The object of this study is the impact of AI-enabled sustainable HR practices on employee performance in India's IT industry. The problem addressed is the lack of empirical evidence on how AI-driven HR practices influence performance, with a focus on the mediating role of employee engagement and the moderating role of conscientiousness.

The research responds to the vital question of how AI-based HR innovations, which include AI-based recruitment and development, AI-enabled performance feedback, organizational sustainability orientation, and AI-based employee empowerment, influence the performance of IT professionals.

Data were collected from 340 Indian IT professionals using structured instruments with snowball sampling method. The findings explore the impact of AI-based HR practices on employee performance in the Indian IT industry. The findings show significant positive effects of AI-driven recruitment ($\beta = 0.116$, $p = 0.007$), performance management ($\beta = 0.180$, $p < 0.001$), and training ($\beta = 0.204$, $p < 0.001$). Employee engagement mediates these relationships ($\beta = 0.136$, $p = 0.002$), while conscientiousness moderates the engagement-performance link ($\beta = 0.150$, $p = 0.006$).

From a practical point of view, the results suggest that it is important for IT managers to adopt future-oriented and viable HR digital solutions that capitalize on both technology and human elements in an effort to enhance productivity in an industry in which the pace of change is rapid

Keywords: AI-driven HR practices, employee performance, employee engagement, conscientiousness, strategy, Indian IT sector

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DESIGN AND ASSESSMENT OF AI-ENABLED SUSTAINABLE HR PRACTICES AFFECTING EMPLOYEE PERFORMANCE WITH ENGAGEMENT MEDIATION AND PERSONALITY MODERATION IN THE INDIAN IT INDUSTRY

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1. Introduction

In today's business landscape, companies are subject to mounting pressure to incorporate sustainability as a core value to drive both economic success and social, environmental goals [1]. At the same time, new innovations in artificial intelligence (AI) have ushered in a digital HRM era, that encompasses technologies to support sustainable goals in HRM development [2]. The incorporation of AI in the HRM functions has offered new prospects for businesses to improve their performance and organizational efficiency, as well as employee performance and/or outcomes by adopting data-based decision-making and automation [3].

Sustainable HRM is now acknowledged as a potential factor in the development of both organizational resilience and competitive advantage, so too in evidence-based sectors like IT [4]. This question is particularly critical in the IT industry, which has high eHR adoption due to rapid technological change, high skill requirements, and dynamic workforce needs [5]. HRM practices and processes with emergent AI to produce human-centered workplace innovations.

Although a great deal of attention has been paid to both sustainable HRM and AI applications, scant empirical research has been done on how sustainable HRM and AI-integrated practices influence technical employees in the context of India's IT sector, which is one of the fastest-growing markets in the world [6]. The sector's unique culture and operation mandate customized research for addressing contextual specificity affecting HRM efficiency. Additionally, employee engagement is found to be an important psychological process through which AI-based HRM practices lead to better performance results [7, 8]. Personality dimensions, in particular conscientiousness, also moderate these relationships by explaining how individuals react to engagement and contextual resources [9].

Based on the job demands-resources model [10], it is possible to suggest that AI-based HR practices are job resources that help reduce work stress and foster employee engagement, leading to better performance. Such a cross-level view draws attention to the importance of including the influence of digital innovation, sustainability, and individual differences on workforce outcomes in the Indian IT context being examined jointly.

Hence, the study on the advancement and integration of AI-enabled sustainable HR practices and its influence on employee performance in the Indian IT industry is very significant. Studying these processes is of utmost importance for advancing the theoretical and empirical knowledge and for developing HRM practices in a fast-changing technological and cultural environment.

2. Literature review and problem statement

Research outcomes for the impact of AI-enabled sustainable HR practices on employee performance in the Indian IT sector are discussed in the paper. Previous research indicates that AI-enabled hiring and placement can have a positive effect on talent retention by being able to apply neutral algorithms and predictive analytics to achieve camaraderie between the ability of the worker and the tasks that are needed to be performed [11]. Yet open questions persist on how to operationalize these AI methods, especially in the context of an employee's performance over time. This could be due to the objective challenges of implementing organizational transformation and the staff technical skills shortage to absorb the new HR AI system [12]. One possible solution to this has been identified as targeted training courses that educate employees to adapt to these technological changes. Success in other fields has involved great costs, technological difficulties, and technological costs [13].

