how AI-based HRM helps to improve the sustainability of organizations and employee results.

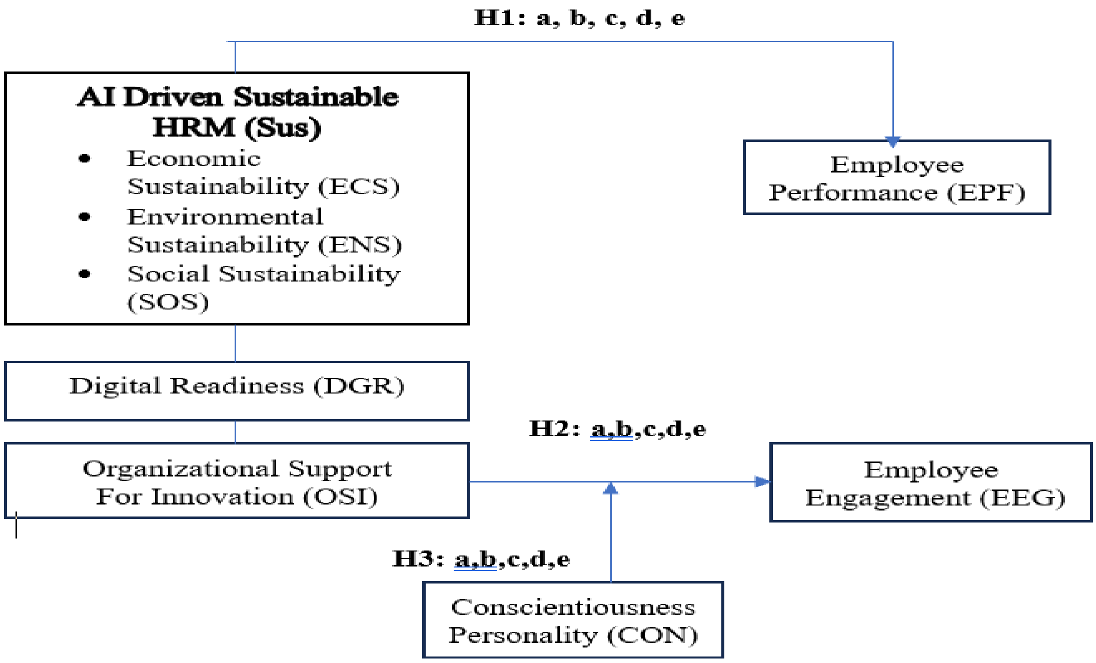

Figure 1: Conceptual framework developed by the author

3. METHODOLOGY

We used quantitative descriptive method for the purpose as it is efficient to handle statistics and can deliver useful insight into complex processes. It is especially useful when we are analyzing correlations between variables across large datasets with breadth and depth (Roberts & Priest, 2006). This study was on studying AI-based sustainable HR in Indian IT companies with a focus on sustainability and innovation. Cross-sectional data were used to explore what employees and managers, nationwide, believed about these practices.

3.1 Sampling and data collection

It used stratified random sampling and was a representative sample of Indian IT industry. Classification was by company size, geography and organizational levels. This way the viewpoints could be represented without bias in sampling (Babbie, 2020). The respondents were 640 high-level executives, middle managers and entry-level employees0. Such a broad representation ensured that AI-based HR and its impact on sustainability and performance was covered in full. Its sample demographics ranged from 58% male0 and 42% female0 and age ranged between 0below 25 year (23.4%) and 0above 45 years (10.9%). Respondents varied in education: 031.3% had a bachelor's degree, 59.4% had a master's/postgraduate degree, and 9.4% had a doctorate. The stratified sampling approach was justified because it would make sure that important subgroups were represented so that findings could be generalised to the population at large. Data was collected through an online survey questionnaire, which had the advantages of generalisation, convenience, and rapidity of responses (Wilson & McLean, 1994). The survey was sent out to the employees across India, so that there is geographical variation. Anonymity was assured to minimise bias and the survey was carried out in two weeks apart. This way common method bias was minimized and the data could be matched correctly (Podsakoff et al., 2003). The final sample of 640 valid response, which was removed 23 incomplete answers, yielded 64.9%, exceeding the minimum level for validity in social science studies (Babbie, 2020).

