

Perceptions of Fresh Graduates and Early-Career Professionals Toward AI-Based Hiring Tools in India: An Extended Technology Acceptance Model Study

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Abstract—Artificial intelligence (AI) is increasingly used to screen, assess, and communicate with job applicants, yet the psychological experience of candidates remains comparatively underexamined in India. The present study examined perceptions of AI-based hiring tools among fresh graduates from the 2024–2025 cohort and early-career professionals employed within the previous five years. An extended Technology Acceptance Model (TAM), incorporating trust, perceived usefulness, AI fairness, technological anxiety, and prior AI experience, was used to examine intention to engage with and actual engagement in AI-mediated recruitment. A quantitative, cross-sectional, correlational design was employed with 116 participants (74 fresh graduates and 42 early-career professionals). Data were collected through an anonymous online questionnaire using a 23-item standardized instrument and analyzed in JASP 0.18 with reliability analysis, descriptive statistics, Pearson correlations, multiple regression, and simple regression. Trust ($\beta = .235$, $p = .014$), perceived usefulness ($\beta = .218$, $p = .045$), and AI fairness ($\beta = .307$, $p < .001$) significantly and positively predicted intention to engage, whereas technological anxiety was not a significant independent predictor ($\beta = -.118$, $p = .114$). Intention to engage significantly predicted actual engagement ($\beta = .287$, $p = .002$), while prior AI experience did not significantly predict technological anxiety ($\beta = -.068$, $p = .468$). The multiple regression model explained 43.5% of the variance in intention to engage. AI fairness was the strongest predictor, indicating that perceived procedural and interpersonal equity may be more consequential than efficiency alone in high-stakes AI-mediated hiring. The findings extend the Indian evidence base on technology acceptance in recruitment and suggest that transparent, explainable, and candidate-centered AI hiring systems may be important for strengthening engagement and organizational legitimacy.

Index Terms—artificial intelligence, AI recruitment, Technology Acceptance Model, AI fairness, trust, technological anxiety, candidate engagement

I. INTRODUCTION

Artificial intelligence has moved rapidly into recruitment and selection, changing how organizations identify, screen, rank, and communicate with applicants. Contemporary systems may include automated résumé parsing, algorithmic candidate scoring, AI-supported video interviews, chatbots, and other forms of automated assessment. The organizational appeal of these systems is closely linked to their ability to process large application volumes quickly and at comparatively low cost (Köchling & Wehner, 2020; Upadhyay & Khandelwal, 2018). In India, the scale and competitiveness of the graduate labor market make technology-supported recruitment particularly salient, especially in sectors such as information technology, banking, financial services, and consulting (Kaur et al., 2023; Upadhyay & Khandelwal, 2018).

Although much of the literature has focused on organizational efficiency, the candidate experience raises a different set of psychological questions. Applicants may wonder whether an AI system is trustworthy, whether its criteria are fair, whether it can recognize individual qualities, and whether being evaluated by a machine produces anxiety or discomfort. Candidate perceptions may subsequently influence willingness to participate, employer attractiveness, organizational evaluations, and actual

engagement with recruitment processes (Acikgoz et al., 2020; Priyanka et al., 2025). The present study therefore treats AI-mediated hiring as a psychological and organizational process rather than only a technological one.

The Technology Acceptance Model (TAM; Davis, 1989) provides a useful starting point for understanding technology adoption. In its standard form, perceived usefulness and perceived ease of use shape intention, which in turn predicts actual use. However, AI hiring differs from many traditional technology-use situations because applicants often do not voluntarily select the technology; instead, they are evaluated through it in a high-stakes context. Trust, fairness, and anxiety therefore become particularly relevant extensions of the original framework. The present study follows the extended framework developed for Indian graduates by Rukadikar and Khandelwal (2025), while extending its application to early-career professionals.