AI-driven performance management systems can be a source of real-time, non-bot-generated feedback which has been found to be conducive to productivity. Yet, open questions remain for how to reconcile those sustainability targets with AI-based performance management. This also raises the ethical issue of how to achieve the balance between organizational objectives and the well-being of workers [14], thus emphasizing the need for more research on digital HRM practices and sustainability integration [15].

A focus on sustainability leads to greater commitment and moral behavior in the workplace on the part of employees, mirroring a general societal objective on both a social and environmental level. However, the direct impact of sustainability practices on employee performance still has uncertain conclusions, which are dependent on the human resource management (HR) practices. The reality of sustainability is difficult because it is expensive and challenging to implement sustainability programs enterprise-wide [16].

The AI tooling, the fact that AI has power, opens room for employees to have autonomy and really contribute to the problem-solving and innovations. Nevertheless, the relationships between empowerment, engagement, performance, and AI at work are somewhat less clear and warrant further investigation, especially in cross-cultural settings where empowerment definitions might differ [17].

Remarkably, HR practices and employee engagement (EE) operate as mediating variables between HR interventions and employee outcomes, since increased vigor and dedication lead to better productivity. Fundamentally, if AI advances, other things being equal, it is also possible to observe higher engagement, but empirical evidence is scant, especially in developing countries like the IT industry in India. This divide has important implications on the feasibility of the use of such findings in the Indian setting.

Second, it has been found that the engagement-performance relationship is moderated by conscientiousness, which reflects diligence and commitment to work and organizations. Although this moderating effect is consistent with what is expected theoretically, the link between conscientiousness and AI-driven HRM development has not been empirically examined thoroughly, especially among Indian IT professionals [18].

Two separate streams of literature have addressed digital HRM and sustainability, and their implementation in Indian IT firms, mediated by personality moderators. In light of the above facts, a long overdue inquiry on AI-led sustainable HR practices, the mediation effect of employee engagement, and the moderating role of conscientiousness is very much needed to address the gaps in the existing research and to provide HRM perspectives in the Indian IT industry [19].

3. The aim and objectives of the study

The study aims to identifying the impact of AI-based sustainable human resource (HR) practices on employee performance, with the mediating role of employee engagement and the moderating effect of conscientiousness in the Indian information technology (IT) industry.

To achieve this aim, the following objectives are accomplished:

– to establish the construct validity of the measurement scales for AI-driven HR practices, employee engagement, conscientiousness, and employee performance using EFA, while also testing the convergent and discriminant validity of the AI-enabled sustainable HR practices and employee outcomes constructs;

– to assess the model fit for the overall model of the hypothesized SEM model on the impact model of AI HR practices to employee performance;

– to examine the direct influence of AI-based recruitment & selection, training & development, performance management, organization's sustainability orientation, and employee empowerment on employee performance;

– to explore the mediating effect of employee engagement on the link between AI-based HR practices and employee performance;

– to examine the moderating role of conscientiousness between employee engagement and employee performance.

4. Materials and methods

The object of this study is the impact of AI-enabled sustainable human resource (HR) practices on employee performance in the Indian IT industry, focusing on the mediation of employee engagement and the moderation of conscientiousness.

The main hypothesis is that AI-enabled HR practices positively influence employee performance, with employee engagement mediating this relationship and conscientiousness moderating the engagement-performance link.

The study assumes that AI-driven HR practices can be effectively implemented in the Indian IT sector and that the participants' responses reflect their actual experiences and perceptions. It also assumes that employee engagement and conscientiousness significantly influence performance outcomes in this context.

The study simplifies the focus by examining only four key AI-driven HR practices recruitment, training, performance management, and employee empowerment while excluding other potentially relevant factors. It also limits the scope to the Indian IT industry and a specific demographic of IT professionals.

The present research applied the quantitative research design to empirically investigate the impact of AI-enabled sustainable HR practices on employees' performance in Indian IT companies. A questionnaire was used to collect the data. The questionnaire was made in standard form by adopting the validated scales from previous studies for the reliability and validity of the measuring instrument [20–22].

The survey contained questions for AI-based recruitment, training, performance appraisal, organizational sustainability orientation, employee empowerment, employee engagement, conscientiousness, and employee performance (Fig. 1). As this was an online survey, it could be widely shared geographically and was easy to participate in.

