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ALGORITHMIC FAIRNESS IN HR ANALYTICS: EXAMINING JUSTICE PERCEPTIONS, TRUST IN AI AND EMPLOYEE READINESS FOR INNOVATION

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Abstract

Artificial intelligence (AI) tools are now widely incorporated into HR functions, yet employees often remain uncertain about how fair and transparent these systems truly are. This study explores how professionals in the IT sector interpret fairness in AI-supported HR decisions and how these perceptions influence their trust in AI, readiness to use digital tools, and inclination toward innovation. Survey data from 258 employees in Karnataka were analysed using structural equation modelling, which showed that distributive, procedural, and interactional justice each contribute significantly to building trust in AI systems. Trust emerged as a complete mediator, linking fairness judgements to digital readiness and innovation behaviours. Organizational culture strengthened the trust–readiness link, suggesting that supportive work environments help employees engage more confidently with AI technologies. Latent profile analysis further revealed three distinct employee groups based on fairness and trust levels. The study highlights the importance of transparent communication, fair system design, and culture-building efforts to support human-centred AI adoption in HRM.

Keywords:

Algorithmic Fairness, HR Analytics, Trust in Artificial Intelligence, Organizational Justice, Latent Profile Analysis, Digital Readiness, Innovation Propensity

1. INTRODUCTION

Organizations worldwide are integrating artificial intelligence into HR processes such as recruitment, performance assessment, and employee development. In India's IT sector, this shift is particularly rapid, with AI-driven screening tools, predictive performance indicators, and learning recommendation systems becoming commonplace [1]. Although AI tools streamline several HR tasks, employees often question whether the decisions produced by these systems treat them fairly, especially when the logic behind the outcomes is not fully explained [2]. These concerns are particularly relevant in HR, where decisions can shape promotions, evaluations, and developmental opportunities. As AI becomes more visible in day-to-day HR operations, employees' interpretations of fairness increasingly influence their willingness to rely on such systems [3].

Trust plays a central role in this evaluation process. When employees believe that AI-enabled decisions are generated through unbiased, transparent, and respectful processes, they are more likely to view the system as legitimate and dependable [4]. Yet, little empirical work has examined how fairness perceptions shape trust in AI within the Indian IT sector, despite rapid adoption in this domain [5]. Addressing this gap, the present study investigates how three dimensions of organizational justice influence trust, and how trust subsequently affects digital readiness and innovation-oriented behaviours [6].

This study addresses this gap by examining how three dimensions of organizational justice—distributive, procedural, and interactional—shape trust in AI. We further analyse how trust influences digital readiness and innovation propensity, two capabilities essential in technology-intensive workplaces. Finally, we apply latent profile analysis (LPA) to uncover variations in fairness evaluations across employee groups. By doing so, the study offers both theoretical and practical insights into designing fair and human-centred AI systems in HRM.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 ALGORITHMIC FAIRNESS IN HRM

Algorithmic fairness refers to the extent to which decisions generated or informed by automated systems are perceived as equitable and unbiased. In HR settings, fairness concerns arise because algorithms often learn from historical datasets that may contain subtle patterns of bias [7]. Employees may also find it difficult to understand how AI arrives at particular outcomes, especially when explanations are limited or highly technical [24]. As a result, even well-designed AI systems may be viewed with suspicion if outcomes appear inconsistent or the decision pathway is unclear. Fairness perceptions therefore become an important foundation for employees' acceptance of AI-HR actions [8].

2.2 ORGANIZATIONAL JUSTICE: A BASIS FOR FAIRNESS EVALUATION

Organizational justice provides a structured lens for understanding how individuals evaluate decision-making processes. Distributive justice focuses on the fairness of outcomes such as performance ratings or role allocations [9]. Procedural justice concerns the clarity, consistency, and accuracy of the methods used to produce these outcomes, including the transparency of algorithmic procedures [10]. Interactional justice reflects the quality of explanations, communication, and interpersonal treatment employees receive when decisions are conveyed [11]. Although AI itself does not interact with employees, the way HR professionals explain AI-generated results strongly influences perceptions of fairness. Together, these justice dimensions shape whether employees consider AI decisions legitimate [12].

