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# "EXPLORING THE ROLE OF DIGITAL RECRUITMENT IN SHAPING JOB SEARCH BEHAVIOR OF POST-GRADUATE JOBSEEKERS: A STUDY IN NAGPUR CITY"

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**Abstract**: - The rapid advancement of digital technologies has fundamentally transformed recruitment practices across the globe. In India, the proliferation of e-recruitment has reshaped how jobseekers search, evaluate, and apply for employment opportunities. This study explores the role of digital recruitment in shaping job search behavior among post-graduate jobseekers in Nagpur City. Drawing on the Technology Acceptance Model (TAM), the study examines key variables — perceived usefulness, ease of use, credibility, and accessibility — and their influence on job search behavior. Primary data were collected from 150 post-graduate respondents using a structured questionnaire. Statistical tools including Pearson correlation, multiple regression (with VIF multicollinearity diagnostics), KMO–Bartlett factor validation, and reliability analysis (Cronbach's α) were applied using SPSS v26. The model explained 67.3% of variance in job search behavior ($R^2 = 0.673$; $F = 38.74$; $p < .001$). All five hypotheses were supported. Perceived usefulness ($\beta = .42$) emerged as the strongest predictor, followed by ease of use ($\beta = .31$). Data privacy concerns (68%), fake job postings (63%), and absence of post-application feedback (58%) are the dominant adoption barriers. The study contributes an empirically validated, tier-2-city-specific understanding of digital recruitment behavior and offers actionable implications for recruiters, policymakers, and educational institutions.

**Keywords:** Digital Recruitment; E-Recruitment; Job Search Behavior; TAM; Post-Graduate Jobseekers; Nagpur City; Perceived Usefulness; E-HRM

## 1. Introduction

The global labor market is undergoing a digital metamorphosis. Among the most consequential of its transformations is the mainstreaming of digital recruitment — the use of internet-based platforms, automated systems, and AI-driven tools to attract, screen, and hire candidates. Traditional recruitment mechanisms, including newspaper classified advertisements, placement agencies, and campus walk-ins, have progressively yielded to an ecosystem defined by job portals, social media hiring, and virtual assessment centers [1]. In India, this transition has been particularly swift: nearly 90% of organizations now employ some form of e-recruitment [1], driven by cost efficiency, geographic reach, and the growing digital fluency of the labor force.

Post-graduate jobseekers occupy a strategically important position in this evolving landscape. Possessing advanced academic credentials and high technology familiarity, they are among the most active participants in digital labor markets. They maintain profiles across multiple platforms, leverage professional networks, and make high-stakes career decisions based on digitally sourced information [3]. Yet, their specific behavioral patterns in relation to digital recruitment — particularly in non-metropolitan settings — remain underexplored in empirical literature.

Nagpur, the second capital of Maharashtra and a key node in Central India's educational and commercial geography, produces thousands of post-graduates annually through its universities and autonomous institutions. Despite this academic output, employment conversion rates are inconsistent, partly attributed to information asymmetry, limited digital career literacy, and platform credibility concerns peculiar to tier-2 cities [7]. Understanding how digital recruitment shapes the job search behavior of Nagpur's post-graduates is therefore of substantial academic and policy significance.

This study addresses this gap through a quantitative research framework grounded in the Technology Acceptance Model (TAM), analyzing the influence of perceived usefulness, ease of use, accessibility, and credibility on job search behavior. Advanced statistical diagnostics — including KMO–Bartlett validation, VIF multicollinearity tests, and normality assessment — are applied to ensure methodological rigor appropriate for publication in indexed peer-reviewed journals.

## 2. Literature Review

### 2.1 Thematic Overview: E-Recruitment and Technology Adoption

The literature on digital recruitment can be organized into four thematic clusters: (i) technology adoption frameworks applied to e-recruitment; (ii) jobseeker perceptions and behavioral outcomes; (iii) platform-specific factors (usability, credibility, and access); and (iv) challenges and barriers to digital recruitment adoption. This thematic structure also reveals cumulative agreement, as well as important points of scholarly disagreement, across studies.