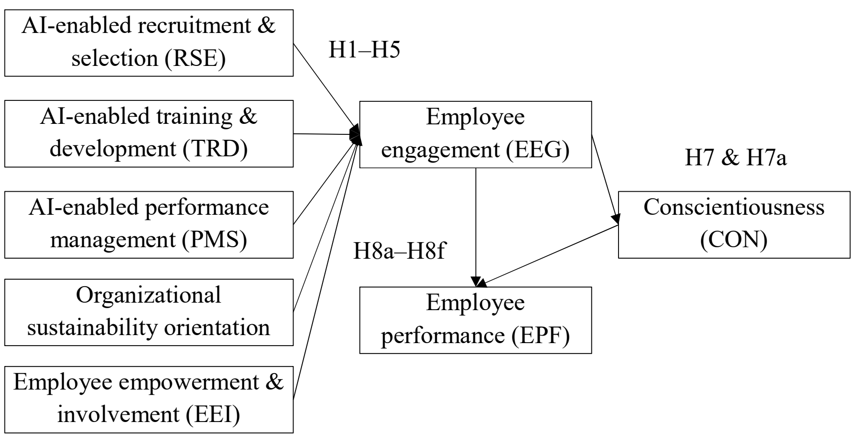

Fig. 1. Conceptual framework

A cross-sectional research design was implemented for gathering data at a particular point in time using the snowball sampling technique to reach out to the highly specialized population of IT professionals throughout India. Purposive sampling was employed, and initial participants were recruited through professional networks and posting on online forums, and were encouraged to notify other eligible participants as well as expand the sample size. The total sample consisted of 340 IT workers.

The multivariate relationships (including mediation and moderation effects) were shown simultaneously using the structural equation model (SEM) as an analysis tool. Confirmatory factor analysis (CFA) was used to test the construct validity and reliability of the measurement model. The goodness of fit of the models was assessed using the established fit indices, such as chi-square/degree of freedom (CMIN/DF), the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Mediation analysis was conducted following the bootstrapping method, which was complemented by the use of the bootstrapping approach to calculate the indirect effects more precisely. Let's also test the moderation by entering an interaction term between employee engagement and conscientiousness in the SEM. A series of common method variance and multicollinearity checks were performed for result robustness.

Statistical analysis was performed using AMOS as the former and latter software can simultaneously process complex latent variable models and offer an extensive model diagnostic.

This methodological approach will help in thorough testing of the hypothesized relationships, upon which it is based, thus contributing to high-quality and generalizable inferences with respect to AI-led sustainable HR practices in the Indian IT industry.

5. Results of AI-enabled sustainable HR practices on employee performance

5. 1. Exploratory factor analysis (EFA) & validity measures

Researchers conducted an EFA to assess their measurement scales' dimensionality and validity (Table 1). Researchers used principal component analysis with Varimax rotation to extract factors so each item loaded heavily on the target construct while ensuring minimal cross-loadings. Verifying discriminant validity across constructs demonstrated the measurement model's integrity according to established research standards.

Table 1

Quality criteria of the constructs

Latent variable	Item	Factor loading	Mean	Standard deviation	AVE	CR	α value
AI-enabled recruitment & selection (RSE)	RSE1	0.829	4.40	1.50	0.696	0.87	0.85
	RSE2	0.861	4.45	1.48			
	RSE3	0.813	4.42	1.52			
AI-enabled training & development (TRD)	TRD1	0.768	4.30	1.55	0.680	0.86	0.84
	TRD2	0.838	4.35	1.60			
	TRD3	0.865	4.38	1.57			
AI-enabled performance management (PMS)	PMS1	0.833	4.50	1.45	0.709	0.88	0.86
	PMS2	0.846	4.55	1.48			
	PMS3	0.846	4.53	1.46			
Organizational sustainability orientation (OSO)	OSO1	0.818	4.40	1.50	0.695	0.87	0.85
	OSO2	0.849	4.42	1.48			
	OSO3	0.833	4.41	1.49			
Employee empowerment & involvement (EEI)	EEI1	0.831	4.50	1.52	0.686	0.87	0.86
	EEI2	0.834	4.48	1.50			
	EEI3	0.820	4.46	1.53			
Employee engagement (EEG)	EEG1	0.841	4.60	1.45	0.714	0.88	0.87
	EEG2	0.863	4.63	1.44			
	EEG3	0.831	4.61	1.46			
Conscientiousness (CON)	CON1	0.784	4.30	1.50	0.715	0.88	0.87
	CON2	0.876	4.55	1.45			
	CON3	0.873	4.53	1.48			
Employee performance (EPF)	EPF1	0.739	4.70	1.50	0.610	0.82	0.81
	EPF2	0.793	4.72	1.47			
	EPF3	0.809	4.75	1.46			

The quality criteria of constructs in Table 1 were assessed using exploratory factor analysis (EFA), employing principal component analysis (PCA) with Varimax rotation to extract the factors. The factor loadings were calculated based on this method, with each item loading heavily on its respective construct. Average variance extracted (AVE) and composite reliability (CR) were used to test convergent validity, while Cronbach's alpha (α) was used to assess internal consistency and reliability. The values for these metrics all met the recommended thresholds, confirming the robustness of the measurement model.