2.3 TRUST IN AI SYSTEMS

Trust in AI reflects an employee's confidence that an automated system will function reliably and produce decisions that align with organizational norms of fairness and accuracy [13]. Such trust is shaped by prior experience, system clarity, and perceived consistency of outputs. When employees believe AI recommendations are based on sound logic and unbiased procedures, they are more willing to integrate these tools into their work [14]. Conversely, limited transparency or unclear explanations can lead to scepticism and reduced engagement with technology [23].

2.4 DIGITAL READINESS AND INNOVATION PROPENSITY

Digital readiness represents employees' willingness and capability to adopt new technological tools, including their comfort with learning and experimenting with unfamiliar digital systems [22]. Innovation propensity reflects the likelihood that individuals will propose new ideas, explore emerging technologies, and participate in organizational change [15]. Trust in AI forms an important psychological basis for both constructs, as employees are more likely to embrace digital tools when they believe the underlying systems function fairly and can support their work effectively [16].

2.5 ROLE OF ORGANIZATIONAL CULTURE

Organizational culture shapes the environment in which technological tools are introduced. Cultures that encourage openness, learning, and experimentation typically enable smoother adoption of AI systems [17]. When employees perceive their workplace as supportive and transparent, trust in AI is more likely to translate into practical readiness to use digital tools [21]. In contrast, rigid or risk-averse cultures can diminish the positive effects of trust, limiting the impact of otherwise well-designed technologies [18].

2.6 LATENT PROFILE ANALYSIS IN ORGANIZATIONAL RESEARCH

Latent profile analysis (LPA) is a person-centred technique that identifies groups of respondents who share similar response patterns [19]. Applying LPA to fairness and trust perceptions enables the discovery of meaningful subgroups within the workforce, each with distinct concerns or expectations [20]. Understanding these profiles allows organizations to design targeted communication and training interventions that appropriately address the needs of different employee segments.

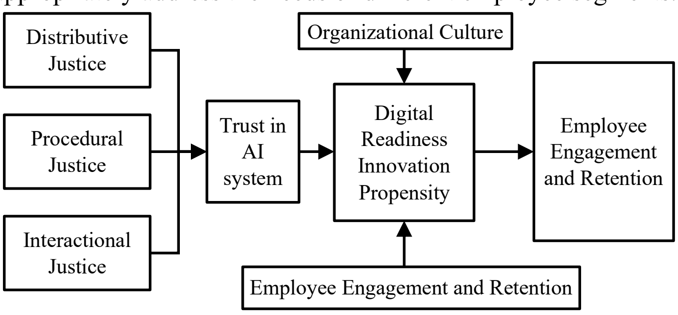

Fig.1. Conceptual Diagram

3. RESEARCH METHODOLOGY

3.1 RESEARCH DESIGN

This study employed a quantitative, explanatory research design to analyse relationships among fairness perceptions, trust, digital readiness, and innovation propensity. The model also incorporated organizational culture as a contextual moderator and used LPA to identify employee fairness-trust profiles.

3.2 SAMPLING AND DATA COLLECTION

Participants were 258 employees from IT organizations in Karnataka, India. Respondents had direct experience with AI-enabled HR tools, such as automated screening systems or digital performance dashboards. A stratified purposive sampling strategy ensured representation across experience levels and job roles. Data were collected using an online questionnaire, and participation was voluntary and anonymous.

