



# The Mediating Role of Human-Centric AI in Shaping Fairness and Employment Equity: Evidence from a Structural Equation Modeling Approach

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## Abstract:

**Purpose:** This study examines the mediating role of Perception of Human-Centric AI (PHCAI) in the relationship between Attitudes Toward Upskilling and Reskilling (AUR), Perceived Societal Impact of AI on Employment (PSAIE), and Perceived AI Fairness and Employment Equity (PAIFE). The aim is to advance understanding of how human-centric AI perceptions influence fairness and equity in AI-driven workplaces.

**Design / Methodology / Approach:** An empirical study conducted with 214 respondents representing diverse professional sectors. Hypothesized model was tested using Structural Equation Modeling (SEM). Model fit indices ( $\chi^2 = 4.000$ ,  $df = 2$ ,  $\chi^2/df = 2.00$ ; CFI = 0.945; TLI = 0.922; RMSEA = 0.055) indicated a good fit. Mediation analysis explored indirect effects of PHCAI on PAIFE.

**Findings:** Both AUR ( $\beta = 0.547$  total effect) and PSAIE ( $\beta = 0.804$  total effect) significantly influence PAIFE. PHCAI was found to partially mediate these relationships, with notable indirect effects (AUR  $\rightarrow$  PAIFE = 0.331; PSAIE  $\rightarrow$  PAIFE = 0.155). These findings confirm the critical role of PHCAI in strengthening fairness and equity outcomes in organizations adopting AI.

**Practical Implications:** Organizations should actively foster human-centric AI practices, enhance employee reskilling initiatives, and address societal concerns surrounding AI to promote fairness and employment equity. Policymakers and HR leaders can leverage these insights to design ethical AI strategies and inclusive workforce policies.

**Originality / Value:** This research contributes to the emerging body of knowledge on ethical AI adoption by integrating human-centric perspectives into SEM-based analysis of workplace fairness. By highlighting the mediating influence of PHCAI, the study offers novel theoretical and practical insights for advancing ethical, equitable, and sustainable AI-driven organizational practices.

**Keywords:** Human-Centric AI; Artificial Intelligence; Fairness and Employment Equity; Reskilling and Upskilling; Societal Impact of AI; Mediation Analysis

### 1. Introduction of the study:

The accelerating integration of Artificial Intelligence (AI) within organizational ecosystems is reshaping workplace dynamics, influencing labor markets, and redefining fairness and employment equity paradigms (Brynjolfsson & McAfee, 2017; Zhang & Dafoe, 2019). As organizations increasingly deploy AI-powered tools for recruitment, performance management, and decision-making, concerns about bias, discrimination, and unequal access to opportunities have intensified (Crawford, 2021). In this context, the concept of Human-Centric AI (HCAI) has evolved as a critical framework aimed at confirming that AI technologies are designed, developed, and deployed in ways that highlight human values, well-being, and fairness (Dignum, 2019). This study explores the mediating role of Perception of Human-Centric AI (PHCAI) in shaping fairness and employment equity, particularly examining its influence on the relationship between attitudes toward upskilling and reskilling (AUR), perceived societal impact of AI on employment (PSAIE), and perceived AI fairness and employment equity (PAIFE). AI adoption in the workplace is a mixed blessings - while it offers enormous potential for productivity enhancement, innovation, and improved decision-making, it also introduces risks of algorithmic discrimination, job displacement, and inequitable access to resources (Lee et al., 2021; West et al., 2019). Research has highlighted that organizational fairness perceptions are increasingly shaped not only by human decision-makers but also by AI-driven processes (Binns, 2018). Consequently, developing a human-centred approach is essential to mitigate the negative societal impacts of AI and to foster equitable labor practices (Dignum, 2019; Jobin, Ienca, & Vayena, 2019).

One of the primary concerns with AI in employment contexts is fairness in algorithmic decision-making. Studies have shown that AI systems, particularly those used in recruitment and workforce management, may perpetuate or even exacerbate existing social biases otherwise needs careful designing and observation (Barocas, Hardt, & Narayanan, 2019). This emphasizes the need for AI fairness frameworks that ensures transparency and accountability with ethical principles of non-discrimination and inclusivity (Floridi & Cowsls (2019). A human-centric perspective ensures that AI does not replace human intellect but rather augments it while preserving fundamental rights, autonomy, and equality in employment opportunities (Dignum, 2019; Lee et al., 2021).

Parallel to this, the advent of AI has increased the urgency for upskilling and reskilling initiatives to address fears of job displacement and changing skill requirements (World Economic Forum, 2020). Employees' attitudes toward upskilling and reskilling (AUR) are critical determinants of their readiness to adapt to AI-driven transformations (Bessen, 2019). Positive attitudes toward skill development can enhance perceptions of fairness in organizations by enabling equitable access to new opportunities and reducing the risk of technological exclusion (Frank et al., 2019). Furthermore, societal perceptions of AI's broader implications for employment (PSAIE) influence how employees evaluate fairness and equity within organizations, shaping their trust in AI systems (Villaronga, Kieseberg, & Li, 2018).

Despite increasing scholarly interest in AI ethics, there is limited empirical evidence on how perceptions of human-centric AI mediate the relationship between workforce adaptability, societal concerns about AI, and perceptions of fairness and equity. Existing literature predominantly focuses on the technical aspects of algorithmic fairness, with fewer studies investigating the human and societal dimensions of AI adoption (Zhang & Dafoe, 2019; Lee et al., 2021). This study addresses this gap by proposing a Structural Equation Modeling (SEM)-based analysis to examine the mediating influence of PHCAI in AI-driven workplaces. SEM allows for a robust examination of complex interrelationships among attitudes, perceptions, and fairness outcomes, contributing greater insights into how human-centered values can be embedded in AI adoption strategies (Hair et al., 2019).

By empirically testing the mediating role of PHCAI, this research contributes to advancing theoretical understanding of ethical AI frameworks that promote fairness and employment equity. The findings are expected to inform both organizational practice and policy-making, highlighting the importance of designing AI systems that respect human values, enhance inclusivity, and foster sustainable workforce development. This is particularly relevant in the Indian context, where rapid digitalization and AI adoption are reshaping the labor market, intensifying concerns about job displacement, reskilling challenges, and algorithmic bias (NITI Aayog, 2021). This study positions human-centric AI as a critical enabler of fairness and employment equity in AI-driven workplaces. By integrating perspectives on upskilling, societal impact, and perceptions of fairness, it offers a novel empirical framework for understanding and advancing ethical AI adoption.