The results in Tables 1, 2 were obtained through a series of statistical analyses. exploratory factor analysis (EFA) was conducted using principal component analysis (PCA) with varimax rotation to extract the factors. Confirmatory factor analysis (CFA) was performed to test the construct validity and fit of the measurement model. Factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach's Alpha (α) were all calculated based on the CFA results to assess the reliability and validity of the constructs.

Table 2

Convergent and discriminant validity

Cons	CR	AVE	MaXR (H)	RSE	TRD	PMS	OSO	EEI	EEG	CON
RSE	0.87	0.696	0.86	1.00	0.58	0.56	0.81	0.83	0.85	0.85
TRD	0.86	0.680	0.84	0.82	1.00	0.80	0.83	0.84	0.84	0.84
PMS	0.88	0.709	0.88	0.84	0.83	1.00	0.80	0.82	0.86	0.86
OSO	0.87	0.695	0.86	0.80	0.79	0.88	1.00	0.79	0.85	0.85
EEI	0.87	0.686	0.86	0.81	0.80	0.84	0.83	1.00	0.80	0.80
EEG	0.88	0.714	0.88	0.83	0.82	0.86	0.84	0.85	1.00	0.85
CON	0.88	0.715	0.88	0.80	0.81	0.85	0.82	0.83	0.87	1.00
EPF	0.82	0.610	0.82	0.78	0.77	0.80	0.79	0.78	0.80	0.79

The analysis of convergent and discriminant validity found strong support of discriminant and convergent validity of the constructs. The CR estimates for all constructs are well above the CR threshold of 0.7, indicating that the internal consistency is substantial. Average variance extracted (AVE) values are between 0.610 and 0.715, which establishes the convergent validity to be acceptable. The discriminant validity is established by the AVE square root of each construct (MaXR) being higher than the correlation between constructs, which do not exceed 0.90, confirming that all the latent variables are different from one another. These results indicate strong construct validity across the model.

5. 2. Model fit assessment

The evaluation of the model followed the measurement model development fit through various indices (Table 3). In this study, the measurement model fit is acceptable because the CMIN/DF value is 2.325.

The model fit statistics indicate a good fit for the model, but some indices are slightly below cut-off levels. CMIN/DF value of 2.325 lies between 1–3. The CFI (0.937), TLI (0.950), and NFI (0.940) suggest a strong fit to the model, with the CFI just below the cut-off figure of 0.95. The AGFI (0.890) is in the range of the acceptable minimum of 0.90, and the SRMR (0.042) and RMSEA (0.058) are both less than 0.05, suggesting a good fit. The PClose of 0.020 indicates a statistically significant difference

Table 3

Model fit indices

Parameter	Output	Threshold
CMIN/DF	2.325	Between 1 and 3
CFI	0.937	≥0.95
TLI	0.950	≥0.95
NFI	0.940	≥0.90
AGFI	0.890	≥0.90
SRMR	0.042	≥0.08
RMSEA	0.058	≥0.06
PClose	0.020	≥0.05

5. 3. Direct impact of AI-enabled sustainable HR practices on employee performance

To examine the direct effects, Structural equation modeling (SEM) was used, where path coefficients (β), t-values, and p-values were estimated using maximum likelihood estimation (MLE). The SEM analysis was performed using AMOS software. For mediation analysis, the bootstrapping method was applied with 5,000 samples and a 95% confidence interval to compute the indirect effects more precisely. The moderation analysis tested the interaction effect between employee engagement and conscientiousness by creating an interaction term and checking its significance. Model fit was assessed using fit indices like CFI, TLI, and RMSEA. The results of hypothesis testing on direct effects, including path coefficients and their significance, are presented in Table 4.

Table 4

Hypothesis testing – direct effects on employee performance (EPF)

Path	Coefficients (β)	t	p	Decision
EPF ← RSE	0.116	2.085	0.007	Accepted
EPF ← PMS	0.180	3.344	<0.001	Accepted
EPF ← TRD	0.204	3.690	<0.001	Accepted
EPF ← OSO	0.016	0.580	0.002	Accepted
EPF ← CON	0.182	3.386	<0.001	Accepted
EPF ← EEG	0.136	2.776	0.002	Accepted
EPF ← EEI	0.107	1.807	0.001	Accepted

Hypotheses testing on direct effect on EPF shows effects of independent variables on EPF with significant relationships. All relationships are statistically significant with p-values less than 0.05, thus providing strong evidence for theorized relationships.