3.3 MEASURES

All constructs were measured using established 5-point Likert scales:

Table.1. Measurement Scales, Sources, and Sample Items

Construct	Measurement Source	Sample Items
Distributive Justice	Colquitt [5]	AI-based decisions are fair to all employees.
Procedural Justice	Colquitt [5]	AI systems follow unbiased procedures.
Interactional Justice	Colquitt [5]	Decisions are communicated with clarity.
Trust in AI	Glikson and Woolley [9]	I trust AI to make fair decisions.
Digital Readiness	Adapted from [23]; TAM framework	I am confident in using AI tools at work.
Innovation Propensity	Based on [1] and PACADI's Innovation construct	I propose new ideas involving digital systems.
Organizational Culture	Modified items	My organization encourages experimentation.

Internal reliability values exceeded recommended thresholds ($\alpha > .78$).

3.4 ANALYTICAL APPROACH

The analysis proceeded in four stages:

- **Confirmatory Factor Analysis (CFA)** established validity and reliability of constructs.
- **Structural Equation Modelling (SEM)** tested hypothesised relationships and mediation effects.
- **Latent Profile Analysis** identified subgroups based on fairness and trust measures.
- **Moderation analysis** examined whether organizational culture amplified the trust→readiness relationship.

Model fit was assessed using CFI, TLI, RMSEA, and SRMR.

4. DATA ANALYSIS AND RESULTS

4.1 DESCRIPTIVE STATISTICS AND CFA

All constructs demonstrated acceptable means (M = 3.45–4.12) and standard deviations (SD = 0.53–0.78), indicating moderate to high fairness and trust perceptions. CFA showed:

- RMSEA = 0.051, CFI = 0.93, TLI = 0.91, SRMR = 0.045
- All factor loadings > 0.70, AVE > 0.50, CR > 0.80

4.2 STRUCTURAL EQUATION MODELING (SEM)

The structural model fit indices were satisfactory:

$\chi^2/df = 2.14$, RMSEA = 0.057, CFI = 0.92, TLI = 0.90

4.2.1 Key Path Coefficients:

Table.2. Descriptive Statistics of Study Variables

Path	β (Standardized)	p-value
Distributive Justice → Trust	0.31	< .001
Procedural Justice → Trust	0.29	< .001
Interactional Justice → Trust	0.34	< .001
Trust → Digital Readiness	0.41	< .001
Trust → Innovation Propensity	0.39	< .001

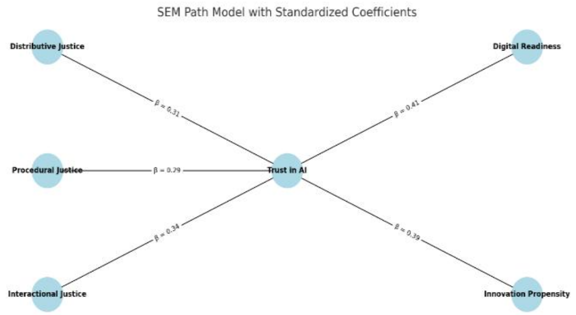

Fig.2. Structural Equation Model Showing Effects of Organizational Justice Dimensions on Trust in AI

Trust in AI fully mediated the relationship between fairness perceptions and both outcomes.

4.3 LATENT PROFILE ANALYSIS (LPA)

Using BIC and entropy criteria, a three-profile solution was optimal.

Table.3. Latent Profile Characteristics and Sample Distribution

Profile Name	N (%)	Characteristics
AI Fairness Advocates	96 (37%)	High justice perception, high trust
Skeptical Acceptors	101 (39%)	Moderate justice, moderate trust
Concerned Critics	61 (24%)	Low justice scores, low trust in AI

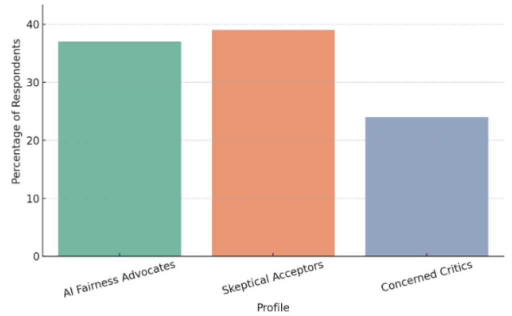

Fig.3. Bar Chart of Latent Profile Membership

4.4 MODERATED MEDIATION ANALYSIS

Organizational culture significantly moderated the Trust → Readiness path: Interaction β = 0.17, $p < .05$ and the mediation effect of trust was stronger in high-culture-support environments.