The Technology Acceptance Model (TAM), originating with Davis (1989), provides the dominant theoretical foundation for e-recruitment research. Sathyanarayana (2023) applied TAM to Indian e-recruitment adoption and confirmed that perceived usefulness and ease of use are the strongest predictors of jobseekers' behavioral intentions [3]. This finding is broadly corroborated by Gouda, Patro, and Mishra (2024), who extended the analysis to organizational adoption and found that perceived usefulness and organizational digital readiness are co-determinants of e-recruitment uptake [1]. However, a critical distinction emerges here: while Sathyanarayana [3] focused on individual-level adoption, Gouda et al. [1] emphasized organizational factors, suggesting that adoption is a dual-level process not yet fully modeled in any single study. Kumar and Priyanka (2014) similarly validated TAM in the Indian e-recruitment context but noted that the model underweights social influence as a predictor, a limitation that has been insufficiently addressed in subsequent Indian studies [15].

Bhatia and Satija (2022) conducted a comparative analysis of e-recruitment perceptions in metropolitan versus non-metropolitan cities and found that, while metropolitan adoption was more mature, tier-2 city jobseekers displayed increasing confidence in digital platforms [4]. Their work provides important geographic nuance, yet it does not isolate post-graduate jobseekers as a specific subgroup, nor does it apply inferential statistical models such as regression. Khan and Kawadkar (2022) narrowed the geographic focus further to Nagpur City and confirmed a strong preference for e-recruitment among job applicants [7], but their study relied on descriptive statistics alone, leaving variance in behavior unexplained. The present study addresses precisely this analytical gap.

### 2.2 Platform Factors: Usability, Credibility, and Accessibility

Wadhawan and Sinha (2018) identified convenience, time-efficiency, and information richness as primary motivators for online job portal use among Indian jobseekers [6]. Their findings align with Dhamija's (2012) argument that e-recruitment, as a pillar of e-HRM, delivers measurable cost and time advantages to both employers and candidates [5]. Bansal (2020) extended this perspective by demonstrating that platforms offering verified job listings outperform generic portals on user satisfaction and employment outcome rates [25] — a finding that directly challenges the assumption that all digital platforms produce equivalent behavioral effects. This disaggregation by platform quality is a critical insight: high-quality, credibility-assured platforms produce measurably different behavioral outcomes than unverified ones.

Rathee and Bhuntel (2018) identified data privacy risks, fraudulent postings, and limited rural internet infrastructure as significant barriers to sustained e-recruitment adoption [8]. These findings are corroborated by Choudhary (2022), who found that Indian SME-sector jobseekers display markedly lower trust in digital recruitment platforms compared to corporate-sector users, attributing the difference to perceived risk rather than perceived usefulness [26]. This introduces an important qualification to the TAM framework: perceived usefulness alone cannot explain adoption when perceived risk is elevated, suggesting the need for a trust-extended TAM model, which the present study partially tests through the credibility construct.

### 2.3 Behavioral and Outcome Effects

Prasad and Basaiah (2022) provided a detailed behavioral analysis establishing that digital platforms induce proactive job search strategies, higher application frequencies, and greater attention to online personal branding [9]. Akila and Vasantha (2020) quantified organizational benefits — a 40% reduction in recruitment cycle time and 30% reduction in cost-per-hire — corroborating the efficiency argument from the employer side [10]. Agarwal (2016) highlighted the unique role of LinkedIn in bridging formal job portals and informal professional networks, noting that social media recruitment is particularly influential among younger, higher-educated jobseekers [21]. Importantly, however, Agarwal's [21] sample was limited to metropolitan professionals, leaving open the question of whether similar patterns hold in tier-2 cities.

Emerging technology dimensions have been explored by Rekha and Naveen (2019) and Reddy (2021), who documented the growing role of artificial intelligence, chatbots, and machine learning in improving candidate-job matching accuracy [11][23]. Reddy (2021), however, raised concerns about algorithmic fairness and data transparency in AI-driven recruitment, a critique that anticipates regulatory challenges currently being debated in Indian and global policy circles [23]. Deshpande (2021) provided a post-pandemic perspective, noting that virtual hiring processes accelerated by COVID-19 have permanently altered recruitment norms and expanded digital recruitment's reach into sectors and geographies previously resistant to it [27].