The indirect effect from AI-mediated recruitment & selection (RSE) to EPF is significant ($\beta = 0.116$, $p = 0.007$), indicating that RSE leads to enhanced EPF. Likewise, the effects of AI-enabled PMS ($\beta = 0.180$, $p < 0.001$), AI-enabled TRD ($\beta = 0.204$, $p < 0.001$), and OSO ($\beta = 0.016$, $p = 0.002$) are all positive and statistically significant on EPF, hence, there is more support regarding the role played by these factors in enhancing employee performance.

Conscientiousness (CON) also significantly positively influences EPF ($\beta = 0.182$, $p < 0.001$), whereas employee engagement (EEG) ($\beta = 0.136$, $p = 0.002$) and employee empowerment & involvement (EEI) ($\beta = 0.107$, $p = 0.001$) have more moderate (yet significant) effects. In conclusion, the proposed model is supported by strong evidence from the model statistical information regarding the AI-enabled practices, personal traits, and engagement for enhancing employee performance, which adds to the stability of the model.

5. 4. Mediation role of employee engagement between ai-driven HR practices and performance

Mediation analysis is performed using bootstrapping to test the indirect effects of employee engagement on the relationship between AI-driven HR practices and employee performance. Table 5 summarizes the total, direct, and indirect effects along with significance values.

Then it is possible to assess the mediation effects in structural model using AMOS. Let's estimate the total, direct, and indirect effects through bootstrapping procedures (Table 5). Let's compute bootstrapped confidence intervals for the indirect effects, ensuring that the mediation paths were statistically significant. This SEM approach in AMOS allowed to verify model fit indices and confirm whether the mediator partially or fully transmitted the effects of the independent variables to the dependent variable. The mediation analysis thoroughly tested the hypothesized relationships.

Table 5

Indirect effects

Path	Total effect (β)	Sig.	Indirect effect (β)	Sig.	Direct effect (β)	Sig.	Mediation type
OSO → EPF	0.016	0.563	0.000	0.982	0.016	0.002	No mediation
TRD → EPF	0.196	0.004	–0.008	0.233	0.204	0.003	No mediation
EEI → EPF	0.155	0.019	0.049	0.025	0.107	0.002	Partial mediation
PMS → EPF	0.207	0.002	0.027	0.016	0.180	0.010	Partial mediation
RSE → EPF	0.162	0.024	0.047	0.025	0.116	0.007	Partial mediation
CON → EPF	0.200	0.000	0.019	0.044	0.182	0.001	Partial mediation
EEG → EPF	0.136	0.036	0.000	–	0.136	0.002	No mediation

Results of the analysis of indirect effects demonstrate the varying mediational strength in the links between predictors and EPF. In most paths, there are strong direct effects, but indirect effects and the type of mediation give more information about what is happening in the relations.

From OSO to EPF there is no mediating effect ($\beta = 0.016$, $p = 0.002$), as the total and direct effects are equal and significant. Similarly, there is no mediation along AI-enabled training & development (TRD) to EPF ($\beta = 0.196$, $p = 0.004$) as the indirect effect is negative, but not significant.

Employee empowerment & involvement (EEI) shows partial mediation ($\beta = 0.155$, $p = 0.019$) with a significant indirect effect ($\beta = 0.049$, $p = 0.025$), indicating that the relationship between EEI and EPF is partially mediated by other variables. Furthermore, AI-enabled performance management (PMS), AI-enabled recruitment & selection (RSE), and conscientiousness (CON) all reveal partial mediation, as they evidence significant indirect effects and direct effects (PMS: $\beta = 0.207$, $p = 0.002$; RSE: $\beta = 0.162$, $p = 0.024$; CON: $\beta = 0.200$, $p = 0.000$).

The route from EEG to EPF is not mediated, as the direct and the total effects are congruent ($t \neq 0$) and significant ($\beta = 0.136$, $p = 0.036$).

