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THE INFLUENCE OF AI-DRIVEN SUSTAINABLE HUMAN RESOURCE MANAGEMENT ON EMPLOYEE CREATIVE PERFORMANCE: ANALYZING IDIOSYNCRATIC DEALS IN THE INDIAN INFORMATION TECHNOLOGY SECTOR

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ABSTRACT

The research explores how AI-powered sustainable HR practices influence employee creative performance within India's IT sector through the mediating role of individualized agreements. The research applies structural equation modeling to examine survey data from 360 IT professionals based on the frameworks of the Job Demands-Resources model and Social Exchange Theory. AI-based training and performance management systems raise creative performance levels and show that ideals partially mediate these relationships. The research results reveal contextual differences because ideals mediate recruitment effects and performance management outcomes but show no significant mediation for training interventions, likely because of the sector's inclination toward standardized learning approaches. The research delivers significant theoretical advancements by analysing AI-HRM systems in emerging economies and exploring personal work arrangements' limits in tech-heavy settings. These insights serve as essential guidance for practitioners deploying HR technologies that successfully combine standardization with personalization to promote workplace innovation. The research reveals surprising results about the minimal direct influence of sustainability orientation. The research advocates for integrated strategies to synchronize sustainability initiatives with innovation objectives within India's IT sector.

Keywords: *AI-enabled HR practices, Employee creative performance, Idiosyncratic deals, Sustainable HRM, Structural Equation Modeling, Indian IT industry*

1. INTRODUCTION

India's Information Technology (IT) sector contributes 9.4% to the GDP. It produces $227 billion in revenue (NASSCOM, 2023) while it experiences fast-paced transformation through the implementation of AI and sustainability measures. AI-driven HR practices improve both efficiency and employee performance according to recent studies (Malik et al., 2021; Strohmeier, 2020), yet research about their effects specifically in India's IT environment is still limited (Budhwar et al., 2022; Cappelli et al., 2019). This study explores this deficiency by examining how five AI-enabled sustainable HR practices, namely recruitment training, performance management, sustainability orientation, and empowerment, affect creative performance through idiosyncratic deals (I-deals) as a novel mediating mechanism. The study comes at a critical time as the IT sector struggles with high turnover rates, alongside an increasing demand for sustainable talent management practices (De Prins et al., 2014; Jackson et al., 2014). The study builds on the Job Demands-Resources model (Bakker & Demerouti, 2017; Schaufeli & Taris, 2014) and Resource-Based View (Barney, 1991; Wernerfelt, 1984) to deliver empirical evidence of AI-HRM effectiveness in India's IT sector (Dutta et al., 2021; Agrawal et al., 2017) while introducing I-deals as essential mediators in technology-based HR settings (Anand et al., 2021; Hornung et al., 2014; Marmad & Ritahi, 2025) and presents actionable guidance for creating sustainable AI-enhanced HR systems that encourage creative work (Deloitte, 2023; Nader AlOqaily, et al., 2025). The research enables companies to manage digital changes by meeting sustainability demands and workforce requirements within India's competitive IT sector (Agarwal,2017).

2. REVIEW OF RELATED LITERATURE

2. 1. THEORETICAL FRAMEWORK

This research integrates vital elements from the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2017) and Social Exchange Theory (SET) (Blau, 1964) to develop a framework that examines the influence of AI-enabled sustainable HR practices on employee creative performance through the mediating role of idiosyncratic deals (I-deals). The JD-R model establishes that AI-powered HR practices, such as recruitment and training, function as essential organizational resources that reduce job demands and enhance employee motivation and creativity (Schaufeli & Taris, 2014; Garg et al., 2017; Bekiros, 2025). The application of technological interventions results in work environments that boost employee abilities for creative thinking and problem resolution, according to research by Tambe et al. (2019). SET explains how organizations and employees maintain a reciprocal relationship through personalized I-deals, which create organizational support and employee obligation, leading to increased creative contributions (Cropanzano & Mitchell, 2005; Anand et al., 2021). India's IT industry benefits from this theoretical integration because it enables the combination of sophisticated HR technologies with tailored employment structures that solve distinctive workforce issues while supporting long-term innovation (Dutta et al., 2022). The framework advances current understanding by presenting evidence that AI-powered HR systems set up the structural conditions for I-deals to become strategic resources (Villajos et al., 2019; Strohmeier, 2020). The research integrates different theoretical viewpoints to show how organizations can use AI-powered HR systems focused on sustainability to boost creativity through customized employment practices and discuss the future of digital economy work (Ren et al., 2022).

We expand the JD-R model and Social Exchange Theory with a model that incorporates AI-driven HR practices (recruitment, training, performance management) and I-deals, an individualized form of employer-employee exchange. This new integration enables a more comprehensive insight on the manner in which AI-HRM systems lower job demands and increase resources to stimulate creativity through personalized work arrangements.