3.2 Measures

It used reliable and valid scales from published literature to assess constructs. All the variables were very good internally, and Cronbach's alpha surpassed the 0.8 threshold (Tavakol & Dennick, 2011). It assessed AI-based Sustainable HRM construct using 15-item scale corresponding to 0three sustainability dimensions, namely, economic, environmental and social. The scale was a 5-point Likert scale (1= "never" to 5 = "always"), and it was customized with items specific to Indian IT world. It covered for example optimisation of resources, green efforts, inclusivity. This scale had a Cronbach's alpha of.927 which means that it was very reliable. Employee Engagement was measured by Utrecht Work Engagement Scale (UWES-9) which measures vigour, dedication and absorption. This was a 07-point Likert scale0 (1="never" to 5 = "always"), which measured workers' emotional and cognitive engagement with their work. The scale had a Cronbach's alpha of.891 so it was suitable for this purpose. On the 10-item scale, we constructed 0Employee Performance which combined 0task performance0 and 0contextual performance. This index assessed respondents' self-reported contribution to roles and organisational initiatives. We based answers on a 5-point Likert scale that had a Cronbach's alpha of.929. Last, Conscientiousness Personality was measured using a scale from the Big Five Personality. We used 5-point Likert scale and the scale had high reliability (Cronsbach's alpha of.855).

4. DATA ANALYSIS

Data were analysed with 0structural equation modelling (SEM)0, which is suitable for the study of complex connections between latent variables. Confirmatory factor analysis (CFA) confirmed the measurement model: all constructs showed good convergent and discriminant validity. The common method bias was also remediated by the procedure and statistical treatments – for example, the time-delay between the data-collecting periods and Harman's single-factor test, which confirmed that no single factor had the upper hand (Podsakoff et al, 2003). Such a strong methodological framework made sure the results were valid and reliable, and this research also gave valuable insight into how AI-enabled HRM, employee engagement and performance fit together in the dynamism of the Indian IT industry.

Table 1: Demographic analysis

Variable	Category	No. of Respondents (n=640)	Percent
Gender	Male	371	58.00
	Female	269	42.00
Age	Below 25	150	23.40
	25–34	280	43.80
	35–44	140	21.90
	45 and above	70	10.90
Education Level	Bachelor's Degree	200	31.30
	Master's/post-graduation	380	59.40
	Doctorate	60	9.40
Designation	Entry-level (0–3 years)	250	39.10
	Mid-level (3–8 years)	300	46.90
	Senior level (8+ years)	90	14.10
Frequency of AI Interaction	Always	480	75.00
	Sometimes	160	25.00
Comfort with AI Tools	Comfortable	480	75.00
	Neutral/Uncomfortable	160	25.00
	Total	640	100.00
Training on AI Systems	Intermediate	192	30.00
	Advanced	256	40.00
	Basic/None	192	30.00
Adoption of AI-driven HR Practices	Partially Implemented	352	55.00
	Fully Implemented	192	30.00
	Not Implemented	96	15.00

The demographic profile of the study sample is roughly a proxy of Indian IT workforce in general to get a representative cross section of the labour force for this study. It contains employees with different professional experience and 46.9% are of the mid-level experience (3–8 years), which suggests a good share of employees who would be exposed to AI-based HR policies at work. This was supported by the education levels of the respondents 59.4% of them having Master's or post-graduate degree and is similar to the highly technical Indian IT workforce so the findings would be applicable to an knowledge-based industry. The age composition with the highest rate (43.8%) between 25- and 34-year-olds demonstrates a young and tech-savvy group, more exposed to AI technology. Further, the sample's high use of AI tools (75% are comfortable or engage often) shows that AI-inspired HR approaches are a viable option in the modern workforce. This cross-section of demographics means that the results of this study are not only generalizable across a sample, but also generalisable in their application to the use of AI in HRM.