A central issue is fairness. AI systems are often promoted as more objective than human decision makers, yet algorithmic decisions can reproduce or amplify biases present in historical data, validation processes, or design assumptions (Köchling & Wehner, 2020; Soleimani et al., 2025). Research indicates that explainability can improve applicants' perceptions of procedural and outcome fairness (Lavanchy et al., 2023; Malin et al., 2025). In recruitment, fairness may therefore represent more than an ethical principle: it may be a psychological determinant of whether applicants accept the legitimacy of the evaluator.

Trust is another central construct. Candidates may value speed and consistency while simultaneously distrusting decisions produced by opaque systems. Prior research suggests that AI-mediated selection can be perceived as efficient but less interpersonally just than human evaluation (Naseer et al., 2025). Conversely, candidate experiences characterized by clarity, responsiveness, and fairness can improve employer evaluations and willingness to accept offers (Priyanka et al., 2025). Perceived usefulness also remains relevant because candidates may be more willing to engage when AI is experienced as beneficial to their job search rather than simply beneficial to the employer (Hosain et al., 2025).

Technological anxiety provides a further psychological pathway. Anxiety may include

nervousness, discomfort, confusion, or apprehension when interacting with technology, particularly when the technology evaluates personal potential. Prior research has linked technology self-efficacy and familiarity with lower technology-related anxiety (Barbeite & Weiss, 2003), while applicant-focused studies have identified technological anxiety as a potential barrier to AI recruitment engagement (Pan et al., 2022). At the same time, a highly AI-literate sample may show restricted variability in both familiarity and anxiety, making such relationships difficult to detect.

The Indian literature has primarily emphasized students and campus recruitment. Rukadikar and Khandelwal (2025), for example, developed and validated a 23-item measure of Indian graduates' perceptions of AI effectiveness in campus hiring. The present study extends this work by including both fresh graduates and early-career professionals, thereby addressing a population that may encounter AI-mediated recruitment repeatedly during lateral movement and early occupational development. It also tests whether everyday AI experience is associated with lower hiring-specific technological anxiety.

II. OBJECTIVES

- To examine perceptions of AI-based hiring tools in terms of trust, perceived usefulness, AI fairness, technological anxiety, intention to engage, and actual engagement.
- To examine whether trust predicts intention to engage with AI-based hiring tools.
- To examine whether perceived usefulness predicts intention to engage.
- To examine whether perceived AI fairness predicts intention to engage.
- To examine whether technological anxiety negatively predicts intention to engage.
- To examine whether intention to engage predicts actual engagement with AI-mediated recruitment.
- To examine whether prior AI experience negatively predicts technological anxiety.

Hypotheses

- H1: Trust positively predicts intention to engage.
- H2: Perceived usefulness positively predicts intention to engage.

- H3: Perceived AI fairness positively predicts intention to engage.
- H4: Technological anxiety negatively predicts intention to engage.
- H5: Intention to engage positively predicts actual engagement.
- H6: Prior AI experience negatively predicts technological anxiety.

III. LITERATURE REVIEW

AI in Recruitment and the Indian Context

AI-supported recruitment has expanded across the recruitment funnel, including résumé screening, candidate matching, automated communication, and video-based assessment. The principal organizational rationale is the ability to handle large volumes of applications efficiently (Pillai & Sivathanu, 2020; Upadhyay & Khandelwal, 2018). However, the adoption of AI also creates new questions concerning transparency, discrimination, candidate dignity, and organizational trust. Systematic evidence indicates that algorithmic systems may reproduce biases rather than eliminate them when the underlying data, human validation, or design assumptions are biased (Köchling & Wehner, 2020).

Within India, research has shown that technology adoption is influenced not only by perceived usefulness but also by broader relational and social factors. Kaur et al. (2023) demonstrated the relevance of social influence and extended TAM processes in India. Pillai and Sivathanu (2020) likewise showed the applicability of TAM to AI-supported talent acquisition in Indian IT/ITeS organizations. These findings provide a foundation for examining candidate-side psychological responses to AI-mediated recruitment.