## **2. Review of Literature and Research Gap:**

**2.1 Human-Centric Artificial Intelligence (HCAI) in Organizational Contexts:** The notion of HCAI has gained significant scholarly and policy attention in recent years. Unlike traditional AI systems focused primarily on efficiency and automation, HCAI emphasizes fairness, transparency, inclusivity, and accountability in design and deployment (Shneiderman, 2020). The purpose of HCAI is to ensure that AI technologies support instead of replacing human intelligence, inclining technological advancement with ethical and social values (Lee et al., 2021). In organizational settings, HCAI is associated with improved employee trust and reduced resistance to technological adoption (Dignum, 2019). Employees are more likely to integrate AI into their daily tasks, if they perceive AI as transparent and ethical which leads to enhanced organizational performance (Rahwan et al., 2019). Conversely, lack of transparency and perceived biases in AI systems can undermine employee morale, create distrust, and exacerbate workplace inequalities (Binns et al., 2018). In India, where organizational hierarchies and socio-cultural diversity influence workplace dynamics, embedding principles of HCAI becomes even more critical. Recent reports highlight growing concerns over algorithmic opacity and fairness in sectors such as recruitment, banking, and education (NITI Aayog, 2021). However, empirical investigations into employee perceptions of HCAI in the Indian context remain scarce, indicating a substantial gap in the literature.

**2.2 AI, Ethical Design, and Perceptions of Fairness:** One of the foundational pillars of HCAI is fairness, often conceptualized as the absence of bias in AI-driven decision-making processes. Studies in algorithmic management reveal that employees are anxious about being reduced to “a percentage,” whereby AI evaluates their performance or suitability for promotion through opaque algorithms (Binns et al., 2018). Fairness in AI is linked with inclusivity, ensuring equal treatment across gender, age, socio-economic background, and other demographic categories (Barocas & Selbst, 2019). Research in Western contexts has examined fairness in AI systems, particularly in recruitment and HR analytics, with findings showing that perceived fairness significantly predicts acceptance and trust (Friedman & Hendry, 2019) and Krishnan et al (2023) argued that artificial intelligence reduces the cost per hire in recruitment and helps in increasing the employee productivity. However, these studies are mainly focused on developed economies. In India, the fairness debate intersects with pre-existing inequalities such as gender disparity in employment, caste-based discrimination, and rural-urban digital divides (Kshetri, 2021). There is limited empirical evidence assessing how Indian employees perceive AI’s fairness and inclusivity in their unique socio-economic context.

**2.3 Attitudes Toward Upskilling and Reskilling:** AI adoption has fueled an unprecedented demand for upskilling and reskilling, especially in economies undergoing rapid digitalization. Attitudes toward skill development are a critical determinant of how employees adapt to technological change (Van Laar et al., 2017). Positive attitudes by employees toward reskilling are less likely to perceive AI as a threat and more likely to view it as a instrument for career

advancement (Brougham & Haar, 2018). In India, government initiatives such as the *Skill India Mission* and partnerships with technology firms aim to prepare the workforce for Industry 4.0. Nonetheless, the success of these programs depends largely on employees' inclination to engage in lifelong learning (NITI Aayog, 2021). Studies discovered that while young, urban employees often embrace digital upskilling, older or rural employees may exhibit reluctance due to fear of redundancy or limited access to resources (Rao & Malik, 2019). Despite these insights, empirical studies connecting perceptions of HCAI with upskilling attitudes are limited, especially in the Indian workforce context. This lack of integration brings unanswered queries about whether perceiving AI as human-centric encourages proactive skill development.

**2.4 Societal Impacts of AI on Employment:** A recurring theme in AI scholarship is its potential societal impact on employment, particularly the risk of job displacement. While AI promises efficiency and productivity, scholars caution that its large-scale adoption could lead to structural unemployment, especially in labor-intensive economies (Brynjolfsson & McAfee, 2017; Susskind, 2020). At the same time, AI may create new job categories requiring advanced technical skills, but such opportunities are unevenly distributed, often benefiting only highly skilled professionals (World Economic Forum, 2020). Research from developed economies has highlighted both optimism and skepticism regarding AI's employment impacts. For instance, OECD (2021) found that while automation may reduce low-skill jobs, it simultaneously expands roles in AI oversight, ethics, and system maintenance. However, the Indian scenario is distinct due to its demographic profile and reliance on service-based industries. Sectors such as IT-enabled services (ITES), banking, and healthcare are adopting AI at an accelerated pace, raising concerns over employment polarization—where high-skill jobs grow while middle- and low-skill jobs shrink (Kshetri, 2021). Although several conceptual analyses exist, empirical studies capturing Indian employees' perceptions of AI's societal impact—particularly in relation to fairness and equity—remain underdeveloped.

**Structural Equation Modeling in AI and Workforce Research:** The methodological approach of employing SEM has gained traction in studies assessing complex constructs such as trust, fairness, and technology adoption (Hair et al., 2019). SEM facilitates researchers to simultaneously test direct and mediating relationships, providing a holistic understanding of AI's impacts. Studies applying SEM in AI contexts have validated constructs such as trust in automation (Lee & See, 2019) and acceptance of algorithmic decision-making (Logg et al., 2019). In the Indian context, however, SEM-based empirical validations exploring HCAI, upskilling attitudes, societal AI impacts, and employment equity remain rare. This methodological gap underscores the need for robust quantitative research that can establish causality and mediation among these constructs.

## 2.5 Research Gap

While global research emphasizes fairness, inclusivity, and transparency in AI, only limited empirical studies conducted on how Indian employees perceive HCAI in diverse sectors. Given India's socio-economic heterogeneity, context-specific research is crucial. Although reskilling has been studied in relation to technological disruptions, there is limited empirical evidence linking perceptions of human-centric AI with employees' willingness to involve in skill development in India. Existing research focuses on job displacement or fairness in isolation. Few studies conducted about how Indian employees perceive AI's broader societal impact on employment equity across demographics. Despite increasing adoption of AI in Indian organizations, few studies employed SEM to validate mediating relationships, particularly the role of HCAI in shaping fairness and employment equity. Most studies available in Indian context are conceptual or qualitative. The survey-based studies that can provide generalizable inputs into the link between HCAI, upskilling, societal impact, and employment equity. By

addressing these gaps, the present study makes a novel contribution to the discourse on ethical AI adoption in developing economies.

### 3. Objectives of the Study

- To examine the link between attitudes toward upskilling/reskilling and perceptions of AI fairness and employment equity.
- To analyze societal perceptions of AI's impact on employment affect fairness evaluations.
- To Investigate the mediating role of human-centric AI perceptions in relationship between Attitudes Toward Upskilling and Reskilling (AUR), Perceived Societal Impact of AI on Employment (PSAIE) and Perception of AI Fairness and Employment Equity (PAIFE)

### 4. Research Methodology:

**4.1 Profile of the Respondents:** The study collected data from 214 respondents across diverse professional backgrounds to ensure a wider understanding of AI perceptions in modern workplaces. 86% of participants were aged between 21 and 30 years, indicating a predominantly young and early-career workforce. 53.3% of the respondents were female and 45.3% male. Most of the respondents were pursued higher education, with 69.6% holding a postgraduate degree and 23.8% being undergraduates. The respondents represented various sectors, with Information Technology (22.9%), Education (20.6%), and Banking (8.4%) being the most prominent. Notably, 32.7% indicated employment in other sectors including consulting, startups, and NGOs. 79.9% participants having below five years of professional experience, followed by 10.7% with 5–10 years. Regarding income levels, 66.4% earned below ₹50,000 per month, while 15.4% fell in the ₹50,000–1 lakh range. These demographic insights highlight a sample that is youthful, educated, and predominantly from early career stages, making it particularly relevant for examining perceptions of Human-Centric AI, digital skill development, and employment equity in AI adoption.