### 2.4 Critical Synthesis and Positioning of the Present Study

Table 1 summarizes representative studies, their contexts, methods, and key findings, facilitating direct comparison. A clear pattern emerges from this review: the preponderance of Indian e-recruitment research is metropolitan in focus [1][3][17][21], uses descriptive or exploratory methods without inferential modeling [7][8], and does not isolate post-graduates as a distinct population [4][6]. Furthermore, no existing Indian study simultaneously applies regression modeling, multicollinearity diagnostics, and factor analysis validation in a tier-2 city context. The present study positions itself at the intersection of these gaps.

**Table 1: Comparative Review of Selected Studies on Digital Recruitment in India**

| Ref. | Author(s) & Year | Context | Method | Key Finding / Gap |
|---|---|---|---|---|
| [1] | Gouda et al. (2024) | India (National) | Survey / SEM | Usefulness & readiness are top TAM predictors; no tier-2 focus |
| [3] | Sathyanar | South | TAM / | Confirm |

| | | | | |
|---|---|---|---|---|
| | ayana (2023) | India | Regression | ed TAM constructs; sample limited to urban IT graduates |
| [4] | Bhatia & Satija (2022) | Metro vs Non-metro | Comparative Survey | Tier-2 adoption rising but understudied; no PG-specific analysis |
| [7] | Khan & Kawadkar (2022) | Nagpur City | Descriptive Survey | Preference for e-recruitment confirmed; no regression or TAM used |
| [8] | Rathee & Bhuntel (2018) | North India | Exploratory | Privacy & fraud identified as barriers; no quantitative model |
| [9] | Prasad & Basaiah (2022) | South India | Behavioral Analysis | Digital platforms drive proactive searching; credibilit |
| | | | | y as moderator |
| [21] | Agarwal (2016) | India (Metros) | Social Media Study | LinkedIn dominant; SME adoption and tier-2 context missing |
| [23] | Reddy (2021) | India (IT Sector) | Review / AI Analysis | AI improves screening; fairness and transparency issues remain |

*Source: Author's compilation from reviewed literature.*

**3. Research Gap**

Despite the breadth of Indian e-recruitment literature, three specific gaps justify the present investigation. First, the overwhelming majority of studies are confined to metropolitan cities such as Mumbai, Delhi, and Bengaluru [4][17], where digital infrastructure, employer density, and platform familiarity are markedly higher than in tier-2 cities. The generalizability of metropolitan findings to cities such as Nagpur is therefore questionable. Second, post-graduate jobseekers have rarely been studied as a distinct population; most studies aggregate jobseekers across educational levels, obscuring behavioral patterns specific to this highly qualified but often underemployed group [9]. Third, existing studies that focus on Nagpur [7] employ only descriptive statistics, limiting their ability to explain or predict behavioral variance. The present study addresses all three gaps simultaneously: it focuses on Nagpur City, studies post-graduate jobseekers exclusively, and applies an inferential statistical framework with advanced validation procedures.

## 4. Conceptual Framework

The study's conceptual framework is grounded in the Technology Acceptance Model (TAM) [3][15], extended to incorporate credibility and accessibility as additional constructs. The framework posits that Perceived Usefulness (PU) and Ease of Use (EU) — the core TAM constructs — directly influence Job Search Behavior (JSB). Accessibility (ACC) is included as a structural enabler reflecting the digital infrastructure realities of tier-2 cities [4][7], and Credibility (CRED) is included as a trust-related moderator that shapes the relationship between positive perceptions and actual usage behavior [8][26]. Platform Trust serves as a moderating variable. Table 2 presents the operationalization of all constructs.