Technology Acceptance Model and Extended TAM

Davis's (1989) TAM proposes that perceived usefulness and perceived ease of use are central determinants of technology acceptance and intention, with intention predicting actual use. The model has been widely applied because it offers a parsimonious explanation of technology adoption. Nevertheless, recruitment differs from voluntary technology adoption because candidates may have little control over whether an organization uses AI and because the outcome can affect employment opportunities.

Consequently, constructs such as trust, fairness, and anxiety may provide explanatory value beyond conventional usefulness perceptions.

Rukadikar and Khandelwal (2025) developed an extended TAM framework for Indian graduates that included trust, perceived usefulness, AI fairness, and technological anxiety. Their work established a direct empirical foundation for the current study. Extending the framework to early-career professionals is important because repeated exposure to recruitment technologies may produce different perceptions from those of candidates encountering AI hiring for the first time.

Trust, Usefulness, and Engagement

Trust refers to the belief that an AI recruitment system is dependable, honest, and sincere in its evaluation. Candidate trust is challenged when algorithmic decisions are opaque or difficult to contest (Acikgoz et al., 2020). Research has also suggested that candidates may view human decision makers as more interpersonally just while regarding AI as more efficient and consistent (Naseer et al., 2025). Thus, trust may bridge technical capability and psychological acceptance.

Perceived usefulness concerns whether candidates believe that AI-supported hiring makes recruitment faster, more efficient, or more beneficial to their job search. The present study retains this central TAM construct but adopts a candidate-centered interpretation. Hosain et al. (2025) found that usefulness can be weakened when applicants lack agency or opportunities to explain contextual aspects of their background. This distinction is important for fresh graduates and early-career professionals whose qualifications may not be fully represented by standardized data.

AI Fairness and Algorithmic Bias

Fairness has become increasingly central to research on AI recruitment. Algorithmic systems can inherit bias from historical recruitment data, human validation, or assumptions embedded in system design (Köchling & Wehner, 2020; Soleimani et al., 2025). Applicants may therefore evaluate AI not simply in terms of accuracy but in terms of whether the process is equitable, transparent, and respectful of individual differences.

Explainability is especially relevant. Lavanchy et al. (2023) reported that explanations of algorithmic decisions can improve applicants' fairness perceptions, while Malin et al. (2025) found that explanations increased perceived procedural and outcome fairness. These findings suggest that perceived fairness may be strengthened through design features that make decision processes understandable and contestable.

Technological Anxiety and Prior AI Experience

Technological anxiety represents nervousness, discomfort, or apprehension associated with interacting with technology. Barbeite and Weiss (2003) distinguished computer self-efficacy from anxiety, suggesting that confidence in one's technological capabilities can shape emotional responses to new systems. Pan et al. (2022) identified applicant-centric psychological factors, including anxiety, as important to AI recruitment adoption. Suen et al. (2019) further examined AI-supported video interviewing and highlighted the role of prior exposure in candidates' experiences.

Everyday AI familiarity may not necessarily translate into comfort with high-stakes hiring. Individuals may be highly comfortable with conversational AI, recommendation systems, or automated services while remaining concerned about the consequences of algorithmic evaluation. This distinction provides the rationale for examining prior AI experience and hiring-specific technological anxiety as related but empirically distinct constructs.

IV. METHOD

Research Design

A quantitative, cross-sectional, correlational design was used. Data were collected at one point in time and analyzed to identify relationships among naturally occurring perceptions and engagement-related variables. The design was appropriate for testing directional associations but does not permit causal conclusions.

Participants

The sample comprised 116 participants from India. Seventy-four participants (63.8%) were fresh graduates from the 2024–2025 cohort and 42 (36.2%) were early-career professionals who had been employed within the previous five years. The sample

included 84 women (72.4%), 31 men (26.7%), and one participant who preferred not to disclose gender (0.9%). Fifty-five participants (47.4%) held an undergraduate degree, 57 (49.1%) held a postgraduate degree, and four (3.4%) held a diploma. Participants represented arts, humanities, and social sciences (45.7%), engineering and technology (25.9%), commerce/finance/accounting (9.5%), and other fields (19.0%). The study used non-probability sampling, with recruitment primarily through academic and professional networks.