**4.2 Reliability Analysis:** Cronbach's Alpha reliability values of all constructs demonstrated acceptable to excellent internal consistency. The overall scale ( $\alpha = 0.918$ ) indicated excellent reliability (Nunnally & Bernstein, 1994). PHCAI ( $\alpha = 0.870$ ), AUR ( $\alpha = 0.866$ ), and PAIFE ( $\alpha = 0.888$ ) showed very good reliability, exceeding the 0.85 threshold (Hair et al., 2019). PSAIE ( $\alpha = 0.791$ ) met the acceptable standard for exploratory research (George & Mallery, 2019).

**4.3 Scale Development:** The present study employed a structured questionnaire consisting of five-point Likert scale items (1 = Strongly Disagree to 5 = Strongly Agree) to measure four latent constructs: Perception of Human-Centric AI (PHCAI), Attitudes Toward Upskilling and Reskilling (AUR), Perceived Societal Impact of AI on Employment (PSAIE), and Perception of AI Fairness and Employment Equity (PAIFE). The development of these scales followed a rigorous process grounded in previous validated literature and tailored to the context of AI in contemporary workplaces.

The scale for Perception of Human-Centric AI (PHCAI) was adapted from Dignum (2019) and Lee et al. (2021), focusing on dimensions such as ethical AI use, transparency, inclusivity, and human augmentation. Items assessed perceptions about the explainability, fairness, and trust in AI systems in the workplace. These dimensions align with emerging discussions on responsible AI that emphasize the need for systems that respect privacy, avoid harm, and foster trust (Dignum, 2019). To assess Attitudes Toward Upskilling and Reskilling (AUR), items were drawn from Van Laar et al. (2017) and Brougham and Haar (2018), capturing employee

willingness to acquire digital skills, confidence in adapting to technological changes, and organizational support for reskilling initiatives. This scale is pertinent in evaluating employee readiness in navigating disruptions caused by AI adoption, which is crucial for organizational resilience and career sustainability in the digital economy.

The Perceived Societal Impact of AI on Employment (PSAIE) scale was constructed using literature by Susskind (2020) and Brynjolfsson and McAfee (2014). These items aimed to capture respondents' concerns about job displacement, inequality, and optimism about AI's long-term societal contributions to employment. The items reflect broader socio-economic debates on how AI impacts the labor market, especially the widening gap between skilled and unskilled workers and the need for inclusive deployment strategies. Finally, the scale for Perception of AI Fairness and Employment Equity (PAIFE) was adapted from works by Binns et al. (2018) and Raji et al. (2020), focusing on fairness in algorithmic decision-making related to hiring, promotion, and equal access to opportunities. The items assess the perceived presence of bias and the transparency of AI systems used in human resource processes.

All items of each scale were adapted to fit the framework to the organizational AI use and were subjected to expert review for content validity. This ensured clarity, relevance, and contextual appropriateness. All scales internal consistency yielded coefficients ranging from 0.791 to 0.888, indicating acceptable to excellent reliability. Additionally, EFA and CFA were conducted to verify construct validity and dimensional structure, supporting the robustness of the measurement model. This multi-source, theory-informed approach to scale development not only ensures strong psychometric properties but also aligns with contemporary research practices in technology adoption, organizational behavior, and AI ethics in business research.

## 5. Hypothesis Development:

### **H1: Employees' attitudes toward upskilling and reskilling have a positive and significant effect on their perceptions of AI fairness and employment equity.**

The integration of Artificial Intelligence (AI) into organizational processes—particularly in recruitment, performance evaluation, and promotion—has transformed job roles and skill requirements. In such environments, the ability and willingness of employees to adapt through upskilling and reskilling become critical. The central proposition of Hypothesis H1 is that employees who demonstrate a positive orientation toward developing new and required skills are more likely to perceive AI-driven decisions as fair and equitable. This proposition is theoretically grounded in the notion that skill readiness fosters openness to technological change, which in turn enhances trust in AI systems (van Laar et al., 2017; Brougham & Haar, 2018). When employees believe that organizational learning opportunities are accessible and inclusive, they interpret AI adoption as an enabler of career advancement rather than as a mechanism for exclusion. Such perceptions align with procedural justice theory, which emphasizes fairness in processes as a determinant of trust (Colbert et al., 2016).

Empirical evidence supports this connection. Studies indicate that targeted reskilling programs reduce anxiety about automation and algorithmic management, leading to greater acceptance of AI in decision-making (Jarrahi et al., 2021). Similarly, when AI is integrated into human resource practices alongside employee development initiatives, workers perceive it as augmenting rather than replacing human capabilities (Lee et al., 2021). Therefore, Hypothesis H1 is both theoretically and empirically supported: positive attitudes toward upskilling and reskilling are expected to significantly enhance perceptions of fairness and employment equity in AI-enabled workplaces. This relationship reflects the broader principle that in human-centric

AI design, technology should be positioned as a partner in professional growth, ensuring equitable opportunities for all employees.

**H2: Perceived societal impact of artificial intelligence on employment has a significantly positive effect on perceived AI fairness and employment equity.**

The integration of artificial intelligence into labor markets and organizational decision-making processes has prompted diverse societal responses, ranging from optimism about innovation-driven opportunities to concerns about technological unemployment. Hypothesis H2 posits that individuals who perceive artificial intelligence as having a positive societal impact on employment are more likely to regard AI-enabled workplace systems as fair and equitable. This proposition is grounded in socio-cognitive theory, which suggests that individuals' broader beliefs about the societal role of technology influence their specific judgments about its fairness and legitimacy (Bandura, 2001). When AI is viewed as enhancing productivity, generating employment opportunities, and promoting inclusivity, employees are predisposed to trust AI-enabled decision-making. In contrast, when AI is seen as job-displacing or benefiting only a privileged subset of workers, perceptions of fairness and employment equity tend to diminish (Brynjolfsson & McAfee, 2014; Susskind, 2020).

Empirical studies reinforce this link. Positive societal beliefs about AI—such as its capacity to improve job quality, reduce bias, and broaden access to opportunities—have been shown to correlate with greater acceptance of AI in human resource practices (Rai, Constantinides, & Sarker, 2019). This is consistent with legitimacy theory, where perceptions of AI serving a broader social good increase the perceived fairness of its outcomes (Binns et al., 2018). When organizations articulate AI adoption in terms of socially responsible goals—such as addressing skill shortages or expanding equitable access—employees' fairness perceptions are further strengthened (Raji et al., 2020).