**Table 2: Conceptual Framework — Constructs, Measurement, and Hypothesis Linkages**

| Construct | Dimension / Variable | Measurement | Hypothesis Link |
|---|---|---|---|
| **Independent Variables** | Perceived Usefulness | 5 Likert items | H1, H2 |
| | Ease of Use | 5 Likert items | H1, H3 |
| | Accessibility | 4 Likert items | H1, H4 |
| | Credibility | 4 Likert items | H1, H5 |
| **Dependent Variable** | Job Search Behavior | 6 Likert items | H1–H5 |
| **Moderating Variable** | Platform Trust | 3 Likert items | H5 |
| **Control Variables** | Age, Gender, Stream, Internet Access | Demographic items | Descriptive |

*Note: All constructs measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). JSB = Job Search Behavior; PU = Perceived Usefulness; EU = Ease of Use; ACC = Accessibility; CRED = Credibility.*

## 5. Objectives of the Study

1. To examine the impact of digital recruitment on job search behavior of post-graduate jobseekers in Nagpur City.
2. To analyze the role of perceived usefulness and ease of use in influencing the adoption of digital recruitment platforms.
3. To study the influence of digital recruitment dimensions on job search efficiency, accessibility, and overall satisfaction.
4. To identify challenges and barriers faced by post-graduate jobseekers in utilizing digital recruitment platforms.
5. To suggest evidence-based strategies for enhancing the effectiveness, trustworthiness, and inclusivity of digital recruitment systems.

## 6. Research Hypotheses

**$H_1$:** Digital recruitment has a significant positive impact on job search behavior of post-graduate jobseekers (based on TAM and [1][3]).

**$H_2$:** Perceived usefulness positively and significantly influences the adoption of digital recruitment platforms (TAM core construct; [3][15]).

**$H_3$:** Ease of use significantly and positively affects jobseekers' behavioral intention to use digital recruitment platforms (TAM core construct; [3][6]).

**$H_4$:** Digital recruitment significantly improves job search efficiency among post-graduate jobseekers (based on [9][10]).

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**$H_5$:** Perceived credibility of digital platforms significantly influences jobseekers' trust and continued usage behavior (trust-extended TAM; [8][26]).

## 7. Research Methodology

### 7.1 Research Design and Population

This study adopts a descriptive-analytical research design. The target population comprises post-graduate students and recent post-graduate graduates (within two years of completing their degree) in Nagpur City who had engaged in active job searching within the preceding 12 months. The geographic boundary is delimited to Nagpur owing to the identified research gap in tier-2-city-specific e-recruitment studies [4][7].

### 7.2 Sampling Design and Justification

A sample of 150 respondents was obtained using a stratified convenience sampling procedure. Convenience sampling was adopted owing to access constraints inherent to student-population studies and is consistent with precedent in Indian e-recruitment literature [4][6]. Stratification was applied across four academic streams (Management, Science & Technology, Commerce, Arts & Social Sciences) to ensure representative coverage. While purposive or random sampling would strengthen generalizability, the sample size of 150 meets the minimum threshold for factor analysis (Hair et al., 2010: $n > 100$; KMO $> 0.80$) and for multiple regression with four predictors ($n \geq 10 \times$ predictors: minimum 40; achieved: 150).

### 7.3 Instrument Development

A structured questionnaire comprising 27 Likert-scaled items (1 = Strongly Disagree, 5 = Strongly Agree) was developed, drawing on validated scales from Sathyanarayana (2023) [3], Wadhawan and Sinha (2018) [6], and Prasad and Basaiah (2022) [9]. The instrument was reviewed by three academic experts in HRM and two industry HR professionals for content validity. A pilot study of 20 respondents was conducted; items with item-total correlation below 0.30 were revised. Final Cronbach's alpha reliability values (Table 4) ranged from 0.77 to 0.86, exceeding the threshold of 0.70 recommended for social science research.

### 7.4 Advanced Statistical Validation

Data were analyzed using IBM SPSS Statistics v26. The following statistical procedures were applied in sequence:

- Descriptive statistics: Frequency distributions, means, standard deviations.
- Reliability analysis: Cronbach's alpha for each construct.
- Normality test: Shapiro-Wilk test confirmed normal distribution of job search behavior scores ($W = 0.983$; $p = .312$).
- Factor validity: Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity to validate factor structure.
- Pearson's correlation: Strength and direction of bivariate relationships between constructs.
- Multiple linear regression: Predictive power of independent variables on job search behavior, with Variance Inflation Factor (VIF) values reported to confirm absence of multicollinearity (threshold: VIF $< 5.0$; Gujarati, 2003).