Instrument

Data were collected using a 23-item standardized questionnaire developed and validated by Rukadikar and Khandelwal (2025), with the present study extending its application to fresh graduates and early-career professionals. The instrument assessed trust, perceived usefulness, AI fairness, technological anxiety, intention to engage, and actual engagement. Prior AI experience was assessed as a self-reported indicator of frequency, variety, and comfort with everyday AI technologies. Items were rated on 5-point Likert-type scales.

Procedure

The questionnaire was administered online using Google Forms. The survey included participant information, electronic informed consent, demographic questions, and the standardized scale. Recruitment occurred through LinkedIn, academic WhatsApp groups, institutional email, and snowball referrals. Participation was voluntary and anonymous. Data collection occurred from January through March 2026, followed by analysis in April 2026. Completion required approximately 10–15 minutes.

Data Analysis

Analyses were conducted using JASP Version 0.18. Internal consistency was evaluated using Cronbach's alpha. Descriptive statistics included means, standard deviations, ranges, and frequency distributions. Pearson correlations were used to examine bivariate relationships. Multiple linear regression tested H1–H4 simultaneously, with intention to engage as the criterion and trust, perceived usefulness, AI fairness, and technological anxiety as predictors. Separate simple linear regressions tested H5 (intention to engage predicting actual engagement) and H6 (prior

AI experience predicting technological anxiety). Statistical significance was evaluated at $\alpha = .05$.

Ethical Considerations

Participation was voluntary, informed consent was obtained electronically, and responses were anonymous. The source study reports that the collected data were stored securely and accessible only to the researcher and supervising guide.

V. RESULTS

Reliability

Five of the six multi-item subscales demonstrated acceptable to excellent internal consistency. Trust showed $\alpha = .858$, perceived usefulness $\alpha = .862$, technological anxiety $\alpha = .890$, intention to engage $\alpha = .800$, and actual engagement $\alpha = .746$. The AI fairness subscale required item reduction because two items (AF3 and AF5) had item-total correlations below .30. The resulting three-item scale had $\alpha = .636$ and was retained with caution. This measurement limitation is important when interpreting findings involving AI fairness.

Table 1 Internal Consistency of Study Measures

Subscale	Items	Cronbach's α
Trust	4	.858
Perceived Usefulness	4	.862
AI Fairness	3	.636
Technological Anxiety	4	.890
Intention to Engage	4	.800
Actual Engagement	3	.746

Note. The AI Fairness scale was reduced from five to three items after item-total correlation analysis; $\alpha = .636$ should therefore be interpreted cautiously.

Descriptive Statistics

The mean scores indicated that trust ($M = 2.77$, $SD = 0.83$) and perceived usefulness ($M = 2.95$, $SD = 0.92$)

were below the theoretical midpoint of 3.00. AI fairness was slightly above the midpoint ($M = 3.21$, $SD = 0.54$), while technological anxiety was below the midpoint ($M = 2.84$, $SD = 0.97$). Intention to engage ($M = 3.35$, $SD = 0.84$) and actual engagement ($M = 3.44$, $SD = 0.74$) were above the midpoint. Prior AI experience had the highest mean ($M = 4.00$, $SD = 0.96$), and 71.6% of participants reported daily AI comfort at levels 4–5.

Table 2 Descriptive Statistics for Study Variables

Variable	M	SD	Range
Trust	2.77	0.83	1.00–4.50
Perceived Usefulness	2.95	0.92	1.00–5.00
AI Fairness	3.21	0.54	1.60–4.60
Technological Anxiety	2.84	0.97	1.00–5.00
Intention to Engage	3.35	0.84	1.00–5.00
Actual Engagement	3.44	0.74	1.00–5.00
Prior AI Experience	4.00	0.96	1.00–5.00

Note. All variables were scored on 1–5 Likert-type scales. The theoretical midpoint was 3.00.