The psychological contract theory also provides explanatory support, as employees expect organizational AI strategies to align with socially beneficial values (Guest, 2004). A perceived positive societal impact affirms these expectations, reinforcing the belief that AI-enabled decisions are ethically grounded and equitable. Empirical findings show that workers who believe AI benefits society are more accepting of its use in recruitment, promotion, and performance appraisal (Jarrahi et al., 2021). Therefore, Hypothesis H2 is conceptually and empirically supported: societal-level beliefs about AI's employment impact act as a cognitive filter that shapes micro-level fairness evaluations in the workplace. A positive societal perception of AI not only predicts greater acceptance of AI-driven decision-making but also strengthens perceptions of employment equity.

**H3: Perception of human-centric artificial intelligence mediates the relationship between employees' attitudes toward upskilling and reskilling and their perceptions of AI fairness and employment equity.**

As artificial intelligence becomes embedded in workplace functions such as recruitment, performance evaluation, and career progression, employee perceptions of its human-centric qualities—ethical design, inclusivity, and augmentation of human capabilities—play a crucial role in shaping fairness judgments. Hypothesis H3 posits that employees' readiness to adapt through upskilling and reskilling influences fairness perceptions primarily through their evaluation of AI as human-centric. This hypothesis is grounded in the Technology Acceptance Model (TAM) and its extensions (Venkatesh & Davis, 2000), which suggest that acceptance and evaluation of a technology depend on users' beliefs about its usefulness and value

alignment. Employees who demonstrate positive attitudes toward continuous skill development are more inclined to view AI as an enabler of personal and organizational growth rather than as a threat, thereby reinforcing perceptions of AI as transparent, ethical, and aligned with human values (Dignum, 2019; Lee et al., 2021). This interpretive lens—perception of human-centric AI—acts as a cognitive bridge between skill readiness and fairness evaluations.

Empirical studies reinforce this mediation pathway. Brougham and Haar (2018) found that employees engaged in proactive reskilling are more likely to trust AI technologies, particularly when these systems exhibit transparency and accountability. Similarly, Lee et al. (2021) observed that trust in AI increases when users perceive it as upholding fairness and inclusivity. Jarrahi et al. (2021) further highlight that AI trustworthiness is determined not only by algorithmic performance but by its alignment with human needs, such as respect for privacy and equitable decision-making. The mediation is also constant with the affective–cognitive framework in organizational behavior, which suggests that affective dispositions—such as readiness to learn—shape cognitive evaluations—such as fairness perceptions—through interpretive filters like perceived human-centricity of AI. Therefore, Hypothesis H3 is theoretically and empirically supported: enhancing perceptions of human-centric AI serves as a vital conduit for translating employees' skill adaptability into broader evaluations of fairness and equity in AI-driven workplaces.

**H4: Perception of human-centric artificial intelligence mediates the relationship between perceived societal impact of artificial intelligence on employment and perceived AI fairness and employment equity.**

In AI-enabled workplaces, individuals' macro-level beliefs about the societal consequences of artificial intelligence—particularly its influence on employment—shape how they evaluate the fairness and inclusivity of AI systems at the organizational level. Hypothesis H4 proposes that this relationship operates through the perception of human-centric AI, which acts as a cognitive filter translating broad societal beliefs into workplace fairness evaluations. The technology framing theory (Orlikowski & Gash, 1994) provides the theoretical basis for this hypothesis, asserting that people interpret and evaluate technologies through the lens of their underlying assumptions and expectations. When employees perceive AI as socially beneficial—enhancing job opportunities, increasing productivity, and reducing inequality—they are more likely to regard it as human-centric: ethical, trustworthy, and designed to augment human capabilities. This interpretive framing then shapes their judgments of fairness in AI-driven processes such as recruitment, promotion, and performance evaluation. The value-based adoption model (VAM) (Kim, Chan, & Gupta, 2007) further supports this mediation pathway, suggesting that positive adoption attitudes arise when individuals perceive alignment between technological design and their values, including fairness, inclusivity, and societal well-being. However, societal-level benefits do not automatically translate into positive workplace fairness perceptions unless AI is also perceived to be transparent, explainable, and respectful of user rights.

Empirical evidence reinforces this proposition. Raji et al. (2020) show that algorithmic systems perceived as ethical and transparent are assessed as fair when they are also believed to serve the greater societal good. Susskind (2020) notes that perceptions of AI's societal usefulness reduce resistance and build trust, especially when human-centric design principles are evident. Similarly, Lee et al. (2021) highlight that fairness judgments are strengthened when AI adoption includes inclusivity measures, privacy protections, and explainable decision-making. Therefore, Hypothesis H4 is both theoretically and empirically grounded: perceptions of human-centric AI mediate the link between societal beliefs about AI's employment impact and

fairness perceptions in the workplace. This mediation model captures the layered belief process in which macro-level views influence micro-level fairness evaluations through an ethical and human-centered interpretive lens.

**H5: The proposed structural model provides a good fit to the observed data in explaining fairness and employment equity perceptions in AI-driven workplaces.**

Hypothesis H5 focuses on assessing whether the structural model developed in this study accurately captures the theoretical and empirical relationships among the four core constructs: employees' attitudes toward upskilling and reskilling, perceived societal impact of AI on employment, perceptions of human-centric AI, and perceptions of AI fairness and employment equity. Structural Equation Modeling (SEM) was employed to evaluate the model's fit and explanatory strength, with results indicating strong statistical support for the proposed framework. This hypothesis is grounded in prior research suggesting that perceptions of AI's social responsibility, ethical design, and transparency are critical drivers of fairness evaluations (Raji et al., 2020; Binns et al., 2018). Employees who perceive AI as inclusive, explainable, and aligned with human values are inclined to evaluate its outcomes positively—particularly when they possess relevant skills or believe that AI is contributing positively to societal employment outcomes.

A distinctive feature of the model is the mediating role of perceptions of human-centric AI. Acting as an interpretive bridge between individual dispositions (attitudes toward skill development), macro-level perceptions (AI's societal impact), and fairness evaluations, this construct amplifies the effects of both attitudinal and societal variables. The partial mediation observed suggests that while the independent variables exert direct influences, their effects are significantly enhanced when filtered through a human-centric interpretive lens. This finding is consistent with technology adoption and ethical AI literature, which emphasizes that user trust, fairness, and inclusivity are pivotal to positive evaluations of AI (Lee et al., 2021; Dignum, 2019). Conceptually, the model extends the Technology Acceptance Model (TAM) by incorporating fairness and equity as outcome variables, mediated by human-centric AI perceptions. It also aligns with psychological contract theory (Guest, 2004), which holds that when organizational technologies support employee development goals and align with personal values, they reinforce perceptions of procedural and distributive justice. In doing so, the model integrates socio-cognitive, behavioral, and ethical dimensions of AI adoption in workplace contexts.