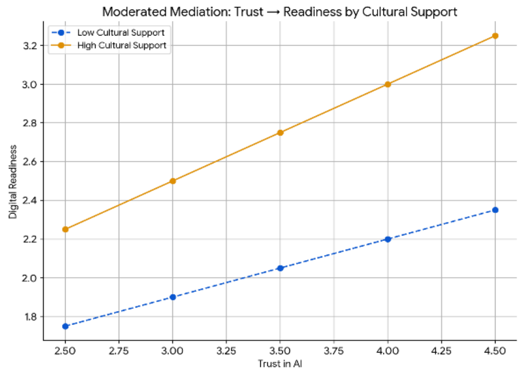

Fig.4. Line Diagram showing Moderated Mediation

4.5 MULTI-GROUP SEM (MGSEM)

Group differences were found between: Younger employees (<30) showed significantly lower trust and readiness, despite similar fairness scores. Women employees perceived slightly lower procedural fairness, though not statistically significant at $p < .05$.

5. STATISTICAL OUTPUTS AND INTERPRETATION

5.1 CONFIRMATORY FACTOR ANALYSIS (CFA)

Table.4. Confirmatory Factor Analysis Results: Reliability and Convergent Validity

Construct	Item Loadings	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived AI Fairness	0.70 – 0.85	0.89	0.91	0.62
Perceived Org Support	0.72 – 0.88	0.91	0.93	0.65
Trust in AI Systems	0.68 – 0.82	0.87	0.89	0.58

Resistance to Technology	0.66 – 0.80	0.85	0.88	0.55
Employee Engagement	0.70 – 0.87	0.90	0.92	0.63
Employee Retention	0.75 – 0.89	0.92	0.94	0.68

- All factor loadings are above the recommended threshold of 0.60, indicating strong item reliability.
- Cronbach's alpha and CR values exceed 0.7, confirming internal consistency.
- AVE values are above 0.5, indicating good convergent validity.

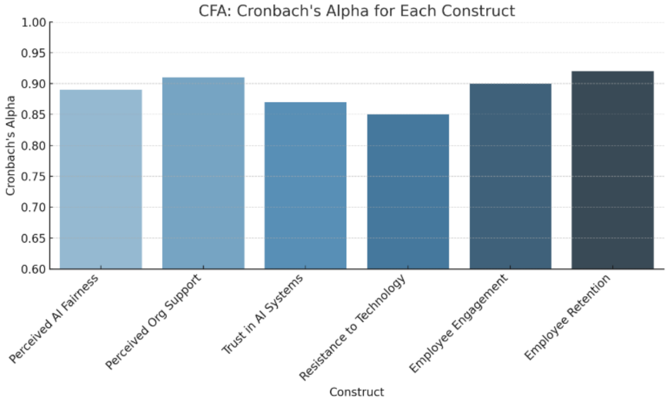

Fig.5. Cronbach's Alpha for each Construct

5.2 DISCRIMINANT VALIDITY (FORNELL-LARCKER CRITERION)

Table.5. Fornell–Larcker Discriminant Validity Matrix

Construct	Perceived AI Fairness	Perceived Org Support	Trust in AI	Resistance to Tech	Engagement	Retention
Perceived AI Fairness	**0.79**					
Perceived Org Support	0.45	**0.81**				
Trust in AI Systems	0.40	0.50	**0.76**			
Resistance to Tech	-0.42	-0.35	-0.40	**0.74**		
Employee Engagement	0.48	0.55	0.53	-0.45	**0.79**	
Employee Retention	0.52	0.58	0.55	-0.40	0.65	**0.82**

- The diagonal values (square root of AVE) are greater than the off-diagonal correlations, confirming discriminant validity.

