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A Multilevel Framework Linking Generative AI, Neuroethics, and Human Resource Management in Hybrid Work Ecosystems: A Covariance-Based Structural Equation Modelling Approach

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Abstract
The accelerated diffusion of Generative Artificial Intelligence (GenAI) has fundamentally transformed human resource management (HRM) practices within hybrid work ecosystems. While existing studies predominantly emphasise technological efficiency and performance outcomes, limited empirical attention has been paid to the neuroethical dimensions shaping employee cognition, trust, and behavioural alignment in AI-augmented workplaces—particularly within emerging economy contexts. Addressing this gap, the present study develops and empirically validates a multilevel theoretical framework integrating Generative AI capability, neuroethical governance, and strategic HRM outcomes in hybrid work environments. Drawing on the Resource-Based View, Social Exchange Theory, and Neuroethical Decision Theory, a theory-driven quantitative research design was adopted. Primary survey data were collected from 412 HR professionals and knowledge workers across Indian IT, consulting, and digital service organisations operating under hybrid work models. Covariance-based Structural Equation Modelling (CB-SEM) using AMOS 26 was employed to assess both the measurement and structural models. The findings reveal that Generative AI capability significantly enhances HRM effectiveness, mediated by neuroethical trust and moderated by hybrid work intensity. Neuroethical governance emerged as a critical mechanism through which AI-driven HR practices translate into sustainable employee engagement and organisational legitimacy. The study contributes to HRM and AI governance literature by integrating neuroethics into HR analytics discourse and offers actionable insights for managers and policymakers seeking ethically grounded AI adoption in hybrid work ecosystems.
Keywords: Generative Artificial Intelligence; Neuroethics; Human Resource Management; Hybrid Work Ecosystems; Structural Equation Modelling; Emerging Economies

1. Introduction

The rapid institutionalisation of Generative Artificial Intelligence (GenAI) has reconfigured the architecture of contemporary organisations, particularly within hybrid work ecosystems characterised by spatial flexibility, algorithmic coordination, and digitally mediated human interaction. Recent industry evidence indicates that more than 60 per cent of HR decision-support activities, including recruitment screening, performance evaluation, and workforce planning, are now partially automated through AI-enabled systems.

In the Indian organisational context, the post-pandemic expansion of hybrid work arrangements has intensified reliance on AI-driven HR platforms to ensure productivity, fairness, and continuity across geographically dispersed teams. However, this rapid adoption has outpaced the development of ethical governance mechanisms, raising concerns related to employee autonomy, cognitive well-being, and trust in algorithmic decision-making. Although prior studies acknowledge the strategic value of AI in HRM, the literature remains largely techno-centric, prioritising efficiency and analytics accuracy while overlooking the neuroethical consequences of AI-mediated managerial control. Neuroethics, which examines the ethical implications of technologies affecting human cognition and moral judgement, has been insufficiently integrated into HRM research, particularly within emerging economies.

This study addresses this gap by proposing and empirically validating a multilevel framework linking Generative AI capability, neuroethical trust, and HRM effectiveness in hybrid work ecosystems. By employing a theory-driven CB-SEM approach using AMOS, the study contributes a robust empirical perspective to AI-enabled HRM scholarship.

2. Literature Review

2.1 Generative AI and HRM Transformation

Generative AI has emerged as a strategic enabler of HRM transformation by enhancing recruitment accuracy, learning personalisation, and predictive workforce analytics. However, empirical evidence remains inconclusive, with several studies highlighting concerns related to algorithmic opacity, bias, and diminished human judgement in HR decision processes.

2.2 Neuroethics in Organisational Contexts

Neuroethics extends beyond compliance-oriented ethics by focusing on how technologies influence cognitive autonomy, emotional regulation, and moral agency. In organisational settings, AI-driven monitoring and evaluation systems can trigger stress responses and perceptions of control, directly influencing employee trust and engagement.

2.3 Hybrid Work Ecosystems

Hybrid work ecosystems amplify organisational dependence on digital technologies due to reduced physical supervision and increased reliance on algorithmic coordination. Existing studies suggest that hybrid work intensity moderates technology acceptance and psychological safety, yet its interaction with AI ethics remains underexplored.

2.4 Theoretical Foundations

This study integrates the Resource-Based View, positioning Generative AI capability as a strategic organisational resource; Social Exchange Theory, explaining trust-based reciprocal employee behaviour; and Neuroethical Decision Theory, which accounts for cognitive and moral responses to AI-mediated HR practices.