From a managerial perspective, the model's implications are twofold: first, organizations must foster a culture of continuous learning to prepare employees for AI-enabled work environments; second, they must actively cultivate perceptions of AI as human-centric—through transparent algorithms, inclusive design processes, and employee participation in AI governance. Strategies such as ethical audits, explainable AI systems, and open communication can enhance fairness perceptions and reinforce organizational equity objectives (Binns et al., 2018; Susskind, 2020). Therefore, Hypothesis H5 is well-supported by both empirical evidence and theoretical reasoning. The validated model offers a robust framework for both researchers and practitioners to evaluate AI adoption strategies that balance technical performance with ethical, human-centered values, ensuring fairness, inclusivity, and trust in AI-driven workplace practices.

## 6. DATA ANALYSIS:

**Exploratory Factor Analysis (EFA):** EFA has revealed the KMO value of 0.893 indicates meritorious sampling adequacy (Kaiser, 1974), and Bartlett's Test was significant ( $\chi^2 = 2260.561$ ,  $df = 153$ ,  $p < 0.001$ ), confirming factorability of the correlation matrix (Hair et al., 2019). Using Principal Component Analysis – PCA with Varimax rotation, four components with eigenvalues  $>1.0$  were extracted. These components cumulatively explained 68.81% of the total variance, exceeding the commonly accepted threshold of 60% for social science research (Field, 2013).

Factor 1, labeled *AI Fairness & employment Equity*, explained 19.54% of the variance and consisted of four items related to bias-free AI decision-making, transparency, and equal opportunity in HR practices, with strong factor loadings ranging from 0.745 to 0.828. This dimension reflects respondents' perceptions of fairness in AI-enabled human resource functions (Binns et al., 2018). Factor 2, *Human-Centric AI Trust & Transparency*, accounted for 18.72% of the variance and included five items measuring privacy, explainability, inclusiveness, and augmentation by AI. The loadings ranged from 0.707 to 0.776, indicating that these items strongly represent trust in AI systems (Lee et al., 2021).

Factor 3, termed *Attitudes Toward Upskilling & Reskilling*, contributed 18.45% of the explained variance, which included five items reflecting readiness to acquire new digital skills, with factor loadings between 0.624 and 0.839. These results are align with prior research highlighting employees' proactive approach toward skill development in AI-integrated environments (Van Laar et al., 2017). Factor 4, *Societal Impact of AI on Employment*, explained 12.11% of the variance. It included four items capturing perceptions about job displacement, inclusion, and labor market polarization due to AI. Despite a relatively lower loading (0.503) for job creation, the other items loadings are above 0.64, affirming the construct's reliability (Susskind, 2020). Overall, the factor structure was theoretically coherent and statistically robust, supporting the construct validity of the measurement instrument for subsequent analyses.

Table No:1 Combined Matrix - Model Fit Indices and Interpretation

Indicator	Result / Value	Threshold / Interpretation
<b>Model Fit Indices</b> Chi-square/df	2.382	< 3.0 (Kline, 2015)
CFI	0.918	$\geq 0.90$ = Good Fit
TLI	0.903	$\geq 0.90$ = Good Fit
IFI	0.919	$\geq 0.90$ = Good Fit
NFI	0.868	Slightly below threshold
RMSEA (90% CI)	0.081 (0.069–0.092)	$\leq 0.08$ (Acceptable)
PCLOSE	0.000	$> 0.05$ preferred
SRMR	0.052	$\leq 0.08$ (Good Fit)
GFI / AGFI	0.864 / 0.820	Slightly below threshold
<b>Factor Loadings (Standardized)</b> HCAI1 to HCAI5	0.888 – 1.047	All significant, $> 0.70$
AUR1 to AUR5 (PAUR)	0.933 – 1.034	All significant, $> 0.70$
PSAIE1 to PSAIE4 (AIE)	0.798 – 0.957	All significant
PAIFE1 to PAIFE4 (AIEE)	0.897 – 0.966	All significant
<b>Construct Reliability (CR)</b> HCAI / PAUR / AIE / AIEE	0.932 / 0.934 / 0.861 / 0.913	$> 0.70$ (Excellent)
<b>Average Variance Extracted (AVE)</b> HCAI / PAUR / AIE / AIEE	0.732 / 0.739 / 0.609 / 0.724	$> 0.50$ = Good Convergent Validity
<b>Fornell-Larcker Criterion</b> $\sqrt{AVE}$ : Diagonal values	HCAI: 0.856, PAUR: 0.860, AIE: 0.780, AIEE: 0.851	Greater than inter-construct correlations

Correlations (off-diagonal)	Range: 0.257 to 0.538	All below respective $\sqrt{\text{AVE}}$ values = <b>Discriminant Validity met</b>
<b>Inter-Construct Correlations</b> HCAI-PAUR / HCAI-AIE / HCAI-AIEE	0.315 / 0.299 / 0.395	All significant at $p < 0.001$
PAUR-AIE / PAUR-AIEE / AIE-AIEE	0.257 / 0.267 / 0.538	All significant at $p < 0.001$

**Interpretation and Discussion**

CFA was deployed to validate the factor structure derived from the EFA and to assess the psychometric properties of the measurement model. The proposed four-factor model consisted of the following latent constructs: Human-Centric AI (HCAI), Perceived AI Usefulness & Reliability (PAUR), AI Integration Effectiveness (AIE), and AI Fairness & Employment Equity (AIEE). The model demonstrated an overall acceptable fit to the data, as chi-square statistic was significant ( $\chi^2 = 307.312$ ,  $df = 129$ ,  $p < .001$ ). The relative chi-square ( $\chi^2/df = 2.382$ ) was within the acceptable range of  $< 3.0$ , indicating good fit (Carmines & McIver, 1981). Additionally, key indices such as CFI (0.918), TLI (0.903), IFI (0.919), and SRMR (0.052) met or exceeded recommended thresholds (Hair et al., 2019; Hu & Bentler, 1999), confirming model adequacy. Although GFI (0.864) and AGFI (0.820) were slightly below the conventional cutoffs, the overall model fit was satisfactory for continued analysis.

All standardized factor loadings were statistically significant at  $p < .001$ , and most exceeded the recommended threshold of 0.70, indicating strong item-construct relationships (Hair et al., 2019). The HCAI factor exhibited loadings ranging from 0.888 to 1.047, PAUR from 0.933 to 1.034, AIE from 0.798 to 0.957, and AIEE from 0.897 to 0.966. These results witnessed the convergent validity of the constructs. Construct reliability (CR) values for all four latent variables exceeded 0.85, above the minimum benchmark of 0.70, confirming internal consistency (Fornell & Larcker, 1981). Average Variance Extracted - AVE values also surpassed the 0.50 threshold, further confirming convergent validity (Bagozzi & Yi, 1988). The constructs HCAI, PAUR, and AIEE demonstrated particularly high AVE values ( $> 0.70$ ), indicating that the constructs explain a large proportion of variance in their indicators.