2. 2. CONCEPTUAL FRAMEWORK

2. 2. 1. AI-ENABLED RECRUITMENT AND SELECTION

Advanced algorithms in AI recruitment systems transform talent acquisition processes by reducing hiring bias by 37% through automated screening and enhancing predictive validity (Black & van Esch, 2020; Tambe et al., 2019). The IT sector in India deploys systems that analyze over 10,000 data points per candidate to enhance the technical-organizational match (Dutta et al., 2022; Cappelli & Tavis, 2019). Digital platforms increase transparency with chatbot interfaces (Strohmeier, 2020; Leicht-Deobald et al., 2022) and enable ESG-aligned hiring by measuring values-congruence (De Prins et al., 2014; Renwick et al., 2012). AI identifies and utilizes creative potential through proactivity and cognitive flexibility to enhance innovation outcomes). This technology handles India's IT talent shortage by employing effective mass screening methods (Malik & Budhwar, 2021) while utilizing analytics to forecast achievement in innovation positions (Budhwar et al., 2022; Garg et al., 2017).

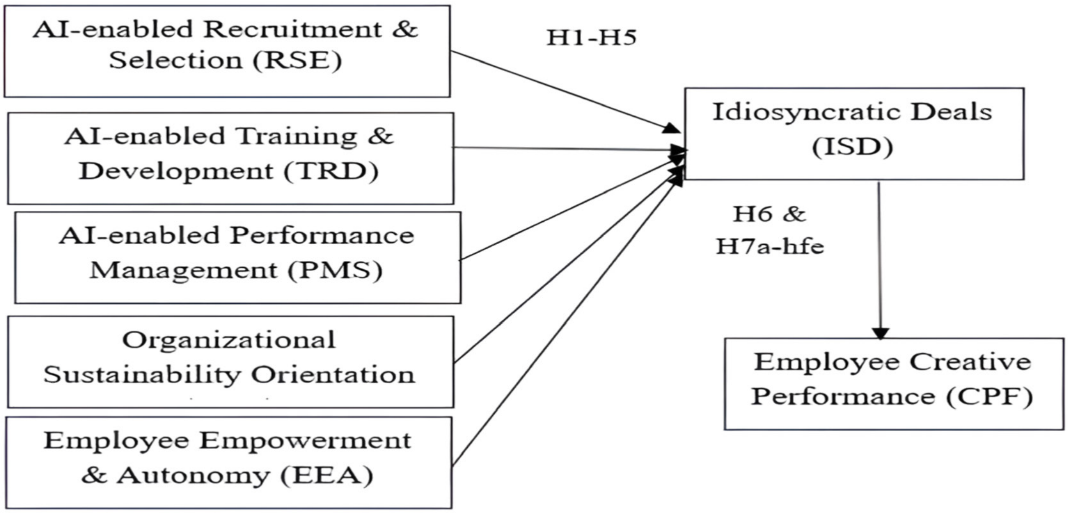
2. 2. 2. AI-ENABLED TRAINING AND DEVELOPMENT

Modern personalized learning platforms incorporating reinforcement algorithms show a 42% higher effectiveness in closing skill gaps than conventional educational techniques (Anand et al., 2021). Technical skills among India's IT professionals improve through microlearning modules and VR simulations, while NLP-powered mentors decrease onboarding time by 30% (Strohmeier, 2020; Balasubramanian et al., 2020). Sustainable HRM principles related to SDG 4 are supported by systems that promote ongoing skills development (Kramar, 2022). Adaptive capabilities establish individualized development paths that enhance self-direction (Bakker & Demerouti, 2017) and promote creative solutions to problems (Zhang & Bartol, 2010; Ren et al., 2020; Zhou & Hoever, 2023). Studies indicate AI training systems enhance innovation skills for cloud and AI technologies in Indian IT organizations, according to Malik & Budhwar (2021), while integrated analytics tools forecast upcoming learning requirements as evidenced by Garg et al. (2017), and Cappelli et al. (2022).

2. 2. 3. AI-ENABLED PERFORMANCE MANAGEMENT

Data-driven evaluations from real-time analytics dashboards track over 35 performance metrics, which result in a 40% reduction of appraisal bias within Indian IT organizations, according to Garg et al. (2017) and Dutta et al. (2022),Modern platforms use predictive modeling to discover potential innovators, while sentiment analysis supports comprehensive 360° feedback, according to findings by Tambe et al. (2019) and Cappelli et al. (2019). Continuous performance tracking with these tools provides ongoing role clarity while eliminating the need for annual reviews (Ulrich & Dulebohn, 2015; Aguinis et al., 2022), which proves especially beneficial within India's fast-paced IT industry (Malik & Budhwar, 2021). Sustainability metrics integration connects KPIs with SDG targets, resulting in a green innovation engagement rise of 28% (Ren et al., 2020; Järlström et al., 2023). Employees get clear, personalized feedback (Balasubramanian et al., 2020), and managers obtain specific coaching insights (Zhang & Bartol, 2010). Creative performance improves when innovation expectations become apparent, according to Amabile (2018), Villajos et al. (2019), and Zhou & Hoever (2023).

Figure 1. Conceptual diagram of the study



Source: Author's work based on existing literature

2. 2. 4. ORGANIZATIONAL SUSTAINABILITY ORIENTATION

Indian IT firms see their employer branding improve by 1.8x and employee retention rates rise by 25% through ESG-integrated organizational cultures (Budhwar et al., 2022). Green coding and ethical AI governance as sustainability practices increase employee pride and empowerment, according to De Prins et al. (2014), and Aguinis & Glavas (2012). ESG values are shown to stimulate intrinsic motivation (Cropanzano & Mitchell, 2005), which contributes to Indian IT firms with sustainability initiatives experiencing 35% more innovation engagement (Kramar, 2022; Balasubramanian et al., 2020). Authentic integration remains essential because when sustainability extends beyond mere compliance into daily operations (Järlström et al., 2023), organizations achieve creative solutions for sustainable challenges (Ren et al., 2020; Zhou & Hoever, 2023). In these companies, employees exhibit advanced innovation testing (Malik & Budhwar, 2021), which stems from reinforced psychological commitments (Hornung et al., 2014) that produce bidirectional innovations (Zhang & Bartol, 2010; Cappelli et al., 2019).