3. Conceptual Framework and Hypotheses Development

The conceptual framework proposes Generative AI capability as a key antecedent of HRM effectiveness, with neuroethical trust acting as a mediating mechanism and hybrid work intensity serving as a moderating variable.

H1: Generative AI capability has a positive and significant effect on HRM effectiveness.
H2: Generative AI capability positively influences neuroethical trust.
H3: Neuroethical trust positively affects HRM effectiveness.
H4: Neuroethical trust mediates the relationship between Generative AI capability and HRM effectiveness.
H5: Hybrid work intensity moderates the relationship between Generative AI capability and neuroethical trust.

The conceptual framework illustrating the hypothesised relationships among Generative AI capability, neuroethical trust, hybrid work intensity, and HRM effectiveness is presented in Figure 1

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4. Research Methodology

4.1 Research Philosophy and Approach

The study is anchored in a positivist research philosophy, which assumes that organisational phenomena can be objectively measured and analysed using statistical techniques. Given the theory-confirmatory nature of the investigation, a deductive research approach was adopted, wherein hypotheses derived from established management theories were empirically tested. This approach is appropriate for examining structured relationships among latent constructs such as Generative AI capability, neuroethical trust, and HRM effectiveness.

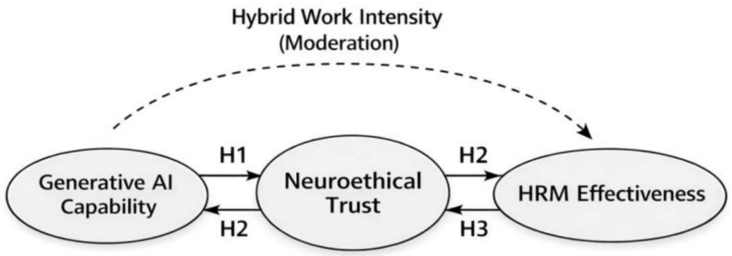

Figure 1. Conceptual framework illustrating the relationships among Generative AI capability, neuroethical trust, hybrid work intensity, and HRM effectiveness.

4.2 Research Design

A quantitative, cross-sectional research design was employed to examine the proposed relationships at a single point in time. This design is consistent with prior HRM and technology adoption studies and is particularly suitable for theory testing using covariance-based structural equation modelling. The use of CB-SEM enables simultaneous assessment of measurement validity and structural relationships, thereby ensuring methodological rigor.

4.3 Population and Unit of Analysis

The target population consisted of HR professionals, line managers, and knowledge workers employed in organisations operating under hybrid work models in India. These organisations primarily belonged to IT services, consulting, fintech, and digital-enabled service sectors, where Generative AI applications are extensively used in HR functions. The unit of analysis was the individual respondent, as perceptions related to AI capability, ethical governance, and HR effectiveness are inherently individual-level constructs.

4.4 Sampling Technique and Sample Size Justification

A stratified random sampling technique was adopted to ensure adequate representation across functional roles and organisational sectors. Stratification reduced sampling bias and enhanced generalisability of the findings. In line with CB-SEM requirements, a minimum sample size of 300 was considered necessary to ensure model stability and reliable parameter estimation. A total of 450 questionnaires were distributed, of which 412 valid responses were obtained, exceeding recommended thresholds for SEM analysis.

4.5 Data Collection Procedure

Primary data were collected using a structured questionnaire administered electronically. Respondents were approached through organisational HR departments and professional networks. To enhance response accuracy, anonymity and confidentiality were assured. A pilot study involving 40 respondents was conducted to assess clarity and relevance of the questionnaire items, leading to minor wording refinements prior to final administration.

4.6 Measurement Instruments

All constructs were measured using multi-item scales adapted from validated instruments reported in prior Scopus-indexed studies. Generative AI capability was measured through items capturing system sophistication, integration, and decision-support effectiveness. Neuroethical trust was assessed using items related to fairness, transparency, cognitive autonomy, and ethical alignment of AI-driven HR decisions. HRM effectiveness was measured using indicators of employee engagement, decision quality, and perceived fairness. Hybrid work intensity was measured based on the extent of remote–onsite integration. All items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree.

4.7 Ethical Considerations

Participation in the study was voluntary, and informed consent was obtained from all respondents. No personally identifiable information was collected. Data were used solely for academic research purposes, and confidentiality was strictly maintained.