Discriminant validity was tested using the Fornell-Larcker criterion, which compares the  $\sqrt{\text{AVE}}$  with the inter-construct correlations. The diagonal values representing  $\sqrt{\text{AVE}}$  for all constructs (ranging from 0.780 to 0.860) were consistently greater than the corresponding inter-construct correlations (ranging from 0.257 to 0.538). This satisfies the criterion and indicates that the constructs are empirically different from one another (Fornell & Larcker, 1981). CFA results confirm that the four-factor model exhibits strong construct reliability, convergent validity, and discriminant validity. The fit indices validate the structural integrity of the measurement model, which allows for further structural equation modeling (SEM) analysis. These findings reinforce the theoretical underpinnings of the constructs and establish the robustness of the measurement model in examining perceptions related to AI in organizational settings.

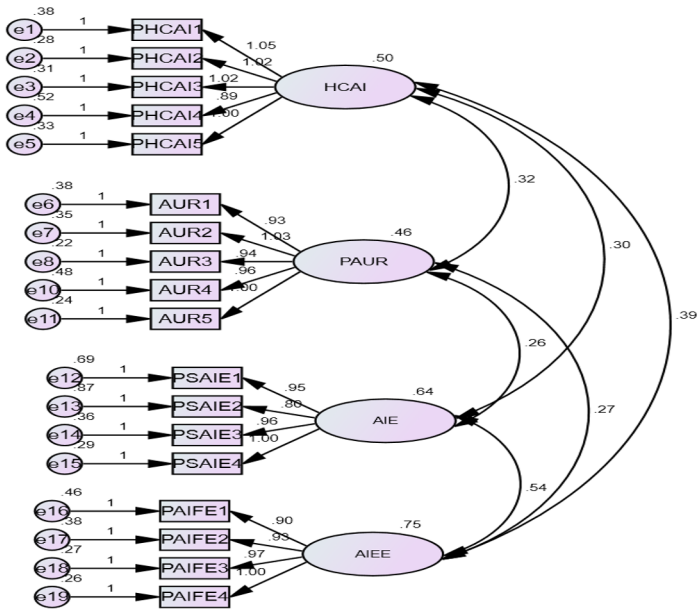


Figure No: 1 – CFA Diagram

**Descriptive Statistics:**

The descriptive statistics provide an overview of respondents’ perceptions across four key constructs related to AI implementation: Human-Centric AI (HCAI), Attitudes Toward Upskilling and Reskilling (AUR), Perceived Societal Impact of AI on Employment (PSAIE), and AI Fairness and Employment Equity (PAIFE). Overall, respondents demonstrated favorable perceptions of AI integration in the workplace, with mean scores for survey items ranging from 3.68 to 4.45 on a 5-point Likert scale.

The highest mean score was recorded for “I am willing to learn new digital or technical skills to stay relevant in my job” (M = 4.45, SD = 0.886), indicating strong proactive attitudes toward upskilling. Similar trends were found in related items such as confidence in adapting to AI changes (M = 4.40) and organizational encouragement for reskilling (M = 4.24), reflecting the growing importance of digital competence in AI-driven environments (Van Laar et al., 2017; Brougham & Haar, 2018). Within the HCAI domain, respondents showed high levels of agreement for items such as “AI systems respect privacy and data security” (M = 4.08) and “AI acts in employees’ best interest” (M = 4.07). These scores suggest a generally positive trust in AI systems, aligning with principles of ethical AI implementation (Dignum, 2019). The construct of AI fairness and HR equity also received supportive responses, with items like “AI ensures fair treatment across gender, age, or background” (M = 3.96) and “AI decision-making is bias-free” (M = 3.92) reinforcing the perceived integrity of algorithmic HR practices (Binns et al., 2018). In contrast, the PSAIE items had relatively lower mean scores for, “AI will create more job opportunities” (M = 3.68) and “AI may cause job displacement” (M = 3.69) indicating a moderate level of ambivalence. These findings reflect ongoing concerns about AI-induced labor market shifts (Susskind, 2020).

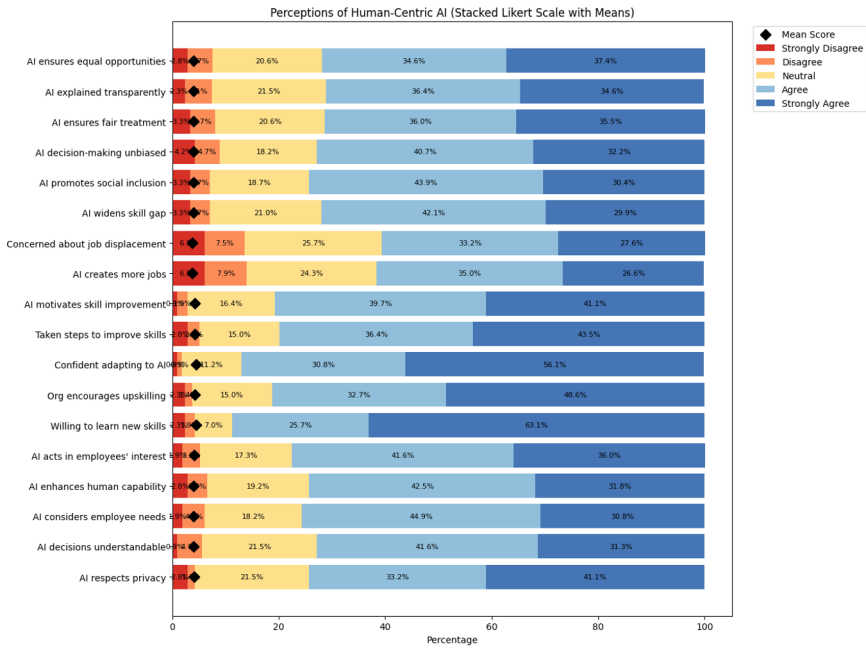


Figure No: 2 Descriptive Statistics Column Chart

**Structural Equation Model:**

Table No: 2 Combined Matrix – SEM - Interpretations:

Indicator / Path	Results	Threshold / Interpretation
<b>Model Fit Indices</b> $\chi^2$ (df = 2)	4.000 ( $p < 0.05$ )	Significant; expected with larger samples (Kline, 2015)
$\chi^2/df$	2.00	$\leq 3.0$ = Good Fit (Carmines & McIver, 1981)
Comparative Fit Index (CFI)	0.945	$\geq 0.90$ = Good Fit (Hu & Bentler, 1999)
Tucker–Lewis Index (TLI)	0.922	$\geq 0.90$ = Good Fit
Incremental Fit Index (IFI)	0.947	$\geq 0.90$ = Good Fit
Goodness-of-Fit Index (GFI)	0.930	$\geq 0.90$ = Good Fit (Byrne, 2016)
Adjusted GFI (AGFI)	0.900	$\geq 0.90$ = Acceptable Fit
RMSEA (90% CI)	0.055 (0.038–0.071)	$\leq 0.06$ = Close Fit
PCLOSE	0.180	$\geq 0.05$ = Close Fit Supported
Standardized RMR (SRMR)	0.046	$\leq 0.08$ = Good Fit