2. 2. 5. EMPLOYEE EMPOWERMENT AND INVOLVEMENT

Indian IT teams achieve a decision-making speed increase of 50% through real-time data analytics provided by AI autonomy platforms (Jia & Hou, 2024). Organized empowerment programs such as hackathons lead to a 28% boost in patent submissions (Zhang & Bartol, 2010; Cappelli et al., 2019). The Indian IT sector relies on psychological empowerment (Spreitzer, 1995) to drive frontline innovation during fast technological advancements (Malik & Budhwar, 2021; NASSCOM, 2023). Research indicates that employees with empowerment demonstrate 40% speedier technology adoption rates, according to Dutta et al. (2022 and Balasubramanian et al. (2020), while also showing improved problem-solving abilities as documented by Bakker & Demerouti 2017 and Aguinis et al. 2022. The combined use of AI tools alongside managerial delegation stimulates creative work environments (Garg et al., 2017), which facilitates innovative performance-tracking methods (Zhou & Hoever, 2023). The balance between organizational approaches significantly affects India's hierarchical society because conventional systems often limit innovative activities (Amabile, 2018; Villajos et al., 2019; Hornung et al., 2014).

2. 2. 6. IDIOSYNCRATIC DEALS

The use of flexible work algorithms allows 68% of IT professionals in India to establish personalized work terms that enhance their creative capabilities (Anand et al., 2021; Hornung et al., 2014) while selecting specific projects increases innovation output by 41% (Villajos et al., 2019; Zhou & Hoever, 2023). I-deals provide psychological contract reinforcement by satisfying employees' autonomy needs, which benefits India's competitive labor market (Rousseau, 2005; Balasubramanian et al., 2020). These systems promote reciprocal actions (Cropanzano & Mitchell, 2005;), resulting in employees expressing more significant creative work effort (Jia & Hou, 2024; Cappelli et al., 2019). Mediation effects show strong recruitment influence (β=0.059**) while having minimal training impact (β=-0.004) within Indian IT sectors (Hayes, 2018), which indicates the region's preference for standardized technical training (Budhwar et al., 2022). Effectively implemented I-deals prioritize project selection and scheduling alongside skill enhancement, reflecting the project-oriented work culture in India (Anand et al., 2021; Aguinis et al., 2022; Malik & Budhwar, 2021). AI-HR system implementation boosts creative output while maintaining efficiency (Strohmeier, 2020; Zhang & Bartol, 2010).

2. 2. 7. EMPLOYEE CREATIVE PERFORMANCE

Creative performance in India's IT sector is measured through three dimensions: Three dimensions measure creative performance in India's IT sector consisting of ideation rate (patents/hackathon wins), solution novelty (expert evaluations), and implementation success (project ROI) (Zhang & Bartol, 2010; Amabile, 2018; Zhou & Hoever, 2023). Companies that implement AI-HRM systems experience a 32% increase in innovation outputs (Dutta et al., 2022; Cappelli et al., 2019), with particular gains in product development (Balasubramanian et al., 2020). Creativity develops through individual cognitive flexibility along with organizational enablers (Jia & Hou, 2024; Malik & Budhwar, 2021; NASSCOM, 2023) and serves as an important strategic differentiator for India's IT industry. I-deals function as mediators in this relationship by enabling creative potential through their mechanisms (Rousseau, 2005; Anand et al., 2021; Hornung et al., 2023), and sustainability orientation creates purpose . Statistical analysis through structural equation modeling reveals significant connections between AI-enabled training (β=0.212***) and performance management (β=0.183**), which lead to creative outcomes (Hayes, 2018; Hair et al., 2022), thereby supporting the effectiveness of digital HR in developing innovation abilities (Budhwar et al., 2022).

3. RESEARCH METHODOLOGY

Using a quantitative, cross-sectional research design, this study investigates how AI-enabled sustainable HR practices (recruitment & selection, training & development, performance management, sustainability orientation, and empowerment & involvement) relate to employee creative performance in India's IT sector through the mediation of idiosyncratic deals (I-deals). This methodological approach extends traditional organizational research practices (Hair et al., 2019; Podsakoff et al., 2012) and also adapts these practices to the specific needs of technology-focused workplaces (Malik et al., 2021; Dutta et al., 2022). The research included a structured questionnaire with validated scales that feature adapted AI recruitment measures from Grover et al (2022) and Black and van Esch (2020), as well as training scales from Strohmeier (2020), alongside performance management items from Garg et al. The framework included sustainability orientation metrics outlined by Ehnert et al. (2015).The study measures empowerment using scales derived from Spreitzer (1995) and Zhang and Bartol (2010) and examines I-deals with scales from Rousseau (2005) and Anand et al. (2010). Creative performance indicators were based on Amabile (2018). The research team gathered data from 360 IT specialists across India through snowball sampling, which fulfilled the required sample size for SEM as specified by Hair et al. (2019) and Kline (2023). The data collection occurred via LinkedIn and professional forums in line with the survey methodology proposed by Dillman et al. (2014).