5. 5. Moderation effect of conscientiousness on the engagement-performance relationship

Moderation analysis was conducted to assess the interaction between employee engagement and conscientiousness in predicting employee performance. The results indicate a significant moderation effect as shown in Table 6. To explore how conscientiousness moderates the connection between employee engagement and performance, let's use AMOS combined with bootstrapping (5000 samples, 95% CI) for moderation analysis (Table 6). The analysis required to generate an interaction term between engagement and conscientiousness to examine its impact on performance. The bootstrapped confidence intervals for the interaction effect excluded zero, which supported statistical significance. The outcomes demonstrate that conscientiousness enhances the beneficial impact of engagement on performance.

Table 6

Moderation analysis – conscientiousness as a moderator on the EEG → EPF relationship

Path	Coefficient (β)	t-value	p-value	Decision
Interaction (employee engagement × conscientiousness) → employee performance	0.150	2.750	0.006	Accepted

The moderating role of conscientiousness: the moderation analysis aims to investigate the moderation effect of conscientiousness on the relationship between EEG and EPF. The interaction effect of employee Engagement and conscientiousness ($\beta = 0.150$, $t = 2.750$, $p = 0.006$) is significant, which suggests that Conscientiousness moderates the EEG → EPF relationship. The positive coefficient indicates that the greater a level of conscientiousness the stronger the drawing force between employee engagement and employee performance is, positively strengthening the effect of employee engagement in the performance outcomes.

The presence of a strong interaction effects offers compelling evidence for the moderation hypothesis and suggests that the effect of employee engagement on employee performance is moderated by individual differences in conscientiousness. This result underscores the role of personality in determining how employee engagement contributes to performance, and particularly the role of conscientiousness. Conscientious workers probably use their high self-motivation, sense of duty and goal-oriented behavior as resources in performing job tasks, and thus increase the effect of employee engagement.

6. Discussion: AI-enabled HR practices and employee performance in the Indian IT industry

This study strongly supports the relationship model of AI-based sustainable HR practices with employee performance in the Indian IT sector. The analysis conducted, including several validity and reliability checks, confirms the robustness of these findings. The results demonstrate significant positive effects of AI-driven HR practices on employee performance, with notable contributions from employee engagement as a mediator and conscientiousness as a moderator.

The results presented in Table 1 demonstrate that all the constructs in the study, including AI-driven HR practices, employee engagement, conscientiousness, and employee performance, show excellent reliability and validity. Specifically, the factor loadings, which exceed 0.7, indicate that all items measure their respective constructs well. The average variance extracted (AVE) values confirm convergent validity, with values ranging from 0.610 to 0.715, indicating that the constructs adequately explain the variance in their respective items. The composite reliability (CR) and Cronbach's Alpha (α) values are well above the threshold of 0.7, indicating internal consistency across the constructs. These results provide confidence in the robustness and reliability of the measurement model used in this study.

As shown in Table 2, the convergent validity is supported by the CR and AVE values, which all meet the recommended thresholds. Additionally, the discriminant validity is confirmed, as the square root of the AVE for each construct is greater than the correlations between the constructs, ensuring that the constructs are distinct from one another. This is crucial for ensuring that the AI-enabled HR practices, engagement, conscientiousness, and performance are accurately captured as separate but related constructs in the model.

In Table 3, the model fit indices demonstrate that the structural equation modeling (SEM) model fits the data well. The CMIN/DF value of 2.325 lies within the recommended range of 1 to 3, indicating an acceptable fit. Other indices, such as the CFI (0.937), TLI (0.950), NFI (0.940), and SRMR (0.042), all suggest a good fit, with only the CFI slightly below the recommended threshold of 0.95. The RMSEA value of 0.058, which is below the acceptable cutoff of 0.06, further confirms the model's adequacy. These indices together indicate that the hypothesized model adequately explains the relationships between AI HR practices and employee performance.

Table 4 provides strong evidence for the direct effects of AI-enabled HR practices on employee performance. The path coefficients for AI-driven recruitment and selection (RSE) ($\beta = 0.116$), performance management systems (PMS) ($\beta = 0.180$), and training and development (TRD) ($\beta = 0.204$) all demonstrate significant positive effects on employee performance. These results support the hypothesis that AI-enabled HR practices directly contribute to improving employee performance in the Indian IT sector. The finding that AI-driven practices have such a direct impact on performance highlights the critical role these technologies play in shaping employee outcomes.

Table 5 presents the results of the mediation analysis, revealing that employee engagement partially mediates the relationship between several AI-driven HR practices and employee performance. Specifically, the mediation effect is significant for employee empowerment and involvement (EEI) ($\beta = 0.049$, $p = 0.025$), performance management (PMS) ($\beta = 0.027$, $p = 0.016$), and recruitment and selection (RSE) ($\beta = 0.047$, $p = 0.025$). This indicates that employee engagement plays a crucial role in enhancing the effect of AI HR practices on performance. The partial mediation effect suggests that while engagement enhances the impact of AI practices, other factors may also contribute to improving performance outcomes.