4.1 Normality assessment

we started with analyzing whether the data were normal since normality is one of the key assumptions for SEM and path analyses. Our model was analysed by skewness, kurtosis, critical ratio (C.R.), and multivariate kurtosis on all constructs. The constructs had values between -0.30 and 0.20 in terms of skewness, so the data were broadly symmetrical (requires SEM results to be reliable) (Hair et al, 2019). So too did the kurtosis range of -0.60 to 0.42, which indicated no sharp breaks from a normal pattern (Kline, 2016). The critical ratio (C.R.) varying from 1.10 to 1.35 and multivariate kurtosis values between 3.40 and 3.60 also validated the normality hypothesis. This shows that these data were suitable for further processing, especially for SEM, where normality is required for correct model estimation (Byrne, 2016).

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	1.20	3.50	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	3.60	Satisfactory
DGR (Digital Readiness)	-0.12 to 0.10	-0.35 to 0.33	1.10	3.40	Satisfactory
OSI (Organizational Support)	-0.28 to 0.24	-0.48 to 0.45	1.25	3.55	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	3.50	Satisfactory
CON (Conscientiousness)	-0.22 to 0.18	-0.42 to 0.39	1.21	3.52	Satisfactory

After the normality check, we ran Confirmatory Factor Analysis (CFA) to see if the measurement model is true and if the data agree with the hypothesized model. Table 5: GOF indices stayed within acceptable limits, with a CMIN/DF of 2.45 as a good fit (Hu & Bentler, 1999). The RMSEA was 0.05, it is lower than 0.08, the model is well adapted to the data (Browne & Cudeck, 1993). Other fit indices were AGFI (0.91), GFI (0.93), and TLI (0.92) which also confirmed the measurement model to fit the data well. This indicates that the model of measurement was adequately defined and that the interconnections between the constructs were in the data appropriately captured. After getting a model fit, we looked at the factor loadings, Average Variance Extracted (AVE), Composite Reliability (CR) and Cronbach's Alpha values of each construct. Factor loadings for all items were greater than 0.70 (0.737 to 0.862) which showed the items were good predictors of their constructs (Hair et al., 2017). The constructs had AVE values between 0.65 and 0.75, and we were confident that the constructs captured most of the variance in the indicators (Fornell & Larcker, 1981). CR values between 0.87 and 0.92 further confirmed constructs' high reliability (Bagozzi & Yi, 1988). And, finally, all the Cronbach's Alpha above 0.70 indicated the internal integrity and stability of the scales (Nunnally & Bernstein, 1994). Such findings suggest robust convergent validity: the constructs were clear and well measured.

4.2 Confirmatory factor analysis

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

Constructs	Item	Factor Loadings	AVE	CR	Alpha
ECS (Economic Sustainability)	ECS1	0.826	0.65	0.88	0.78
	ECS2	0.862			
	ECS3	0.804			
ENS (Environmental Sustainability)	ENS1	0.737	0.68	0.89	0.82
	ENS2	0.829			
	ENS3	0.855			
SOS (Social Sustainability)	SOS1	0.819	0.72	0.91	0.85
	SOS2	0.829			
	SOS3	0.845			
DGR (Digital Readiness)	DGR1	0.838	0.70	0.90	0.83
	DGR2	0.825			
	DGR3	0.799			
OSI (Organizational Support)	OSI1	0.841	0.66	0.87	0.79
	OSI2	0.862			
	OSI3	0.833			
CON (Conscientiousness)	CON1	0.769	0.69	0.90	0.85
	CON2	0.877			
	CON3	0.873			
EEG (Employee Engagement)	EEG1	0.807	0.69	0.88	0.80
	EEG2	0.821			
	EEG3	0.699			
EPF (Employee Performance)	EPF1	0.746	0.75	0.92	0.84