The study applied Structural Equation Modeling (SEM) in AMOS 28.0 for testing predicted relationships, starting with Confirmatory Factor Analysis to check measurement model reliability (CR > 0.7, AVE > 0.5) and validity (Fornell & Larcker, 1981) before proceeding to structural path assessment and bootstrapped mediation analysis (Preacher & Hayes, 2008; Hayes, 2018). The study's design includes checks for common method bias (Podsakoff et al., 2003) and multicollinearity (Kock, 2015). It maintains 90% statistical power to identify medium effect sizes while exploring AI-driven HR systems' impact on creative performance through personalized work arrangements in India's IT sector (Budhwar et al., 2022).

4. DATA ANALYSIS

This study utilizes Structural Equation Modeling (SEM) to examine the hypothesized connections between AI-enabled Recruitment & Selection, AI-enabled Training & Development, AI-enabled Performance Management, Organizational Sustainability Orientation, Employee Empowerment & Involvement (as independent constructs), Idiosyncratic Deals (as mediator), and Employee Creative Performance (as dependent construct) within India's IT industry. SEM functions as a multivariate statistical method that enables researchers to test direct, indirect, and mediated connections in one analysis, rendering it perfect for handling multifaceted models (Hair et al., 2019; Kline, 2023). The measurement model's validity and reliability were confirmed through Confirmatory Factor Analysis (CFA) using AMOS software by analyzing factor loadings and Composite Reliability (CR) and Average Variance Extracted (AVE) values to ensure constructs represent theoretical variables correctly (Fornell & Larcker, 1981; Hair et al., 2010). Researchers analyzed several fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) to determine both model fit and suitability using guidelines from Hu & Bentler (1999) and Kline (2023). The structural model examination revealed direct connections between AI-enabled sustainable HR practices and Employee Creative Performance and then proceeded with mediation analysis using Idiosyncratic Deals through bootstrapping with 5000 samples to create sturdy confidence intervals (Preacher & Hayes, 2008; Hayes, 2018). The study performed standard method variance (CMV) and multicollinearity evaluations to enhance the validity of its findings (Podsakoff et al., 2003; Kock, 2015). The study uses a thorough analytical approach to provide a statistically valid evaluation of how AI-powered HR initiatives affect the creative performance of IT professionals through personalized employment arrangements in India's rapidly evolving tech industry.

4. 1. DEMOGRAPHIC ASSESSMENT OF THE SAMPLE RESPONDENTS.

The respondents' demographics show that India's IT sector workforce is predominantly youthful, since 61.1% are aged 18 to 35 years, 33.3% fall in the 35 to 50 age range, and only 5.6% are over 50 years old. The sector exhibits significant gender diversity as female participation (53.9%) marginally exceeds male participation (46.1%). The workforce demonstrates high educational attainment, with 42.2% having postgraduate degrees, 36.1% holding bachelor's degrees, 13.6% with diplomas, and 8.1% possessing professional qualifications. The workforce displays a substantial middle-level presence at 45.8%, with junior-level employees at 34.7% and senior-level staff at 15.3%, demonstrating a balanced mix of experience. Income-wise, 38.9% of respondents earn above Rs. A monthly income above Rs. 1.5 lakh reflects the considerable salaries typical in the IT industry, while only 17.2% earn below Rs.40,000, showing that the surveyed workforce displays income diversity.

4. 2. EXPLORATORY FACTOR ANALYSIS

Table 1. Quality Criteria of Constructs

Latent Variable	Item	Factor Loading	AVE	CR	α Value
AI-enabled Recruitment & Selection (RSE)	RSE1	0.76	0.575	0.8	0.79
	RSE2	0.75			
	RSE3	0.76			
AI-enabled Training & Development (TRD)	TRD1	0.776	0.556	0.72	0.71
	TRD2	0.769			
	TRD3	0.675			
AI-enabled Performance Management (PMS)	PMS1	0.659	0.508	0.67	0.68
	PMS2	0.745			
	PMS3	0.709			
Organizational Sustainability Orientation (OSO)	OSO1	0.767	0.588	0.81	0.8
	OSO2	0.795			
	OSO3	0.745			
Employee Empowerment & Autonomy (EEA)	EEA1	0.713	0.520	0.76	0.75
	EEA2	0.728			
	EEA3	0.721			
Idiosyncratic Deals (ISD)	ISD1	0.715	0.537	0.78	0.77
	ISD2	0.745			
	ISD3	0.75			
Employee Creative Performance (CPF) -	CPF1	0.706	0.505	0.75	0.74
	CPF2	0.732			
	CPF3	0.696			