Finally, the moderation analysis in Table 6 reveals that conscientiousness significantly moderates the relationship between employee engagement and performance ($\beta = 0.150$, $t = 2.750$, $p = 0.006$). This suggests that individuals with higher levels of conscientiousness benefit more from engagement in terms of their performance outcomes. Conscientious employees, who are characterized by their diligence and goal-oriented behavior, likely use their personal resources more effectively to perform tasks, thereby amplifying the positive effects of engagement on their performance.

This study contributes valuable insights into how AI-based HR practices affect employee performance in the Indian IT sector. The results suggest that AI HR practices influence performance both directly and indirectly, through employee engagement. The partial mediation of engagement in Table 5 extends the Job Demands-Resources (JD-R) model by demonstrating the psychological mechanisms through which AI HR practices enhance employee outcomes. The dual role of AI HR practices, both as direct influencers and as enablers of engagement, provides a deeper understanding of their effectiveness. Additionally, the moderating role of conscientiousness highlights the importance of personality traits in optimizing the impact of AI HR practices on performance.

The findings of this study provide substantial evidence for the effectiveness of AI-enabled HR practices in improving employee performance within the rapidly evolving Indian IT industry. Specifically, Table 4 highlights the significant direct effects of AI-enabled recruitment, performance management, and training on performance. What makes these effects even more powerful is the mediating role of employee engagement and the moderating role of conscientiousness, as further explored in Tables 5 and 6.

The study extends the JD-R model by showing that engagement not only serves as a mediator but also helps convert AI-driven interventions into tangible employee outcomes. The dual role of AI HR practices – both as direct drivers of performance and as enablers of engagement provides a nuanced understanding of how AI HR systems can improve productivity. This finding has important implications for HR practitioners, who can enhance AI HR practices by focusing on fostering employee engagement and recognizing the importance of individual personality traits like conscientiousness.

This study offers several advantages over previous research. One of the primary contributions is the introduction of conscientiousness as a moderating factor in understanding the relationship between employee engagement and employee performance in the context of AI-driven HR practices. While previous studies have explored various HRM practices, the role of personality traits in moderating the effects of these practices has largely been overlooked, especially in the context of the Indian IT sector. This research provides new insights into how individual personality traits, particularly conscientiousness, enhance the relationship between engagement and performance.

Prior studies have primarily focused on the technological and organizational dimensions of AI-driven HR practices (e.g., AI recruitment, performance management) and their direct impact on performance. For instance, the direct effect of AI recruitment tools on employee outcomes [23], while the role of AI in streamlining performance management processes [24]. However, these studies have not fully integrated psychological factors such as employee engagement and personality traits into the analysis.

In contrast, this study brings conscientiousness into the equation, offering a psychological perspective that adds depth to the understanding of AI HR practices. By incorporating both the mediation of employee engagement and the moderation of conscientiousness, this research presents a more comprehensive view of the factors influencing employee performance in the rapidly evolving IT sector. These contributions are in line with the eudaimonic model of engagement, which emphasizes well-being, motivation, and personal growth, extending it to the AI-driven workplace.

Moreover, the dual role of AI practices in this study both as direct drivers of performance and as enablers of engagement aligns with findings on the importance of engagement in mediating the effects of organizational practices but adds new value by integrating conscientiousness into this framework [25]. The moderating effect of conscientiousness found in this study is consistent with the Big Five Personality Model, which has shown that conscientious individuals exhibit higher work engagement and better performance outcomes [26].

This study's integration of both mediation (employee engagement) and moderation (conscientiousness) perspectives into a single model provides a more nuanced understanding of employee performance. While previous research has largely focused on technological or organizational aspects of HRM, this research highlights the psychological value of incorporating personality traits and employee engagement into AI HR models.

The findings of this study challenge and extend prior research by showing that AI HR practices are not only effective because they automate and streamline HR processes but also because they engage employees and are more impactful for individuals with high levels of conscientiousness. These results help to bridge the gap between technology and human-centered organizational values, making a compelling case for incorporating both personality traits and engagement in future AI HR research.