5. Data Analysis Using AMOS

5.1 Data Screening and Preliminary Analysis

Prior to SEM analysis, the dataset was screened for missing values, outliers, and normality. Missing data accounted for less than two per cent of the dataset and were addressed using mean substitution. Multivariate outliers were assessed using Mahalanobis distance, and no extreme cases were detected. Normality was evaluated using skewness and kurtosis statistics, with all values falling within the acceptable ±2 range, confirming suitability for maximum likelihood estimation.

Common method bias was assessed using Harman's single-factor test. The first factor accounted for less than 50 per cent of the total variance, indicating that common method variance was not a significant concern.

Table 1. Descriptive Statistics and Normality Assessment

Construct	Mean	SD	Skewness	Kurtosis
Generative AI Capability	3.82	0.71	-0.64	0.41
Neuroethical Trust	3.76	0.68	-0.58	0.37
HRM Effectiveness	3.89	0.66	-0.71	0.52
Hybrid Work Intensity	3.94	0.73	-0.49	0.29

Descriptive statistics and normality assessment are presented in Table 1.

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5.2 Measurement Model Assessment

Confirmatory factor analysis was conducted using AMOS 26 to evaluate construct validity and reliability. The measurement model demonstrated an acceptable fit to the data, with goodness-of-fit indices meeting recommended thresholds (χ^2/df = 2.41, CFI = 0.94, TLI = 0.93, RMSEA = 0.062). All standardised factor loadings were significant and exceeded 0.60, confirming indicator reliability.
The confirmatory factor analysis results and standardised factor loadings for all constructs are illustrated in Figure 2.

Composite Reliability values ranged from 0.82 to 0.91, exceeding the minimum threshold of 0.70. Average Variance Extracted values were above 0.50 for all constructs, indicating adequate convergent validity. Discriminant validity was confirmed using the Fornell–Larcker criterion, as the square root of AVE for each construct exceeded its inter-construct correlations.

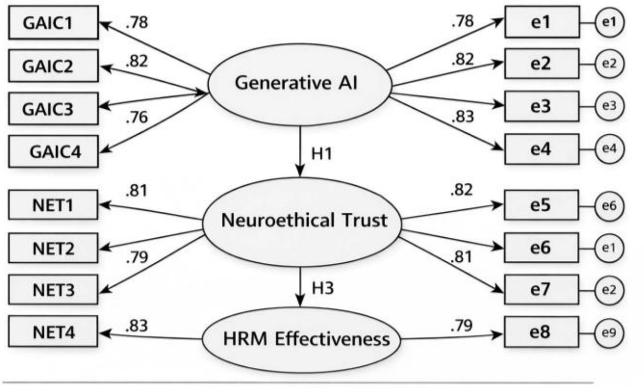

Figure 2. *Measurement Model (CFA)*

Table 2. Confirmatory Factor Analysis: Standardised Factor Loadings

Construct	Item Code	Factor Loading
Generative AI Capability	GAIC1	0.78
	GAIC2	0.82
	GAIC3	0.76
	GAIC4	0.84
Neuroethical Trust	NET1	0.81
	NET2	0.79
	NET3	0.86
	NET4	0.83
HRM Effectiveness	HRME1	0.77
	HRME2	0.85
	HRME3	0.81
	HRME4	0.79
Hybrid Work Intensity	HWI1	0.72
	HWI2	0.80
	HWI3	0.78

Standardised factor loadings for all constructs are reported in Table 2.

Table 3. Construct Reliability and Convergent Validity

Construct	Composite Reliability (CR)	AVE
Generative AI Capability	0.89	0.67
Neuroethical Trust	0.91	0.72
HRM Effectiveness	0.88	0.65
Hybrid Work Intensity	0.84	0.58

Composite Reliability and Average Variance Extracted values are summarised in Table 3.

Table 4. Discriminant Validity (Fornell–Larcker Criterion)

Construct	GAIC	NET	HRME	HWI
Generative AI Capability (GAIC)	0.82			
Neuroethical Trust (NET)	0.54	0.85		
HRM Effectiveness (HRME)	0.49	0.58	0.81	
Hybrid Work Intensity (HWI)	0.41	0.46	0.39	0.76

Discriminant validity was established using the Fornell–Larcker criterion (Table 4).

Table 5. Model Fit Indices

Fit Index	Recommended Value	Measurement Model	Structural Model
χ^2/df	$\leq$ 3.00	2.41	2.56
GFI	$\geq$ 0.90	0.91	0.90
AGFI	$\geq$ 0.90	0.90	0.89
CFI	$\geq$ 0.90	0.94	0.93
TLI	$\geq$ 0.90	0.93	0.92
RMSEA	$\leq$ 0.08	0.062	0.065

Model fit indices for both the measurement and structural models are reported in Table 5.