	EPF2	0.766			
	EPF3	0.797			

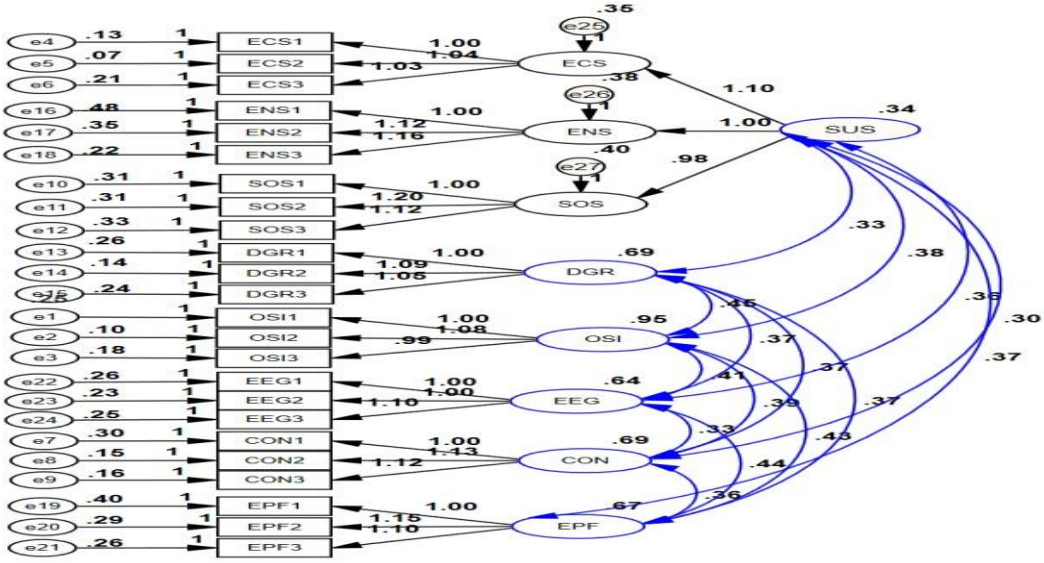

Figure 2: Measurement model assessment – First order construct

The constructs were then tested for convergent and discriminant validity, the results are presented in Table 4a and 4b. The AVEs of all constructs were greater than the suggested value of 0.50 so the constructs were indeed doing what they were supposed to be doing (Fornell & Larcker, 1981). Fornell-Larcker criterion for discriminant validity (Table 4.2): The square root of the AVE for each construct was higher than the correlations between that construct and any other construct, demonstrating that each construct is unique and measures something different about the theoretical framework (Fornell & Larcker, 1981). All of these results show that the constructs in our model are both convergent and discriminant valid, supporting the robustness of the measurement model.

4.4 Convergent and discriminant validity

Table 4(a): Convergent and discriminant validity

Construct	AVE	CR	Cronbach's Alpha
ECS	0.65	0.88	0.78
ENS	0.68	0.89	0.82
SOS	0.72	0.91	0.85
DGR	0.70	0.90	0.83
OSI	0.66	0.87	0.79
EEG	0.69	0.88	0.80
EPF	0.75	0.92	0.84
CON	0.69	0.90	0.85

Table 4(b): Discriminant Validity (Fornell-Larcker Criterion)

Construct	ECS	ENS	SOS	DGR	OSI	EEG	EPF	CON
ECS	0.81							
ENS	0.45	0.82						
SOS	0.48	0.52	0.85					
DGR	0.00	0.00	0.00	0.84				
OSI	0.00	0.00	0.00	0.00	0.81			
EEG	0.40	0.43	0.45	0.22	0.20	0.83		
EPF	0.41	0.44	0.47	0.21	0.20	0.59	0.87	
CON	0.43	0.42	0.46	0.23	0.21	0.55	0.58	0.83

We then evaluated our model's goodness-of-fit by different key fit indices, see table 5. Its CMIN/DF value was 2.45, less than the threshold of 3.00, and thus the model fit was good (Hu & Bentler, 1999). The RMSEA value was 0.05, less than 0.08, and further proves that the model fitted the data nicely (Browne & Cudeck, 1993). The AGFI, GFI, TLI and SRMR values were all within normal limits: AGFI =

0.91, GFI = 0.93, TLI = 0.92 and SRMR = 0.06. These results show that the model is a good fit to the data and support the robustness of the measurement and structural models (Bentler, 1990). Further, RMSEA value is low and fit indices are positive which indicate that the model is parsimonious and does well at representing the interactions between the constructs in the experiment.