Pearson Correlations

The correlation matrix showed a coherent pattern. Trust correlated positively with perceived usefulness ($r = .643$, $p < .001$) and AI fairness ($r = .429$, $p < .001$). Trust, perceived usefulness, and AI fairness were each positively associated with intention to engage ($r = .520$, $.574$, and $.537$, respectively; all $ps < .001$). Technological anxiety was negatively related to intention to engage ($r = -.198$, $p = .033$). Intention to engage was positively associated with actual engagement ($r = .287$, $p = .002$). AI fairness was the only predictor variable significantly correlated with actual engagement ($r = .361$, $p < .001$).

Table 3 Pearson Correlations Among Study Constructs

Variable	1	2	3	4	5	6
1. Trust	—	.643***	.429***	-.122	.520***	.115

2. Perceived Usefulness		—	.588***	-.217*	.574***	.162
3. AI Fairness			—	-.015	.537***	.361***
4. Technological Anxiety				—	-.198*	.064
5. Intention to Engage					—	.287**
6. Actual Engagement						—

Note. * $p < .05$. ** $p < .01$. *** $p < .001$. Two-tailed tests.

Multiple Regression Predicting Intention to Engage

A multiple linear regression model including trust, perceived usefulness, AI fairness, and technological anxiety significantly predicted intention to engage, $R^2 = .435$, adjusted $R^2 = .415$, $F(4, 111) = 21.37$, $p < .001$. Thus, the four predictors jointly explained 43.5% of the variance in intention to engage. Trust significantly

and positively predicted intention to engage ($\beta = .235$, $p = .014$), as did perceived usefulness ($\beta = .218$, $p = .045$) and AI fairness ($\beta = .307$, $p < .001$). AI fairness was the strongest predictor. Technological anxiety showed the expected negative direction but did not make a significant independent contribution ($\beta = -.118$, $p = .114$).

Table 4 Multiple Regression Predicting Intention to Engage

Predictor	B	SE B	β	p
Trust	0.239	0.095	.235	.014
Perceived Usefulness	0.199	0.098	.218	.045
AI Fairness	0.482	0.141	.307	< .001
Technological Anxiety	-0.102	0.098	-.118	.114

Note. $R^2 = .435$, adjusted $R^2 = .415$, $F(4, 111) = 21.37$, $p < .001$.

Simple Regression Analyses

H5 was supported. Intention to engage significantly predicted actual engagement, $\beta = .287$, $t = 3.193$, $p = .002$, $R^2 = .082$, adjusted $R^2 = .074$, $F(1, 114) = 10.20$, $p = .002$. Intention therefore accounted for 8.2% of the variance in actual engagement.

H6 was not supported. Prior AI experience did not significantly predict technological anxiety, $\beta = -.068$, $t = -0.728$, $p = .468$, $R^2 = .005$, adjusted $R^2 = -.004$, $F(1, 114) = 0.531$, $p = .468$. Although the coefficient was negative in the predicted direction, the magnitude was very small.

Hypothesis Testing Summary

Table 5 Summary of Hypothesis Testing

Hypothesis	β	p	Outcome
H1: Trust $\rightarrow$ Intention to Engage	.235	.014	Supported
H2: Perceived Usefulness $\rightarrow$ Intention to Engage	.218	.045	Supported
H3: AI Fairness $\rightarrow$ Intention to Engage	.307	< .001	Supported; strongest

H4: Technological Anxiety → Intention to Engage	-.118	.114	Not supported
H5: Intention to Engage → Actual Engagement	.287	.002	Supported
H6: Prior AI Experience → Technological Anxiety	-.068	.468	Not supported

VI. DISCUSSION

The purpose of this study was to examine how fresh graduates and early-career professionals in India perceive and engage with AI-based hiring tools using an extended TAM framework. Four of the six directional hypotheses were supported. Trust, perceived usefulness, and AI fairness independently predicted intention to engage, with AI fairness emerging as the strongest predictor. Intention to engage also predicted actual engagement. Technological anxiety did not independently predict intention in the multivariate model, and prior AI experience did not significantly predict technological anxiety.