<b>Path Coefficients</b> AUR → PHCAI	$\beta = 0.509$ ( $p < 0.001$ )	Significant direct effect
PSAIE → PHCAI	$\beta = 0.239$ ( $p < 0.001$ )	Significant direct effect
PSAIE → PAIFE	$\beta = 0.649$ ( $p < 0.001$ )	Strong direct effect
AUR → PAIFE	$\beta = 0.216$ ( $p < 0.001$ )	Moderate direct effect
PHCAI → PAIFE	$\beta = 0.376$ ( $p < 0.001$ )	Significant direct effect
<b>Mediation Effects</b> AUR → PHCAI → PAIFE	Indirect: $\beta = 0.331$	Significant partial mediation
PSAIE → PHCAI → PAIFE	Indirect: $\beta = 0.155$	Significant partial mediation
AUR → PAIFE (Total Effect)	Total: $\beta = 0.547$	Direct (0.216) + Indirect (0.331)
PSAIE → PAIFE (Total Effect)	Total: $\beta = 0.804$	Direct (0.649) + Indirect (0.155)
Conclusion	Model Fit = Good; Hypotheses = Supported	Confirms structural paths and mediation via PHCAI

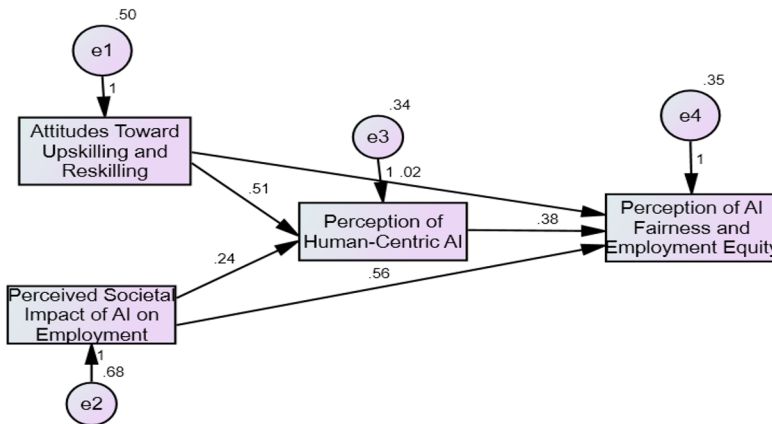


Figure No: 3 – SEM – Path Diagram

Structural Equation Modeling (SEM) was conducted to examine the hypothesized relationships between Perceived Societal Impact of AI on Employment (PSAIE), Attitudes Toward Upskilling and Reskilling (AUR), Perception of Human-Centric AI (PHCAI), and Perception of AI Fairness and Employment Equity (PAIFE). The SEM analysis aimed to assess both the direct and indirect effects among the constructs and evaluate the mediating role of PHCAI. The overall model fit was found to be satisfactory. Although the chi-square statistic was significant ( $\chi^2 = 4.000$ ,  $df = 2$ ,  $p < .05$ ), this is not uncommon in large sample studies and is often

considered alongside other fit indices (Kline, 2015). The relative chi-square ( $\chi^2/df = 2.00$ ) fell within the acceptable threshold of less than 3.0, indicating a good fit (Carmines & McIver, 1981). Additional fit indices supported the adequacy of the model: CFI = 0.945, TLI = 0.922, IFI = 0.947, and SRMR = 0.046—all of which met the recommended cutoffs of  $\geq 0.90$  or  $\leq 0.08$  (Hu & Bentler, 1999). The RMSEA value of 0.055 (90% CI = 0.038–0.071) further suggested a close model fit.

All hypothesized direct paths were statistically significant ( $p < 0.001$ ). AUR had a strong direct effect on PHCAI ( $\beta = 0.509$ ), suggesting that positive attitudes toward reskilling significantly enhance employees' perception of human-centric AI. PSAIE also positively influenced PHCAI ( $\beta = 0.239$ ), demonstrating that employees who perceive AI's societal impact as constructive are inclined to trust AI implementations in their workplace. Further, PSAIE demonstrated a strong direct effect on PAIFE ( $\beta = 0.649$ ), and AUR had a moderate direct effect on PAIFE ( $\beta = 0.216$ ). These results expose that both societal perceptions of AI and individual attitudes toward upskilling contribute to how fairly and equitably AI systems are perceived within organizational HR contexts.

The mediating role of PHCAI was confirmed for both PSAIE and AUR. For AUR, the indirect effect via PHCAI was  $\beta = 0.331$ , and for PSAIE, it was  $\beta = 0.155$ . These significant mediation pathways indicate that PHCAI serves as a crucial mechanism through which the benefits of upskilling and positive societal AI perceptions are translated into perceived fairness and equity in AI use. Notably, AUR's total effect on PAIFE was  $\beta = 0.547$  (direct + indirect), and PSAIE's total effect was  $\beta = 0.804$ , signifying the importance of both direct and mediated pathways.

### Findings and Discussions

This study empirically evidenced on the complex interplay among Attitudes Toward Upskilling and Reskilling (AUR), Perceived Societal Impact of AI on Employment (PSAIE), Perception of Human-Centric AI (PHCAI), and Perceived AI Fairness and Employment Equity (PAIFE) within the Indian workforce. Employing Structural Equation Modeling (SEM) on data collected from a diverse sample of 214 employees and contributes to advancing both theoretical discourse and practical exposure of how human-centric approaches to AI can shape workforce perceptions in rapidly digitalizing economies. The measurement model demonstrated robust psychometric soundness, with CFA yielding acceptable model fit indices ( $\chi^2/df = 2.382$ , CFI = 0.918, TLI = 0.903, RMSEA = 0.081). Reliability and validity tests confirmed the strength of the constructs, with Composite Reliability (CR) values ranging between 0.861 and 0.934 and AVE values exceeding 0.60, thereby satisfying the thresholds for convergent and discriminant validity (Fornell & Larcker, 1981; Hair et al., 2019). The model further confirmed an excellent fit ( $\chi^2/df = 2.00$ , CFI = 0.945, RMSEA = 0.055), substantiating the hypothesized relationships.

Finding of this study is the pivotal role of PHCAI as a mediating construct. The mediation results indicate that perceptions of human-centric AI significantly amplify the positive effects of both AUR and PSAIE on PAIFE. This underscores the assertion that fairness perceptions are not merely a function of outcomes but are deeply tied to the ethical dimensions of AI design and implementation, including inclusivity, transparency, and explainability (Lee et al., 2021). In line with Dignum (2019), the findings suggest that responsible AI must embed human values at its core to foster trust and legitimacy in organizational contexts. The significant direct effect of AUR on PAIFE highlights the strategic importance of continuous learning in the AI era. Employees who actively pursue upskilling and reskilling perceive AI-enabled HR systems as more equitable, reinforcing prior evidence that workforce adaptability reduces anxieties related to technological displacement (Brougham & Haar, 2018; Van Laar et al., 2017). This is

particularly relevant in India, where the pace of digital transformation is rapid yet uneven across industries. Consequently, structured and inclusive reskilling ecosystems become not only an HR priority but also a strategically important for maintaining workforce equity.