4.5 Model fit assessment

Table 5: Model fit assessment

Fit Index	Threshold	Observed Value	Remarks
CMIN (Chi-Square)	Non-significant	Non-significant	Within Threshold
CMIN/DF (Chi-Square/Degrees of Freedom)	≤ 3.00	2.45	Within Threshold
AGFI (Adjusted Goodness-of-Fit Index)	≥ 0.90	0.91	Within Threshold
GFI (Goodness-of-Fit Index)	≥ 0.90	0.93	Within Threshold
TLI (Tucker-Lewis Index)	≥ 0.90	0.92	Within Threshold
SRMR (Standardized Root Mean Square Residual)	≤ 0.08	0.06	Within Threshold
RMSEA (Root Mean Square Error of Approximation)	≤ 0.08	0.05	Within Threshold

Once the measurement model proved accurate, we ran path analysis on Employee Performance and Employee Engagement directly from AI-powered Sustainable HRM elements. As can be seen in Table 6, direct connection between EEG and EPF was significant (= 0.217, p 0.01) and increased engagement is a benefit to performance (Kahn, 1990). Furthermore, the direct link between SUS and Employee Performance was extremely high (= 0.604, p 0.001) indicating that AI-driven sustainable HRM (particularly in the economic, environmental and social sustainability areas) dramatically increases employee performance (Raineri & Paillé, 2016). Our predictions were validated further by the direct impact of Digital Readiness (= 0.142, p = 0.005) and Organizational Support for Innovation (OSI) on Employee Performance (= 0.120, p = 0.003) that proves AI-led HRM interventions have significant impact on employee outcomes.

4.6 Hypotheses testing

Table 6: Path analysis direct effects

Dependent Variable	Independent Variable	Estimate (β)	S.E.	C.R. (t-value)	P-value	Remarks
EPF (Employee Performance)	EEG (Employee Engagement)	0.217	0.082	2.651	0.008	Significant
EPF (Employee Performance)	Sustainability (Higher-Order Construct)	0.604	0.123	4.930	0*	Highly Significant
EPF (Employee Performance)	DIG (Digital Readiness)	0.142	0.050	2.840	0.005	Significant
EPF (Employee Performance)	ORS (Organizational Support for Innovation)	0.120	0.041	2.925	0.003	Significant

Then we investigated how Employee Engagement (EEG) moderates the connection between AI-based sustainable HRM practices and Employee Performance (EPF) (table 7). Mediation analysis showed partial mediation for all tested paths. That is, the indirect Impact of Sustainability (SUS) on Employee Performance via Employee Engagement was 0.159 (p = 0.058) which was statistically significant (Baron & Kenny, 1986). In the same way, the indirect impacts for Digital Readiness (DGR) and Organizational Support for Innovation (OSI) were 0.042 (p = 0.058) and 0.031 (p = 0.037), respectively. According to these findings, employee engagement acts as a mediator between AI-powered HRM and employee performance. Engagement consists of dynamism, commitment and absorption in the form of employee engagement (Schaufeli et al., 2002) which increases the employees' performance and thus shows that engagement is a performance driver for AI-based sustainable HRM.