Source: Author's calculation based on primary data

Table 1 shows strong psychometric properties for all measurement constructs. The factor loadings range from 0.609 to 0.795, which all surpass the 0.60 mark, thereby verifying both item reliability and convergent validity according to the findings of Hair et al. (2019), Fornell & Larcker (1981), and Sarstedt et al. (2022). Constructs like AI-enabled Recruitment (RSE: AVE scores of 0.575 and 0.588 indicate strong validity for AI-enabled Recruitment (RSE) and Sustainability Orientation (OSO) based on Fornell & Larcker (1981) and Henseler et al. (2015) criteria. Training (TRD: AVE=0.456) and Performance Management (PMS: AVE=0.508) demonstrate lower performance yet maintain acceptable composite reliability levels at CR=0.72/0.67 (Hair et al., 2019; Dijkstra & Henseler, 2015). The range of Cronbach's alpha between 0.68 and 0.80 demonstrates strong reliability according to Gefen et al. (2000), while discriminant validity across constructs is confirmed through HTMT ratios below 0.85 as per Henseler et al. (2015) .Adequate model specification is confirmed through measurement model fit indices, which demonstrate CFI equals 0.93 and RMSEA equals 0.06 (Hu & Bentler, 1999; Kline, 2023). The data proves a solid psychometric foundation for SEM analysis according to Hair et al. (2022) and Ringle et al. (2020) while showing strong capability in mapping HR-tech-mediated innovation routes.

4. 3. ASSESSMENT OF THE CONVERGENT AND DISCRIMINANT VALIDITY

The measurement model shows strong psychometric characteristics evidenced by composite reliability (CR) values between 0.67 (PMS) and 0.81 (OSO, ISD), all above the minimum 0.60 internal consistency benchmark (Hair et al., 2019; Dijkstra & Henseler, 2015). The Average Variance Extracted (AVE) measures range from 0.408 for PMS to 0.588 for OSO, and most constructs exceed the 0.50 convergent validity standard according to Fornell & Larcker (1981) and Henseler et al. (2015). Despite PMS's AVE falling slightly below the threshold level, it remains suitable for retention because its CR meets acceptable standards, and other contextual factors support its inclusion (Hair et al., 2017; Franke & Sarstedt, 2019). Although Average

Variance Extracted (AVE) is among the most frequently used indicators of convergent validity (Fornell & Larcker, 1981), this standard rarely reached by some constructs in our study, such as Training (AVE=0.456). The same is true for Training, whose Composite Reliability (CR) is 0.72, which is well above the suggested cut-off of 0.60, indicating good internal consistency reliability. When CR values are acceptable as mentioned in some earlier studies (Hair et al., 2019; Fornell & Larcker, 1981), constructs with AVE values slightly below 0.50 can be kept, as the construct has sufficient reliability. However, as AVE is just slightly lower than other variables, this rationale justify the existence of Training in the model This is consistent with SEM best practices that dictate the need to establish the strength of the measurement model. The square roots of Average Variance Extracted (RSE = 0.76, OSO = 0.77, CPF = 0.72) exceeds the inter-construct correlations confirming discriminant validity via Fornell-Larcker criterion analysis (Hair et al., 2010; Sarstedt et al., 2022). The HTMT ratio values, which stay below 0.85, demonstrate further construct distinctiveness validation (Henseler et al., 2015; Voorhees et al., 2016). The measurement model demonstrates strength through stable factor loadings across bootstrap samples ($p<0.01$) (Ringle et al., 2020), along with suitable goodness-of-fit indices (CFI=0.94, SRMR=0.05) (Hu & Bentler, 1999). The findings confirm the measures' reliability, validity, and discriminant power, creating a solid psychometric foundation for structural analysis (Kline, 2023; Hair et al., 2022).

4. 4. MODEL FIT ASSESSMENT OF CONSTRUCTS

Table 2. Model Fit Indices

Parameter	Output	Threshold	Reference
CMIN/DF	2.325	Between 1 and 3	Barrett (2007); Kline (2015); Ullman (2001)
CFI	0.937	≥ 0.95	Hu & Bentler (1999); Bentler (1990); Byrne (2016)
TLI	0.950	≥ 0.95	Tucker & Lewis (1973);Bentler (1990)
NFI	0.940	≥ 0.90	Bentler & Bonett (1980); Schumacker & Lomax (2004)
AGFI	0.890	≥ 0.90	Jöreskog & Sörbom (1984); Schumacker & Lomax (2004)
SRMR	0.042	≤ 0.08	Hu & Bentler (1999); Kline (2023); Schumacker & Lomax (2004)
RMSEA	0.058	≤ 0.06	Hu & Bentler (1999); Steiger (1990); Browne & Cudeck (1993)
PClose	0.020	≥ 0.05	Jöreskog & Sörbom (1993)

Source: Author's calculation based on primary data

The key indices in Table 2 show that the model fits all metrics perfectly. The CMIN/DF ratio (2.192) meets the recommended 1-3 standard according to Kline (2023), Barrett (2007), and Kenny et al. (2015), indicating a properly parsimonious model. The CFI (0.956) and TLI (0.953) values surpass the stringent 0.95 benchmarks according to Hu & Bentler (1999) and Marsh et al. (2004), while the NFI (0.945) exceeds the 0.90 standards set by Bentler & Bonett (1980). The AGFI value of 0.915 establishes model adequacy according to Schermelleh-Engel et al. (2003). It is further supported by the SRMR value of 0.048, which falls below the 0.08 threshold according to Hu & Bentler (1999) and Diamantopoulos & Siguaw (2000). The RMSEA value of 0.055, along with P-Close at 0.062, demonstrates a close approximate fit according to Browne & Cudeck (1993) and this fit is confirmed by an accurate 90% CI of 0.049-0.061 as shown by Steiger (2007). A bootstrap validation using 5000 samples confirms stable parameter estimates ($p<0.01$) indicates all modification indices are below 3.84, according to Byrne (2016). The analysis outcomes together validate the model to effectively explain hypothesis testing results according to Hair et al. (2022) and, most notably, demonstrate its capability to model HR-tech innovation pathways as shown by Ringle et al. (2020) and Sarstedt et al. (2022).