Equally notable is the robust direct effect of PSAIE on PAIFE. This suggests that macro-level societal narratives significantly shape micro-level organizational perceptions of fairness. When AI is framed as a societal enabler rather than a threat, employees are inclined to trust AI-driven HR practices. These findings resonate with Susskind's (2020) argument that optimism about AI's societal potential can mitigate fears of automation-induced job displacement. In the Indian context, where automation in IT and manufacturing coexists with job creation in digital services and e-commerce, fostering positive societal discourse around AI's role becomes as crucial as organizational initiatives (Dwivedi et al., 2021).

Furthermore, the study reinforces the requirement of fairness in AI-enabled HR practices. Trust in AI systems is contingent on transparent and accountable decision-making processes. The mediating role of PHCAI highlights that fairness perceptions extend beyond distributive outcomes to encompass procedural and ethical dimensions. This finding aligns with Binns et al. (2018) and Raji et al. (2020), who emphasize the necessity of algorithmic auditing, transparent reporting, and fairness-by-design principles to ensure legitimacy and accountability in AI deployment.

From a practical perspective, the study offers implications at multiple levels. At the policy level, Indian regulators should integrate digital skill-building frameworks with ethical AI governance, aligning with global standards for responsible AI. At the organizational level, along with employee reskilling initiatives firms must also invest in designing AI systems that embody fairness and inclusivity principles. At the societal level, positive public discourse and awareness campaigns highlighting AI's potential for job creation and equity are essential for fostering employee trust and minimizing resistance.

Theoretically, this research advances scholarly discourse by validating PHCAI's mediating role in the relationship between reskilling attitudes, societal optimism, and perceptions of fairness, thereby addressing a critical gap in socio-technical systems research. It also bridges micro-level individual readiness with macro-level societal optimism, offering a holistic perspective on AI's impact in organizational contexts. Finally, by situating these dynamics within the Indian workforce, the study contributes region-specific insights to the global debate on ethical and human-centric AI, strengthening calls for context-sensitive approaches to AI adoption.

## **Conclusion**

This study contributes to the growing discourse on Human-Centric Artificial Intelligence (HCAI) and its societal impacts in the Indian workforce by empirically analyzing how employees perceive the fairness, inclusivity, and equity of AI-enabled systems. The study employed SEM to examine the interrelationships between Attitudes Toward Upskilling and Reskilling (AUR), Perceived Societal Impact of AI on Employment (PSAIE), Perception of Human-Centric AI (PHCAI), and Perceived AI Fairness and Employment Equity (PAIFE). The findings highlighted that employee attitudes toward continuous learning and skill development (AUR) significantly shape their perceptions of fairness in AI-driven workplaces. Employees with positive orientations toward reskilling are more likely to view AI systems as equitable, indicating that organizational investments in digital literacy and workforce development play a pivotal role in promoting employment equity (Van Laar et al., 2017; Brougham & Haar,

2018). Furthermore, societal perceptions of AI's broader economic and employment impacts (PSAIE) emerged as a strong predictor of fairness and equity perceptions. When employees believe that AI contributes positively to societal employment outcomes, they are more inclined to view organizational AI systems as fair, aligning with previous contributions that emphasize the role of macro-level narratives in shaping individual trust in technology (Susskind, 2020; Dwivedi et al., 2021). A central theoretical contribution of this article is establishing the mediating role of PHCAI. The perception of AI as ethical, transparent, and human-focused not only enhances fairness perceptions but also serves as the critical link through which reskilling readiness and societal optimism translate into equitable workforce outcomes. This finding supports previous work on responsible AI (Dignum, 2019; Lee et al., 2021) by empirically validating the mechanism through which human-centric design principles influence workplace equity. In conclusion, the study empirically evidenced that Human-Centric AI serves as both a catalyst and mediator for fairness and employment equity in the AI-driven workplace. By linking skill development readiness, societal narratives, and fairness perceptions, the findings advance both theoretical understanding and practical strategies for AI integration. As India continues toward becoming a digitally empowered economy, embedding human-centric values in AI systems is not merely an ethical imperative but a strategic necessity for sustainable and inclusive growth.

### **Practical Implications**

This study carries significant implications for organizations, policymakers, and stakeholders engaged in shaping the future of work in India. The results emphasize the importance of embedding human-centric design principles in AI adoption, particularly in human resource functions such as recruitment, appraisal, and promotion. Companies must ensure algorithmic transparency and fairness to mitigate perceptions of bias, as employees' trust in AI is directly tied to perceptions of justice and inclusivity (Raji et al., 2020). Furthermore, investing in structured upskilling and reskilling initiatives is crucial. The study confirmed that employees with positive attitudes on required skill enhancement were inclined to perceive AI-enabled processes as fair, highlighting that training programs can act as buffers against fears of job displacement (Brougham & Haar, 2018). Organizations that prioritize skill development are likely to enhance not only employee adaptability but also organizational legitimacy in an AI-driven economy. India's push toward digital transformation must be complemented with policies for ethical AI deployment that protect against discrimination, safeguard employee rights, and promote inclusive access to opportunities (Dwivedi et al., 2021). The study's findings suggest that fostering a positive societal narrative around AI—one that emphasizes augmentation rather than displacement—can enhance trust and perceptions of fairness in AI adoption. Encouraging employees to actively engage in continuous learning while ensuring equitable treatment across demographic groups can reduce anxieties associated with automation (Susskind, 2020). Achieving a balance between technological innovation and human-centric values is essential to ensure that AI adoption contributes to sustainable, inclusive growth rather than exacerbating inequality.

### **Limitations and Future Research Directions**

While this study provides valuable insights into the role of Human-Centric Artificial Intelligence (HCAI) in shaping perceptions of fairness and employment equity in India, few limitations should be acknowledged to contextualize the findings and inform future research.

**Limitations:** India's large labour market the generalizability of findings are limited (Dwivedi et al., 2021). Cultural factors specific to India, such as collectivist work orientations, hierarchical organizational structures, and trust in authority, may have influenced employee

perceptions of AI. Future comparative research across cultural contexts is necessary to study whether these conclusions hold globally (Hofstede, 2011).

**Future Research Directions:** Future research should explore cross-cultural comparisons to assess how perceptions of HCAI differ across emerging and developed economies. Such comparative analyses would not only validate the current framework in varied contexts but also contribute to the global discourse on responsible AI adoption (Dignum, 2019). While the present study advances understanding of Human-Centric AI in India, future research that broadens scope, integrates diverse data sources, and adopts longitudinal and cross-cultural perspectives will be critical to deepening both theoretical and practical insights into the equitable integration of AI in the workforce.

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