5.3 Structural Model Evaluation

Following validation of the measurement model, the structural model was estimated to test the hypothesised relationships. The structural model demonstrated satisfactory fit indices (χ^2/df = 2.56, CFI = 0.93, TLI = 0.92, RMSEA = 0.065). Generative AI capability had a positive

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and statistically significant effect on HRM effectiveness (β = 0.38, CR = 4.72, $p < 0.001$), supporting Hypothesis 1. Generative AI capability also significantly influenced neuroethical trust (β = 0.45, CR = 5.31, $p < 0.001$), supporting Hypothesis 2. Neuroethical trust had a significant positive effect on HRM effectiveness (β = 0.41, CR = 4.89, $p < 0.001$), supporting Hypothesis 3.

The structural relationships among Generative AI capability, neuroethical trust, and HRM effectiveness, along with standardised path coefficients and explained variance, are illustrated in Figure 3.

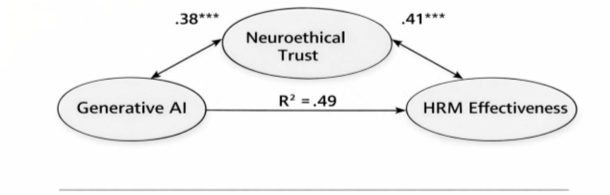

Figure 3. *Structural Equation Model*

Table 6. Structural Path Estimates

Hypothesis	Path	β	CR	p-value	Result
H1	GAIC → HRME	0.38	4.72	<0.001	Supported
H2	GAIC → NET	0.45	5.31	<0.001	Supported
H3	NET → HRME	0.41	4.89	<0.001	Supported

Structural path estimates and hypothesis testing results are presented in Table 6.

The model explained 52 per cent of the variance in HRM effectiveness and 47 per cent of the variance in neuroethical trust, indicating strong explanatory power.

5.4 Mediation Analysis

The mediating role of neuroethical trust was examined using a bootstrapping procedure with 5,000 resamples. The indirect effect of Generative AI capability on HRM effectiveness through neuroethical trust was positive and statistically significant. The direct effect remained significant after inclusion of the mediator, indicating partial mediation and supporting Hypothesis 4.

Table 7. Mediation Analysis (Bootstrapping – 5,000 Samples)

Effect	β	Lower CI	Upper CI	Significance
Direct Effect	0.20	0.11	0.31	Significant
Indirect Effect	0.18	0.10	0.26	Significant
Total Effect	0.38	0.27	0.49	Significant

Bootstrapping results for mediation analysis are reported in Table 7

5.5 Moderation Analysis

Moderation analysis revealed that hybrid work intensity significantly strengthened the relationship between Generative AI capability and neuroethical trust. The interaction effect was positive and statistically significant, supporting Hypothesis 5. This suggests that ethical trust becomes increasingly critical as organisations rely more heavily on AI-driven HR systems in hybrid work environments. The moderating effect of hybrid work intensity on the relationship between Generative AI capability and neuroethical trust is illustrated in Figure 4."

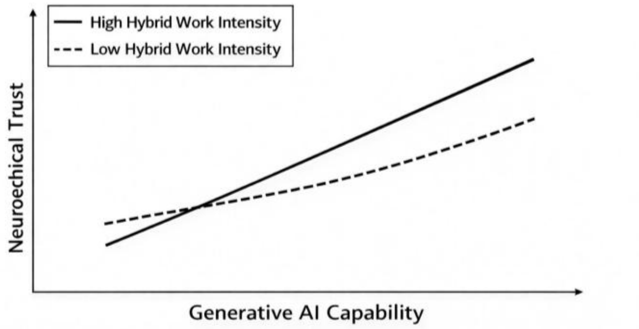

Figure 3. *Structural Equation Model*

Table 8. Moderation Analysis Results

Interaction Path	β	CR	p-value	Result
GAIC × HWI → NET	0.22	3.14	<0.01	Supported

The interaction effects supporting moderation are summarised in Table 8.