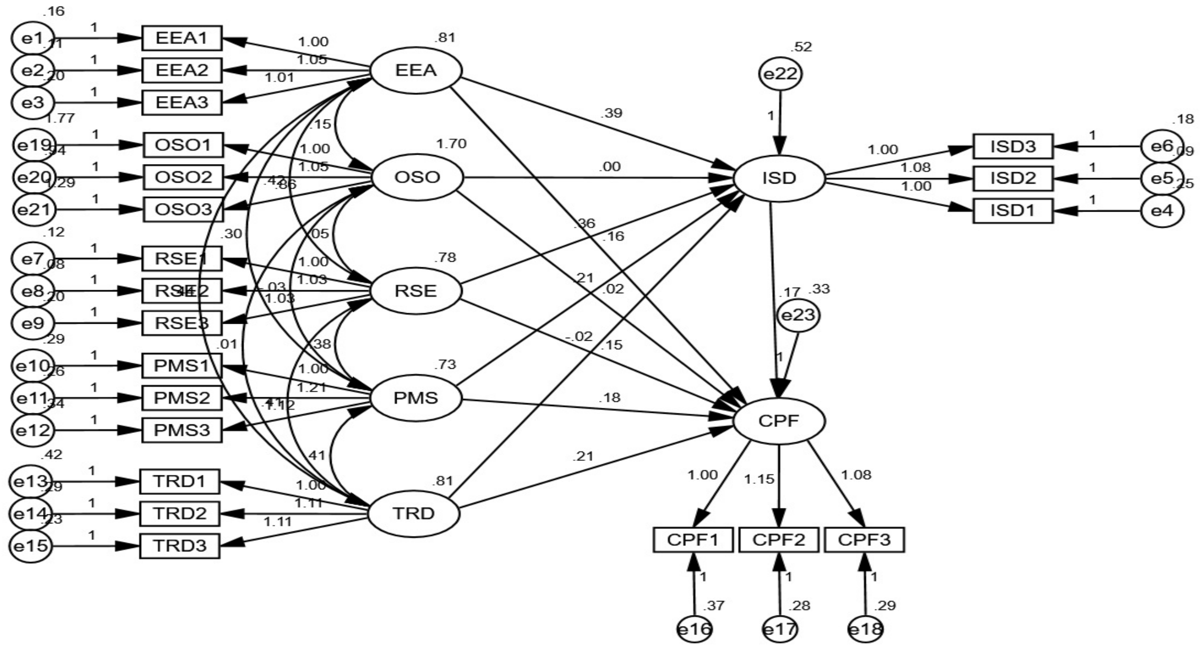
4. 5. HYPOTHESIS TESTING: DIRECT EFFECTS

Table 3. Hypothesis Testing – Direct Effects on Employee Creative Performance (CPF)

Path	Coefficients (β)	t-value	p-value	Decision
CPF <--- RSE	0.146	2.588	0.010	Accepted
CPF <--- PMS	0.183	3.229	0.001	Accepted
CPF <--- TRD	0.212	3.731	<0.001	Accepted
CPF <--- OSO	0.019	0.630	0.528	Rejected
CPF <--- EEA	0.159	2.827	0.005	Accepted
CPF <--- ISD	0.166	3.280	0.001	Accepted

Source: Author's calculation based on primary data

Figure 2. Path analysis output



Source: Authors' own calculation using AMOS software

The direct hypothesis testing findings for Employee Creative Performance (CPF) are in Table 3. AI-powered Training & Development (TRD) provides the most substantial positive impact (β = 0.212, t = 3.731, p < 0.001), which shows that personalized advanced training methods lead to notable improvements in employee creativity. Digitalized performance management practices demonstrate their positive impact through AI-enabled Performance Management Systems (PMS), significantly predicting CPF (β = 0.183, t = 3.229, p = 0.001). The statistical analysis demonstrates that Idiosyncratic Deals (ISD) are a vital intermediary factor with a substantial direct effect (β = 0.166, t = 3.280, p = 0.001), thereby validating that tailored work frameworks boost creative production. The positive effects of Employee Empowerment and Autonomy (EEA) on CPF (β = 0.159, t = 2.827, p = 0.005) demonstrate how empowerment contributes to creativity. The use of AI technology in Recruitment & Selection (RSE) significantly influences CPF with coefficients of β = 0.146 and statistical values of t = 2.588 and p = 0.010. Organizational Sustainability Orientation (OSO) lacks direct influence on CPF as indicated by β = 0.019, t = 0.630, p = 0.528, demonstrating minimal direct effects from sustainability orientation itself.