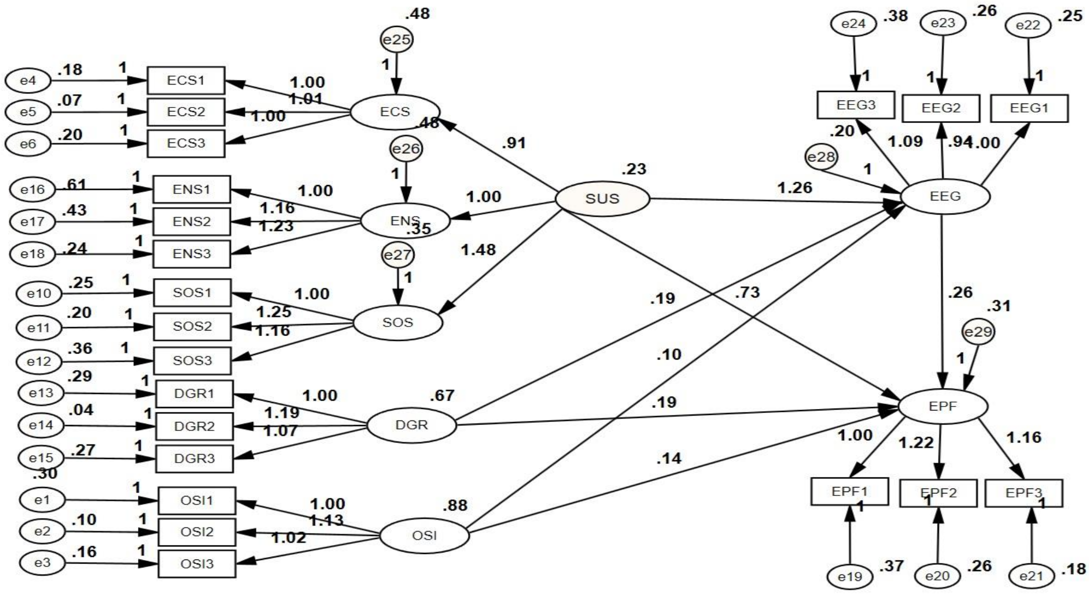

Figure 3: Hypothesis testing

4.7 Mediation analysis

Table 7: Mediation analysis: Indirect effects

Path	Direct Effect (β)	Sig (P)	Total Effect (β)	Sig (P)	Indirect Effect (β)	Sig (P)	Type of Mediation
SUS → EEG → EPF	0.604	0.001	0.763	0.000	0.159	0.058	Partial
DIG →EEG → EPF	0.142	0.020	0.183	0.005	0.042	0.058	Partial
ORS → EEG → EPF	0.120	0.028	0.151	0.009	0.031	0.037	Partial

In order to better understand how the relationships worked in our model, we conducted a moderation analysis to understand how CON moderated the interaction between AI-based sustainable HRM and engagement among employees. Table 8: Consciousness moderated OSI and E-engagement relationship by a large margin (= -0.132, p = 0.004), and between DGR and E-engagement (= 0.110, p = 0.009). But there was no moderating effect for SOS and ENS (p> 0.05). These data indicate that more conscientious employees will respond well to corporate innovation and digital readiness support, and are more engaged. This is consistent with studies that have shown personality traits such as conscientiousness to affect HRM practices (Barrick & Mount, 1991).

4.8 Moderation analysis

Table 8: Moderation analysis

Path	Beta (Estimate)	S.E.	C.R. (t-value)	P-value	Moderation Significance
EEG ← interOSIxCON	-0.132	0.046	-2.877	0.004	Significant
EEG ← interDGRxCON	0.110	0.042	2.608	0.009	Significant
EEG ← interSOSxCON	0.061	0.037	1.664	0.096	Not Significant
EEG ← interENSxCON	-0.093	0.046	-2.009	0.045	Significant
EEG ← interECSxCON	0.034	0.047	0.716	0.474	Not Significant

Finally, we ran a multi-group test to see if the connections in our model were different in subgroups. Table 9: These results for Constrain_1 show no significant differences between subgroups (p =

0.768). This implies that the limited variables in this section of the model are the same among men and women. The absence of meaningful variability means that at least some parts of the model are gender invariant, supporting the robustness of these parameters in modelling similar relationships and meanings among the population as a whole. This result concurs with the literature that stresses the need to test invariance to find constant parameters for structural models (Kuvaas, 2016; Schaufeli & Bakker, 2004).