AI Fairness as the Strongest Predictor

The most important finding was the dominance of AI fairness. AI fairness had the largest standardized coefficient in the model ($\beta = .307, p < .001$), exceeding trust and perceived usefulness. This result suggests that candidates' willingness to engage with AI hiring is strongly linked to whether they believe the system will evaluate them equitably, avoid discrimination, and recognize relevant human qualities. The result is consistent with literature emphasizing fairness, transparency, and explainability as central to applicant acceptance (Lavanchy et al., 2023; Malin et al., 2025; Rigotti & Fosch-Villaronga, 2024).

The finding also extends the standard TAM perspective. In conventional technology adoption, usefulness is often treated as a primary driver of acceptance (Davis, 1989). In AI hiring, however, the candidate is not necessarily adopting a tool for personal productivity; the candidate is being evaluated by a tool. This changes the psychological structure of the interaction. A system can be fast and efficient while still being perceived as illegitimate or unfair. The present findings therefore support the argument

that justice-related constructs deserve a more central position in models of high-stakes AI acceptance.

Trust and Perceived Usefulness

Trust significantly predicted intention to engage ($\beta = .235, p = .014$), replicating the importance of confidence in the integrity of AI recruitment systems. Candidates who viewed AI as dependable, honest, and sincere were more willing to participate. This finding is consistent with the Indian evidence reported by Rukadikar and Khandelwal (2025) and with research describing a persistent legitimacy and trust deficit in AI-mediated selection (Acikgoz et al., 2020; Naseer et al., 2025).

Perceived usefulness also predicted intention ($\beta = .218, p = .045$), supporting the central TAM proposition that people are more willing to engage with technologies they believe are beneficial. Nevertheless, its effect was weaker than that of AI fairness. The descriptive result is also informative: perceived usefulness was slightly below the scale midpoint ($M = 2.95$), indicating that participants were not strongly convinced that AI hiring was beneficial to them. This may reflect the distinction between organizational efficiency and candidate-centered usefulness described by Hosain et al. (2025).

Technological Anxiety and Prior AI Experience

Technological anxiety was negatively associated with intention at the bivariate level ($r = -.198, p = .033$), but it did not remain significant when trust, perceived usefulness, and AI fairness were simultaneously controlled ($\beta = -.118, p = .114$). This pattern suggests that the apparent effect of anxiety may overlap with other candidate perceptions. In particular, anxiety was negatively correlated with perceived usefulness ($r = -.217$), indicating that anxious candidates may also perceive AI hiring as less useful. Once these related constructs were considered together, anxiety did not explain unique variance in intention.

The lack of support for H6 may reflect restricted variability. Prior AI experience was high in this sample ($M = 4.00$), with 71.6% of participants reporting daily AI comfort at levels 4–5. Technological anxiety was comparatively low ($M = 2.84$). When participants cluster toward the upper end of familiarity and below the midpoint of anxiety, the statistical range available for detecting a relationship is limited. The null finding therefore does not necessarily invalidate the theoretical expectation that familiarity can reduce anxiety; instead, it suggests that the relationship may be more detectable in samples with wider differences in AI exposure.

Intention and Actual Engagement

Intention to engage significantly predicted actual engagement ($\beta = .287$, $p = .002$), supporting the basic behavioral-intention pathway of TAM. However, the effect explained only 8.2% of the variance in actual engagement. The distinction between intention and behavior is important because applicants do not always control whether they encounter AI hiring tools. Actual exposure depends partly on the practices of organizations and industries. Thus, an applicant may be willing to participate in AI recruitment but have limited opportunities to act on that intention.

VII. IMPLICATIONS

Theoretical Implications

The study contributes to the literature in three principal ways. First, it extends the Indian extended TAM framework beyond a campus-only population by including early-career professionals. Second, it provides evidence that AI fairness may be a stronger determinant of engagement intention than perceived usefulness in a high-stakes evaluative setting. This supports closer integration of organizational justice perspectives with technology acceptance models. Third, the non-significant anxiety and prior-experience findings identify potential boundary conditions: the role of these constructs may depend on sample characteristics, AI familiarity, and variability in technology exposure.