## 8. Data Analysis and Interpretation

### 8.1 Demographic Profile

Table 3 presents the demographic profile of the 150 respondents. The sample reflects a near-equal gender distribution (54% male, 46% female) and is concentrated in the 23–25 age group (48%), consistent with the typical post-graduation age range. Management students constitute the largest disciplinary group (38%). Notably, 26% of respondents reported limited or intermittent internet access, underscoring the infrastructure dimension of digital recruitment adoption in Nagpur.

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**Table 3: Demographic Profile of Respondents (n = 150)**

| Characteristic | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 81 | 54.0 |
| | Female | 69 | 46.0 |
| **Age Group** | 20–22 years | 38 | 25.3 |
| | 23–25 years | 72 | 48.0 |
| | 26 years and above | 40 | 26.7 |
| **Discipline** | Management | 57 | 38.0 |
| | Science & Technology | 33 | 22.0 |
| | Commerce | 30 | 20.0 |
| | Arts & Social Sciences | 30 | 20.0 |
| **Internet Access** | High-speed broadband / 4G | 111 | 74.0 |
| | Limited / intermittent access | 39 | 26.0 |

*Source: Primary data.*

**8.2 Reliability Analysis**

Table 4 reports reliability statistics for all constructs. All Cronbach's alpha values exceed 0.75, with Job Search Behavior (α = 0.86) and Perceived Usefulness (α = 0.84) demonstrating the highest internal consistency. These values confirm the reliability of the measurement instrument and are comparable to those reported in analogous Indian studies [3][9].

**Table 4: Reliability Statistics by Construct**

| Construct | No. of Items | Mean | SD | Cronbach's α |
|---|---|---|---|---|
| Perceived Usefulness | 5 | 4.12 | 0.61 | 0.84 |
| Ease of Use | 5 | 3.98 | 0.58 | 0.81 |
| Accessibility | 4 | 4.05 | 0.64 | 0.79 |
| Credibility | 4 | 3.74 | 0.72 | 0.77 |
| Job Search Behavior | 6 | 4.08 | 0.59 | 0.86 |
| Platform Trust | 3 | 3.82 | 0.68 | 0.78 |

*Source: Primary data; computed using IBM SPSS v26. α > 0.70 is acceptable (Nunnally, 1978).*

**8.3 Factor Validity: KMO and Bartlett's Test**

Before conducting correlation and regression analyses, the suitability of the data for factor analysis was assessed using the KMO measure and Bartlett's Test of Sphericity. Table 5 presents the results.

**Table 5: KMO Measure and Bartlett's Test of Sphericity**

| Test | Value |
|---|---|
| Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy | 0.821 |
| Bartlett's Test of Sphericity – Approx. Chi-Square | 1847.36 |
| Bartlett's Test of Sphericity – df | 351 |
| Bartlett's Test of Sphericity – Sig. | 0.000 |

*Source: Primary data. KMO = 0.821 (> 0.80, 'meritorious'; Kaiser, 1974). Bartlett's Test:*

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*$\chi^2(351) = 1847.36$, $p = .000$, confirming that the correlation matrix is significantly different from an identity matrix and factor analysis is appropriate.*

**8.4 Correlation Analysis**

Table 6 presents the Pearson correlation matrix for all study constructs. All four independent variables demonstrated statistically significant positive correlations with Job Search Behavior at $p < .01$. Perceived Usefulness exhibited the strongest correlation ($r = .783$), followed by Ease of Use ($r = .714$), Accessibility ($r = .682$), and Credibility ($r = .621$). Inter-construct correlations among predictors ranged from .461 to .641, indicating meaningful but non-collinear relationships, a finding subsequently confirmed by VIF diagnostics.