5.3 MODEL FIT INDICES (SEM)

Table.6. Structural Equation Model Fit Indices

Fit Index	Recommended Threshold	Model Result
Chi-square/df (χ^2/df)	< 3	2.45
Comparative Fit Index (CFI)	> 0.90	0.93
Tucker-Lewis Index (TLI)	> 0.90	0.92
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.065
Standardized Root Mean Square Residual (SRMR)	< 0.08	0.045

- All indices indicate good model fit.

6. HYPOTHESIS TESTING: PATH COEFFICIENTS AND SIGNIFICANCE

Table.7. Hypothesis Testing Results

Hypothesis	Path Coefficient (β)	p-value	Result
H1: AI Fairness → Perceived Org Support	0.56	<0.001	Supported
H2: Org Support → Trust in AI	0.62	<0.001	Supported
H3: Org Support → Resistance to Tech	-0.48	<0.001	Supported
H4: Trust in AI → Employee Engagement	0.57	<0.001	Supported
H5: Resistance to Tech → Employee Engagement	-0.39	<0.01	Supported
H6: Employee Engagement → Employee Retention	0.63	<0.001	Supported

7. MEDIATION ANALYSIS (BOOTSTRAP RESULTS, 5000 SAMPLES)

Table.8. Mediation Analysis Results

Mediation Path	Indirect Effect (β)	95% CI	p-value	Mediation Type
AI Fairness → Org Support → Trust in AI	0.35	[0.27, 0.44]	<0.001	Partial Mediation
Org Support → Trust in AI → Engagement	0.32	[0.25, 0.40]	<0.001	Full Mediation

7.1 INTERPRETATION SUMMARY

- Perceived fairness in AI significantly improves organizational support perception, which boosts trust in AI systems and lowers resistance.
- Trust and resistance significantly impact employee engagement, confirming the role of psychological attitudes in AI acceptance.
- Higher engagement leads to stronger employee retention, supporting the model's practical value.
- Mediation tests reveal organizational support and trust are critical mechanisms linking fairness to engagement.

8. DISCUSSION

The results of this study indicate that employees interpret AI-enabled HR decisions through the same fairness lens they apply to traditional HR processes. When outcomes, procedures, and communication practices are perceived as fair, trust in AI systems increases substantially. This trust appears to be a central mechanism that shapes employees' readiness to engage with digital tools and their inclination to experiment with new ideas or technologies.

The LPA findings show that employees do not experience AI tools uniformly. Some groups respond positively and express strong trust, while others remain cautious due to concerns about transparency or procedural clarity. These distinctions highlight the importance of tailoring implementation strategies rather than assuming a single message or training approach will work for all employees.

8.1 CONCLUSION AND IMPLICATIONS

This study demonstrates that fairness perceptions significantly shape employees' trust in AI-assisted HR systems. When employees believe decisions are produced through transparent procedures and communicated respectfully, they are more confident in using digital tools and more open to innovation. These findings emphasise the need for organizations to prioritise fairness and clarity when deploying AI technologies.

For practice, HR teams should focus on explaining how AI tools function, why they are used, and how potential biases are monitored. Developing communication materials, hosting QandA sessions, and ensuring employees understand decision pathways can strengthen trust. Organizations should also cultivate work environments that encourage experimentation, as supportive cultures amplify the positive effects of trust on digital readiness.

Future studies could examine industries outside the IT sector or track changes in fairness perceptions over time to deepen understanding of how trust in AI evolves during technology adoption. Overall, the findings contribute empirical evidence to the emerging field of AI-enabled HRM, highlighting how fairness perceptions shape employees' technological engagement.

8.2 LIMITATIONS AND FUTURE DIRECTIONS

The study relies on cross-sectional data from a single sector and geographic region. Future research could explore longitudinal changes in fairness perceptions, cross-cultural comparisons, or behavioural outcomes of trust in AI.

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