Practical Implications

For HR practitioners and AI system developers, the findings indicate that improving perceived fairness should be a central design and communication

priority. Candidate-facing systems may benefit from clear explanations of assessment criteria, transparent communication about how AI is used, visible mechanisms for raising concerns, and meaningful opportunities for human review or intervention. Bias auditing and attention to the diversity and relevance of training data are also consistent with the concerns identified in the literature (Soleimani et al., 2025).

The relatively low mean for trust ($M = 2.77$) suggests that organizations should not assume that candidates automatically trust AI because it is technologically sophisticated. Trust may need to be earned through transparency, consistency, explainability, and credible safeguards. Similarly, perceived usefulness may improve when systems communicate how AI benefits candidates rather than only how it reduces organizational workload.

Academic institutions and career services may also prepare graduates for algorithmically mediated recruitment by increasing AI literacy, explaining common forms of automated screening, and teaching applicants how to interpret and respond to AI-mediated assessment processes. Such preparation should complement, rather than replace, organizational responsibility for fair and transparent system design.

VIII. LIMITATIONS

Several limitations should be considered when interpreting the findings. First, the cross-sectional design prevents causal inference. Regression coefficients indicate statistical prediction within the observed data but do not establish that changes in trust, fairness, usefulness, or anxiety cause changes in engagement. Second, non-probability sampling limits generalizability. The sample was predominantly female, urban, and connected to academic and professional networks, with substantial representation from social sciences and humanities.

Third, all major constructs were measured through self-report within the same survey, creating potential common method variance. Actual engagement may be measured more robustly in future work through verified behavioral indicators. Fourth, the AI fairness subscale demonstrated below-threshold internal consistency ($\alpha = .636$) after item reduction. Although fairness remained the strongest predictor, the measurement limitation should temper interpretation.

Fifth, prior AI experience was represented through a self-reported composite indicator rather than a comprehensive multi-item measure, limiting the precision with which the construct could be assessed.

IX. FUTURE RESEARCH

Future research should replicate the study using larger and more demographically diverse samples, including participants from Tier-2 and Tier-3 cities, non-graduate workers, and groups with lower baseline AI exposure. Such sampling would provide greater variability in AI familiarity and may clarify the anxiety-related relationships that were not significant in the present study.

A more comprehensive AI fairness measure should be developed for the Indian recruitment context, incorporating procedural, distributive, interpersonal, and informational dimensions of justice. Longitudinal research could examine whether repeated exposure to AI recruitment changes trust and fairness perceptions over time. Structural equation modelling could test the full extended TAM architecture and examine whether the career stage moderates relationships among the constructs.

Experimental studies could manipulate specific AI hiring features, such as decision explanations, visible bias-audit information, human override options, and opportunities for candidate feedback. Such designs would permit stronger causal conclusions about which system characteristics increase perceived fairness, trust, and engagement. Future studies could also examine differences between fresh graduates and early-career professionals directly rather than combining them within one sample.

X. CONCLUSION

This study demonstrates that candidates' acceptance of AI-based hiring in India cannot be understood solely through technological efficiency. Among the 116 fresh graduates and early-career professionals examined, AI fairness was the strongest predictor of intention to engage, followed by trust and perceived usefulness. Intention also predicted actual engagement, whereas technological anxiety and prior AI experience did not make significant independent contributions in the tested models.

The findings suggest that AI hiring systems must be not only efficient but also demonstrably fair, understandable, and candidate-centered. In high-stakes evaluative contexts, perceptions of equity may determine whether applicants regard an AI system as legitimate enough to engage with. Extending TAM with fairness and trust constructs therefore provides a more context-sensitive account of technology acceptance in recruitment. The study contributes to an emerging Indian evidence base and highlights the importance of designing recruitment technologies around both organizational performance and candidate dignity.

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