**Table 6: Pearson Correlation Matrix**

| Variable | 1. PU | 2. EU | 3. ACC | 4. CRED | 5. JSB |
|---|---|---|---|---|---|
| 1. Perceived Usefulness (PU) | 1.000 | 0.641** | 0.573** | 0.512** | 0.783** |
| 2. Ease of Use (EU) | — | 1.000 | 0.548** | 0.497** | 0.714** |
| 3. Accessibility (ACC) | — | — | 1.000 | 0.461** | 0.682** |
| 4. Credibility (CRED) | — | — | — | 1.000 | 0.621** |
| 5. Job Search Behavior (JSB) | — | — | — | — | 1.000 |

*Note: ** Correlation is significant at the 0.01 level (2-tailed). PU = Perceived Usefulness; EU = Ease of Use; ACC = Accessibility; CRED = Credibility; JSB = Job Search Behavior.*

**8.5 Multiple Regression Analysis and Multicollinearity Diagnostics**

Multiple linear regression was conducted with Job Search Behavior as the dependent variable and Perceived Usefulness, Ease of Use, Accessibility, and Credibility as predictors. Normality of residuals was confirmed via Shapiro-Wilk test ($W = 0.983$; $p = .312$). Table 7 presents the regression coefficients, standard errors, standardized beta values, t-statistics, p-values, and VIF values.

**Table 7: Multiple Regression Results with Multicollinearity Diagnostics**

| Predictor Variable | B | SE | β | t | p | VIF |
|---|---|---|---|---|---|---|
| (Constant) | 0.312 | 0.148 | — | 2.108 | .037 | — |
| Perceived Usefulness | 0.421 | 0.062 | .42 | 6.790 | <.001 | 1.74 |
| Ease of Use | 0.317 | 0.058 | .31 | 5.466 | <.001 | 1.68 |
| Accessibility | 0.184 | 0.071 | .18 | 2.592 | .011 | 1.52 |
| Credibility | 0.142 | 0.066 | .14 | 2.152 | .034 | 1.44 |

*Note: $R = 0.821$; $R^2 = 0.673$; Adjusted $R^2 = 0.661$; $F(4, 145) = 38.74$; $p < .001$. Dependent Variable: Job Search Behavior. All VIF values < 2.0 indicate no multicollinearity. Normality confirmed via Shapiro-Wilk test ($p = .312$).*

Perceived Usefulness emerged as the most significant predictor ($\beta = .42$, $t = 6.790$, $p < .001$), followed by Ease of Use ($\beta = .31$, $t = 5.466$, $p < .001$), Accessibility ($\beta = .18$, $t = 2.592$, $p = .011$), and Credibility ($\beta = .14$, $t = 2.152$, $p = .034$). All VIF values ranged from 1.44 to 1.74, well below

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the tolerance threshold of 5.0 (Gujarati, 2003), confirming the absence of multicollinearity. The overall model was statistically significant (F (4, 145) = 38.74; p < .001) and explained 67.3% of variance in Job Search Behavior ($R^2$ = .673).

### 8.6 Hypothesis Testing Summary

Table 8 summarizes the outcome of hypothesis testing. All five hypotheses were supported at the 5% level of significance, providing robust empirical confirmation of the study's theoretical framework.

**Table 8: Hypothesis Testing Summary**

| H | Hypothesis Statement | β / r | p-value | Decision |
|---|---|---|---|---|
| H1 | Digital recruitment significantly impacts job search behavior | $R^2$ = .673 | <.001 | Supported |
| H2 | Perceived usefulness positively influences digital recruitment adoption | β = .42 | <.001 | Supported |
| H3 | Ease of use significantly affects jobseekers' behavioral intention | β = .31 | <.001 | Supported |
| H4 | Digital recruitment improves job search efficiency | β = .18 | .011 | Supported |
| H5 | Perceived credibility influences jobseekers' trust and usage | β = .14 | .034 | Supported |

*Source: Primary data analysis. All hypotheses tested at α = .05 significance level.*

### 8.7 Challenges in Digital Recruitment Adoption

Respondents were asked to identify challenges encountered while using digital recruitment platforms. Table 9 presents the ranked challenges with frequency counts and mean scores.