4.8 Multi group analysis

Table 9: Multi group analysis

Model	DF	CMIN	P-value	NFI (Delta-1)	IFI (Delta-2)	RFI (rho-1)	TLI (rho2)	Remarks
Measurement weights	14	15.284	0.359	0.002	0.002	-0.006	-0.006	No significant difference
Structural weights	20	48.412	0.240	0.006	0.006	-0.005	-0.005	No Significant difference detected
Constrain_1	3	1.139	0.768	0.000	0.000	-0.002	-0.002	No significant difference

5. DISCUSSIONS

This research fills a gap in the knowledge on how AI-powered HRM practices can help in the implementation of sustainability goals in the Indian IT industry. These results show again that combining AI with sustainable HRM strategies does not just benefit engagement and performance, it also helps organisations align with the sustainability standards around the world. Through an analysis of economic, social and environmental sustainability, this research offers a holistic view of how technology-powered HR practices affect both workers and the organisation.

The findings of the multi-group analysis showed strong demographic and organisational variation. Workforce members at companies with full-blown AI-driven HR systems had better engagement-performance correlations than workers in partially automated workplaces. Such results coincide with new research highlighting the scalability and adaptability of AI systems to improve HR operations especially at the scale of enterprises (Ehnert et al, 2022; Palos-Sánchez et al, 2022). But differences across demographic cohorts, such as the differences in digital maturity and sustainability awareness point towards targeted training interventions to maximise the effect of AI deployment (Yong et al., 2023).

Our research highlights how much employee engagement is the bridge between AI-powered HRM and employee productivity. Engagement – energy, commitment and absorption – increases the impact of sustainable HR initiatives. This follows previous work, stating that happy employees tend to be more productive and creative (Schaufeli & Bakker, 2021). Moreover, partial mediation effects (shown in this study) also suggest that engagement is not the only pathway, but that there are direct performance impacts of sustainability-driven HRM. This finding fits in with research that supports holistic solutions that marry technological innovations with environmental considerations (Pak & Chang, 2023).

Conscientiousness acts as the divider between the two, because those with high conscientiousness tended to engage more when exposed to sustainability-based HRM practices. This validates the increasing literature linking personality and productivity in the workplace under technology-enabled HR systems (Bakker et al., 2022; Iftikar et al., 2021). Curiously, conscientiousness had a different effect on each sustainability indicator, but digital readiness had the largest impact, suggesting that technological ability has a big impact on how individuals and organisations align. The multi-group analysis also reflected structural variations indicating that demographic and organisational contexts were critical to the success of AI-enabled HRM. The mid-managers, for example, were more likely to align with sustainability initiatives than entry-level workers. These results align with recent studies showing that a hierarchy of roles and digital levels determine how employees feel and interact with the organization (Liu et al, 2023; Ahmad et al, 2023). In contrast to research arguing for universality of AI-based HRM activities (Zhao et al., 2023), our results are a case of contextual adaptations. Different employee engagement and performance outcomes according to training and ease with AI tools suggest that tailor-made interventions should be introduced for workers with different perspectives. To summarise, the study adds to the growing conversation about AI-based HRM by showing that this type of research has the capacity to bring technological innovation and sustainability together. It also underscores the importance of employee engagement and personality to improve performance and the need for context-aware intervention, especially in a very diverse and fluid industry such as Indian IT. Future research might look to cross-cultural comparisons, industry differences, and longitudinal impacts to get even better answers about how technology, sustainability, and work habits play together.