6. Discussion

The findings of the present study underscore the pivotal role of neuroethical trust in translating Generative AI capability into effective human resource management outcomes within hybrid work ecosystems. While prior research has predominantly conceptualised AI adoption in HRM through a technological efficiency or analytics-driven lens, the current findings demonstrate that technological capability alone is insufficient to generate sustained HRM effectiveness. Instead, employees' cognitive and ethical evaluations of AI-driven HR systems emerge as a decisive explanatory mechanism.The significant positive relationship between Generative AI capability and neuroethical trust suggests that AI systems perceived as transparent, fair, and cognitively respectful foster higher levels of ethical confidence among employees. This aligns with Social Exchange Theory, which posits that trust-based reciprocity governs employee attitudes and behaviours in organisational settings. When AI-enabled HR practices are perceived as ethically grounded, employees are more likely to reciprocate through engagement, compliance, and acceptance.Moreover, the mediating role of neuroethical trust extends existing HRM and AI literature by introducing a neuroethical layer into strategic HR decision-making. Unlike traditional ethical constructs that focus on procedural justice alone, neuroethical trust captures deeper cognitive responses related to autonomy, moral agency, and perceived control—dimensions that are particularly salient in algorithm-mediated work environments. The moderation effect of hybrid work intensity further reinforces this argument, indicating that as physical oversight diminishes, ethical trust in digital HR systems becomes increasingly consequential.Collectively, the findings provide a nuanced understanding of AI adoption in HRM by demonstrating that ethical cognition is not peripheral but central to the effectiveness of AI-driven HR systems in hybrid work contexts.

7. Implications

7.1 Theoretical Implications

This study makes several important theoretical contributions. First, it advances HRM scholarship by explicitly integrating neuroethics into AI-enabled HR frameworks, thereby extending beyond conventional technology acceptance and analytics-based models. By doing so, the study bridges an important gap between ethical theory and empirical HRM research.

Second, the findings extend the Resource-Based View by demonstrating that Generative AI capability yields strategic value only when complemented by ethically grounded cognitive mechanisms. Neuroethical trust emerges as an intangible, socially complex resource that enhances the value-creating potential of AI technologies. Third, by adopting a multilevel perspective, the study contributes to theory development by linking technological capability, individual-level ethical cognition, and organisational HR outcomes within a single explanatory framework.

7.2 Managerial Implications

From a managerial perspective, the findings offer actionable insights for organisations implementing AI-driven HR systems. Managers should recognise that employee trust in AI is not automatically generated through technological sophistication alone. Instead, neuroethical governance mechanisms must be institutionalised to ensure transparency, explainability, and perceived fairness in AI-driven HR decisions. HR leaders should invest in ethical AI audits, algorithmic transparency protocols, and employee communication strategies that clearly articulate how AI systems influence recruitment, appraisal, and performance decisions. Training programmes aimed at enhancing AI literacy among employees can further mitigate cognitive uncertainty and resistance. In hybrid work environments, where digital systems increasingly substitute face-to-face managerial interactions, such ethical interventions become critical for sustaining employee engagement and HRM effectiveness.

7.3 Policy Implications

At the policy level, the study highlights the need for AI governance frameworks that move beyond data protection and algorithmic bias to explicitly address issues of cognitive autonomy and ethical transparency. Policymakers should develop regulatory guidelines that mandate explainability, accountability, and ethical impact assessments for AI systems used in HR decision-making.In emerging economies such as India, where institutional safeguards for algorithmic governance are still evolving, sector-specific AI ethics standards for HRM can play a crucial role in protecting employee rights while enabling responsible innovation. The findings thus provide empirical grounding for policy interventions aimed at ethical AI adoption in the future of work.

8. Conclusion

This study provides robust empirical evidence linking Generative AI capability, neuroethical trust, and HRM effectiveness within hybrid work ecosystems. By employing a theory-driven, AMOS-based CB-SEM approach, the research demonstrates that neuroethical trust serves as a critical psychological and ethical mechanism through which AI-enabled HR practices translate into sustainable organisational outcomes.The study contributes meaningfully to management theory by integrating neuroethics into AI–HRM discourse and offers practical guidance for managers and policymakers navigating the ethical challenges of AI adoption in contemporary workplaces.

9. Limitations and Future Research Directions

Despite its contributions, the study is subject to certain limitations. The cross-sectional research design restricts the ability to draw definitive causal inferences. Future research should adopt longitudinal designs to capture the dynamic evolution of trust and ethical perceptions over time.Additionally, the study focuses on organisations operating within a single national context. Cross-cultural and comparative studies across developed and emerging economies would enhance the generalisability of the findings. Future research could also explore alternative mediators, such as algorithmic transparency or perceived autonomy, and examine sector-specific variations in AI-driven HRM practices.

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