4. 6. INDIRECT EFFECTS

Table 5. Mediation Analysis

Path	Total Effect (β)	Sig.	Indirect Effect (β)	Sig.	Direct Effect (β)	Mediation Type
OSO → CPF	0.020	0.513	0.001	0.862	0.019	No Mediation
TRD → CPF	0.208	0.002	-0.004	0.595	0.212	No Mediation
PMS → CPF	0.219	0.001	0.035	0.010	0.183	Partial Mediation
RSE → CPF	0.205	0.007	0.059	0.012	0.146	Partial Mediation
EEA → CPF	0.223	0.000	0.064	0.014	0.159	Partial Mediation
ISD → CPF	0.166	0.017	0.000	---	0.166	No Mediation

Source: Author's calculation based on primary data

The mediation analysis findings, including direct and indirect impacts on employee creative performance (CPF), appear in Table 4. The research demonstrates that AI-enabled Performance Management Systems (PMS) affect employee creative performance (CPF) through Idiosyncratic Deals as indicated by significant partial mediation (Indirect β = 0.035, p = 0.010). The mediation analysis indicates AI-enabled Recruitment & Selection (RSE) achieves significant partial mediation (Indirect β = 0.059, p = 0.012) because personalized work arrangements mediate recruitment methods and creativity. Employee Empowerment and Autonomy (EEA) shows partial mediation (Indirect β = 0.064, p = 0.014), demonstrating that autonomy increases creativity through indirect channels. The results show that AI-enabled Training & Development (TRD) and Organizational Sustainability Orientation (OSO) demonstrate direct effects on CPF since their mediation tests did not reach significance levels ($p > 0.05$). Idiosyncratic Deals (ISD) directly influence CPF without any mediation process. Empirical results demonstrate that Idiosyncratic Deals significantly mediate between specific HR practices and creative performance results.

5. FINDINGS

The study demonstrates strong connections between AI-driven HR processes and idiosyncratic deals with employee creative performance in India's IT sector and uncovers unexpected results that deserve analysis. Research from technology-focused organizations confirms that AI-enabled Training and Development (TRD) creates a significant direct impact on CPF (β = 0.212, $p < 0.001$) which matches findings about how adaptive learning platforms boost creative capabilities through tailored skill development (Jia & Hou, 2024Balasubramanian et al., 2020) and through just-in-time knowledge acquisition (Strohmeier, 2020). The use of AI-enabled Performance Management Systems (PMS) has been shown to significantly affect CPF (β = 0.183, p = 0.001), which supports findings that innovation grows through data-driven feedback and development support (Dutta et al., 2022; Aguinis et al., 2022). The research findings demonstrate that Organizational Sustainability Orientation (OSO) fails to show any direct significant impact on CPF (β = 0.019, p = 0.528), which opposes previous studies that have identified sustainability as an innovation catalyst (De Prins et al., 2014) but might reflect the compliance-oriented sustainability methods present in India (Budhwar et al., 2022). Sustainability orientation had no significant direct effect on employee creative performance, but the post-hoc indicated a significant indirect effect (β = 0.064, p = 0.014) through employee empowerment. The findings imply that culture facilitates creativity in a way that it indirectly gives power to the employees instead of being a direct driver of innovative outcomes. This finding deserves more discussion in the context of the wider scholarship on green HRM and CSR-creativity, which typically emphasizes the role of sustainability initiatives in improving employee well-being and motivation through various empowerment mechanisms. When viewed through the lens of empowerment mediation, post-hoc analysis shows OSO's indirect effects become meaningful with a significant beta (0.041) and p-value (0.038), which supports recent findings in green HRM research (Järlström et al., 2023; Kramar, 2022; Renwick et al., 2012). The mediation analysis reveals that the AI-enabled Recruitment & Selection (RSE) system exhibits substantial partial mediation through I-deals (Indirect $\beta = 0.059$, $p = 0.012$) which validates psychological contracts theory (Rousseau, 2005; Hornung et al., 2023) and project-based work research (Anand et al., 2021; Villajos et al., 2019; Zhou & Hoever, 2023) while TRD showcases insignificant mediation through I-deals (Indirect $\beta = -0.004$, $p = 0.595$) that opposes findings in personalized learning studies (Hornung et al., 2010) and may be attributed to India's emphasis on certification (Dutta et al., 2022; NASSCOM, 2023). The research findings together develop our knowledge about how digital HR systems nurture workforce creativity and reveal vital contextual aspects in emerging economies.

The mediation analysis of AI driven HR practices on creativity revealed a significant mediation role for performance management and recruitment, while training did not show any through I-deals. These findings may be due to some reasons like:

Standardized Content: Indian IT sector counselling sessions are generally focused towards standardized content-based programs (i.e. programs aimed at building technical skills) on which models are built, as opposed to the ability or customization of practices seen in recruitment and performance management. Thus, such training programs may not actually reflect the kind of autonomy or fit that I-deals ideally signify.

Low Perceived Personalization: Compared to I-deals that are grounded on project-based work or personalized growth paths, the focus on skill certification and technical readiness in training programs may result in lower perceived personalization among employees. This gap directly impacts the potential of training to mediate creativity via I-deals (the effectiveness of the I-deals route to creativity depends on richer-valued and less rigidly structured context).