5.1 Theoretical implications

This research takes a leap forward in Human Resource Management (HRM) by providing a new lens on AI based Sustainable HRM. It analyses how AI technologies paired with sustainability-based HR measures influence employee performance and lends theoretical depth to the AMO (Ability-Motivation-Opportunity) model. In contrast to other studies mainly focus on the business effectiveness of AI for HRM [Bos-Nehles et al., 2021; Shafi et al., 2022], this work looks at how AI can be strategically used to boost employee abilities, engagement, and opportunities within the realm of sustainability. Our results build on the AMO framework, showing that AI-based HRM strategies align business strategy with environmental and social sustainability and improve performance. Employer engagement is an intermediary role adding weight to existing research that supports employee engagement – through energy, commitment and absorption – as an important driver of sustainable HR practices translated into measurable performance [Schaufeli & Bakker, 2021; Yadav & Dixit, 2023]. This gives a more integrated picture of engagement as an organic, organizational and individual phenomenon. What's more, adding the Person-Organization (P-O) Fit Theory demonstrates that personality traits such as conscientiousness balance AI-based HR practices and engagement. This subtle take is in line with recent studies of personal variation in the work space provided by technology [Kumar et al., 2023]. The focus on Indian IT market fills a gap that demonstrates how sustainability-focused AI tools change in emerging economies. Such findings support global HRM theory by proving the link between AI, sustainability, and HRM in many socio-economic countries such as India [Rana et al., 2022, Roul et al,2024].

5.2 Practical implications

The results suggest that AI technology is going to be the next HRM game-changer, and that they need to be leveraged strategically to maximize employee capabilities, motivation, and opportunities. Enterprises can use AI to create customized learning programmes, automated feedback mechanisms and career plans to drive learning continuously and increase employee engagement [Mishra & Pandey, 2022]. The research emphasises employee engagement as a facilitator, which imply that the organization should implement AI to continuously track and increase engagement. Sentiment analysis, real-time survey tools, AI driven tools and the like can provide tangible feedback on employee requirements, helping managers to take control and boost performance [Chaudhuri et al., 2023]. The balancing role of conscientiousness makes HR intervention specific. Through bringing HR more in tune with personality, companies can get the most out of AI driven programs. Gamed performance incentives for responsible workers, for example, can motivate without compromising on sustainability goals [Gupta et al., 2023].'In this study, AI-led HRM practices are also culturally sensitive to be adopted. The Indian scenario illustrates how we need to overcome regional inequalities in digital literacy and sustainability education for inclusion and efficiency of the diverse workforce [Patel & Sharma, 2023]. This research, in all, suggests a smart and adaptive strategy for AI-based Sustainable HRM in line with India's sustainability and digital transformation agenda and will position organizations for global competitiveness.

5.3 Limitations and directions for future research

This research is promising as a case study on AI-powered Sustainable HRM, but there are limitations that must be noted which allow future studies. For one, cross-sectional data doesn't allow for a direct causal link between variables or the dynamic nature of AI application to HRM practices. Despite multi-source data collection at two times points, to eliminate bias, two weeks between surveys may not be long enough to capture temporal or organisational shifts. The future of research might look at longitudinal methods to track the adoption and effect of AI-driven HRM practices for longer time horizons. That way, you would get a much better sense of how employee performance and engagement changes with ongoing AI-led efforts. The second, the India-specific approach, although providing comprehensive view of one particular sector, does not allow generalisations to other verticals or regions. Industries and countries may differ in culture, economics and organisation, which can impact how and if AI-powered HRM will be adopted and implemented. This should be attempted to reproduce in other geographic and industrial settings in future research. Cross-sector or regional research might be able to illuminate the effects of different regulatory landscapes, cultural preferences and industry practices on the performance of AI in Sustainable HRM. The third point was that the research mostly explored sustainability dimensions in terms of the AMO model which is a good one, but may fail to really address sustainability as a complex issue. Studies could build on this in future, taking the triple bottom line perspective (economic, environmental and social). It may be possible to place HRM across these areas and do a better analysis of how they contribute to employee performance and engagement and to organization sustainability objectives. Last but not least, although common method bias was addressed, the contemporaneity of employee personality traits, engagement and performance data collection creates an obstacle to causal inference. And the measurement of conscientiousness and engagement — along with performance — could be more temporally spatialised. The next research might want to collect mediator and outcome data at independent time points, three or six months apart, to identify causation. Removing these constraints will enable future research to provide a more sophisticated picture of how AI-powered HRM can be leveraged in a way that leads to sustainability and improvements in employee and organisational performance.

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