While the findings of this study contribute valuable insights, several limitations must be acknowledged. First, the study's sample is limited to Indian IT professionals, which may limit the generalizability of the results to other sectors or geographic regions. Future research should explore the applicability of these findings in different industries or countries with diverse cultural and organizational contexts. Additionally, the study primarily focused on conscientiousness as a moderating factor; other personality traits, such as emotional stability or openness to experience, could also play a significant role in shaping responses to AI-driven HR practices and should be examined in future studies.

Another limitation is the cross-sectional design of the study, which limits the ability to draw conclusions about causality. Longitudinal studies could provide more robust insights into the long-term effects of AI-enabled HR practices on employee performance and engagement.

The primary disadvantage of the study lies in the simplification of the HR practices analyzed. By focusing only on four key HR practices (recruitment, training, performance management, and employee empowerment), the study overlooks other potentially impactful HR practices that could also influence employee performance. Future research should explore the broader range of AI-enabled HR practices and their collective impact on performance outcomes.

Building on the findings of this study, future research should expand the scope to include a more diverse range of AI-driven HR practices, personality traits, and contextual variables. Exploring additional sectors, such as manufacturing or healthcare, could provide a more comprehensive understanding of how AI technologies can be leveraged to improve performance across industries. Additionally, future studies should investigate the long-term effects of AI-enabled HR practices on employee performance and engagement, and consider the role of organizational culture in moderating these relationships.

7. Conclusions

1. The construct validity of the measurement scales for AI-based HR practices, employee engagement, conscientiousness, and employee performance was rigorously established through Exploratory factor analysis (EFA). Convergent and discriminant validity were confirmed, with factor loadings ranging from 0.768 to 0.876, composite reliability (CR) values exceeding 0.86, and average variance extracted (AVE) ranging from 0.610 to 0.715. These validations ensure that the constructs of AI-supported sustainable HR practices and employee outcomes are measured accurately and reliably. These results were quantitatively validated, confirming that the measurement scales are robust and reliable.

2. The goodness of fit for the final structural equation modeling (SEM) model demonstrated that the model adequately explains the effects of AI-driven HR practices on employee performance. The CFI was 0.937, the TLI was 0.950, and the RMSEA was 0.058, all within acceptable fit indices, indicating a strong model fit. These indices demonstrate that the SEM model accurately represents the relationships among AI HR practices, employee engagement, conscientiousness, and employee performance, validating the appropriateness of the SEM approach for this research.

3. The direct effects of AI-based recruitment & selection, training & development, performance management, organizational sustainability orientation, and employee empowerment on employee performance were found to be significantly positive. Specifically:

– Recruitment & selection (RSE): $\beta = 0.116$, $p = 0.007$;

– Performance management systems (PMS): $\beta = 0.180$, $p < 0.001$;

– Training & development (TRD): $\beta = 0.204$, $p < 0.001$;

– Employee empowerment & involvement (EEI): $\beta = 0.107$, $p = 0.001$;

– Organizational sustainability orientation (OSO): $\beta = 0.016$, $p = 0.002$.

These results support the hypothesis that AI-enabled HR practices directly enhance employee productivity in the Indian IT industry, confirming that each of these HR practices positively contributes to employee performance.

4. Employee engagement was found to mediate the relationship between AI-based HR practices and employee performance. The mediation effect further supports and extends the job demands-resources (JD-R) model, positioning engagement as a psychological process that enables the positive influence of AI HR interventions on performance outcomes. For instance:

– Employee empowerment (EEI): Indirect effect $\beta = 0.049$, $p = 0.025$;

– Performance management systems (PMS): indirect effect $\beta = 0.027$, $p = 0.016$;

– Recruitment & selection (RSE): indirect effect $\beta = 0.047$, $p = 0.025$.

These findings underscore the importance of fostering employee engagement as part of AI-based HR practices to improve employee performance. The mediation effect suggests that engagement enhances the impact of AI-driven HR practices on employee outcomes, consistent with the JD-R model.

5. The study found that conscientiousness significantly moderates the relationship between employee engagement and employee performance. The moderation analysis showed that the positive link between engagement and performance was stronger among employees with higher levels of conscientiousness. Specifically, the interaction term for engagement × conscientiousness was signifi-

cant (β = 0.150, $p = 0.006$). This suggests that individual personality traits, particularly conscientiousness, play a crucial role in shaping how employees respond to AI-driven HR interventions. It highlights the importance of considering individual differences in HR strategy design, ensuring that HR practices cater to various personality traits to maximize performance.

Conflict of interest

The authors declare that they have no conflict of interest related to this study, whether financial, personal, authorship, or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their verified data, described in the research methodology section.

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