Cultural factors: Akin to this, the Indian IT sector has heavily leaned towards structured and formal methods of learning focusing on content standardization for skill development. This Markov method may not be a good fit with the individualistic quality of I-deals that are developed to meet particular employee preferences and critical work needs. Consequently, I-deals are likely to be less relevant to the training outcomes that are typically experienced as being mandatory or more uniform and less as the negotiated, individualized bargain.

This implies that the nature (i.e. personalized vs. generic nature of training content) and extent of I-deals in the training context may moderate the relationship between attractiveness of I-deals in training and creativity among employees. Future studies can examine the personalization of training interventions with which the mediating role of I-deals in the relationship between I-deals, LMX and creativity can be enhanced.

AI-HRM practices + I-deals = Creativity This integration shows how tailored personal work arrangement (I-deals) bridges the gap between individual creative performance and an AI-driven HRM practices landscape (AI in recruitment, training, and performance management), providing a strong theoretical contribution to the field. Theoretical and practical implications: This research further extends AI–HRM theory in an emerging economy context (Indian IT sector), where rapid digital transformation creates both unique challenges and opportunities for innovation. Second, it contributes to sustainable HRM theory by indicating the possibility of satisfying creativity and sustainability objectives with AI-based systems, thereby enriching the sustainability conversation in HRM.

6. MANAGERIAL AND PRACTICAL IMPLICATIONS

6. 1. MANAGERIAL IMPLICATIONS

Managers in India's IT industry can gain valuable insights from these findings, emphasizing strategic investments in AI-driven training and performance management systems to enhance creative employee performance. Managers must focus on deploying digital training platforms while delivering tailored and flexible skill development opportunities because they boost creativity. Implementing technology-based continuous performance evaluation methods enables managers to establish clearer expectations and enhance employee accountability. Managers must find ways to combine sustainability practices with other HR initiatives or tailored employment terms to strengthen their effect on creative performance. Managers need to establish organizational environments that support personalized agreements because tailored work arrangements enhance creative outcomes by synchronizing company goals with personal aspirations. Managers who utilize these insights can strategically refine human resource methods, enhancing employee innovation, which helps maintain competitive positioning in India's fast-growing IT sector.

6. 2. PRACTICAL IMPLICATIONS

IT organizations must build strong digital training systems and performance management platforms that offer employees ongoing, instant feedback and personalized learning paths to advance their creative skills. Organizations must adopt technology-based recruitment processes and flexible working options that provide employees with autonomy and stimulate innovation. Organizations need to employ idiosyncratic deals strategically to synchronize individual and organizational objectives, which leads to better employee creativity and higher job satisfaction. Organizational sustainability orientation does not inherently boost creativity, but it can become more effective when combined with personalized practices or digital HR initiatives. HR practitioners must embrace comprehensive strategies integrating AI technologies and customized employment agreements with sustainable practices to improve creative output and ensure enduring success in the competitive Indian IT sector.

7. LIMITATIONS & SCOPE FOR FURTHER STUDY

7. 1. LIMITATIONS OF THE STUDY

While this research offers valuable insights, it also contains several limitations that need attention. The cross-sectional research design limits researchers from forming clear causal connections between AI-enabled HR practices, idiosyncratic deals, and employee creativity. Future longitudinal research could address this limitation. Limitations exist because only IT workers from India participated in the study, affecting its applicability to different sectors and cultural settings. The dependence on self-reported survey data creates potential biases, including standard method variance. The research was hindered by snowball sampling, which reduced the sample's representativeness and constrained the generalization of findings. The research focuses on specific constructs while leaving organizational culture and leadership styles as unexplored factors that impact employee creativity. Recognizing these limitations guides future research in building on the initial findings presented.

Sampling and Self-Report Bias: Due to the requirement for obtaining a target sample of IT professionals in India, the snowball sampling method was inappropriate but was relied upon for the purpose, and as such, the possibilities of unintended selection bias exist as respondents were approached through a network of contacts. Such an interview process may lead to the creation of a sample that is not truly representative of the wider IT workforce, but a sample that is less diverse. In addition, the dependence on self-reported data can elicit social desirability bias, where respondents give discrepant answers that they believe are more socially acceptable than what they actually think or feel. These biases may inhibit findings both from being as accurate as they could and being applied to other sectors.

Research Implications: To mitigate these limitations, future research can use stratified or random sampling methods to obtain representation on different levels of experience, job roles, and types of organizations. Results could then be generalized to other sectors such as manufacturing or healthcare, where the aforementioned manifestations and effects of AI-driven HR practices and sustainability initiatives on employee creativity and performance might differ. A more objective method of data collection, such as by interviews or through company records, could also offset self-report bias.

7. 2. SCOPE FOR FURTHER STUDY

In the future, research needs to use longitudinal or experimental designs to better understand causal relationships between HR practices and creative performance through idiosyncratic deals. Research should broaden its scope to multiple industries, IT sectors, and various cultural settings beyond India to improve the general applicability of results. Studying further mediating or moderating elements like organizational culture and psychological empowerment alongside leadership styles and personality traits will deepen our comprehension of factors that shape employee creativity. Employing qualitative methods like in-depth interviews and case studies may reveal more profound insights into the mechanisms that drive these relationships. Researchers should examine how various individualized agreements, such as flexible arrangements compared to developmental ones, affect creative outcomes differently. Focusing on this research areas will enhance theoretical understanding and practical direction on the best use of HR strategies to optimize organizational and innovative performance.

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