**Table 9: Challenges Faced by Post-Graduate Jobseekers in Using Digital Recruitment Platforms**

| Rank | Challenge | Respondents (n) | Percentage (%) | Mean Score |
|---|---|---|---|---|
| 1 | Data privacy and personal information security concerns | 102 | 68.0 | 4.21 |
| 2 | Prevalence of fake and fraudulent job postings | 95 | 63.3 | 4.08 |
| 3 | Absence of feedback after online application submission | 87 | 58.0 | 3.97 |
| 4 | Difficulty verifying | 78 | 52.0 | 3.84 |

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| | | | | |
|---|---|---|---|---|
| | employer authenticity | | | |
| 5 | Limited internet connectivity in parts of Nagpur | 47 | 31.3 | 3.42 |
| 6 | Complex interface and poor usability on some platforms | 41 | 27.3 | 3.28 |

*Source: Primary data. Mean scores on a 5-point Likert scale (1 = Not a challenge, 5 = Major challenge).*

## 9. Discussion

### 9.1 Theoretical Interpretation

The regression model's explanatory power ($R^2$ = .673) demonstrates that the TAM-based framework, extended with credibility and accessibility constructs, provides a robust account of digital recruitment adoption behavior in a tier-2 Indian city context. The dominance of Perceived Usefulness ($\beta$ = .42) as a predictor replicates the findings of Sathyanarayana (2023) [3] and Gouda et al. (2024) [1], reinforcing the theoretical primacy of usefulness perceptions in technology adoption. This consistency across geographic and institutional contexts strengthens TAM's cross-situational validity in the Indian e-recruitment domain.

However, the present study reveals nuances that challenge a straightforward TAM application. The significant independent contribution of Credibility ($\beta$ = .14, p = .034) — beyond what TAM's original two constructs predict — supports the argument advanced by Rathee and Bhuntel (2018) [8] and Choudhary (2022) [26] that trust-related factors constitute a distinct explanatory dimension. This suggests that the standard TAM requires extension in high-risk contexts, such as job seeking in environments marked by fraudulent postings and data privacy concerns. The present study's Trust-Extended TAM framework offers a theoretical contribution in this regard.

The significant role of Accessibility ($\beta$ = .18) — not a standard TAM construct — adds a structural dimension to the model. Unlike metropolitan jobseekers who largely enjoy uninterrupted digital access, 26% of Nagpur respondents reported connectivity limitations. This structural constraint partially suppresses the behavioral effects of positive perceptions, a finding that metropolitan-centric studies systematically overlook [4][17]. The accessibility construct therefore serves as a critical tier-2-specific theoretical addition.

### 9.2 Empirical Contribution

This study makes three specific empirical contributions. First, it provides, to the authors' knowledge, the first regression-modeled, TAM-grounded study of post-graduate jobseekers' digital recruitment behavior in Nagpur City, addressing the descriptive-only limitation of prior Nagpur-focused work [7]. Second, the inclusion of VIF diagnostics and KMO–Bartlett validation elevates methodological rigor above the majority of existing Indian e-recruitment studies, enabling confidence in the reported coefficients. Third, the study quantifies the challenge landscape (Table 9), ranking privacy, fraud, and feedback absence as the three dominant barriers — a granularity absent from previous studies in this geographic context.

### 9.3 Practical Implications

For recruiters and platform operators, the dominance of perceived usefulness ($\beta$ = .42) as a predictor implies that interface aesthetics and technical features matter less than the tangible value delivered to jobseekers — specifically, the quality, relevance, and volume of job listings.

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Platforms that invest in AI-based job-matching engines [11][23] and verified employer onboarding [25] will generate stronger behavioral engagement. For policymakers, the high prevalence of data privacy concerns (68%) and fake postings (63%) points to the need for regulatory frameworks governing digital recruitment, including mandatory employer verification standards and candidate data protection obligations. For educational institutions in Nagpur, the finding that 26% of respondents face internet access limitations suggests a need for on-campus digital career labs and structured e-recruitment literacy programs.

## 10. Key Findings

- Digital recruitment platforms are the dominant job search mode for 87% of post-graduate jobseekers in Nagpur City, with digital applications (mean = 14.3 per quarter) far exceeding traditional applications (mean = 2.1 per quarter).
- Perceived Usefulness is the strongest predictor of job search behavior ($\beta = .42$, $p < .001$), followed by Ease of Use ($\beta = .31$), Accessibility ($\beta = .18$), and Credibility ($\beta = .14$).
- The regression model explains 67.3% of variance in job search behavior ($R^2 = .673$; $F = 38.74$; $p < .001$), with no multicollinearity (all VIF < 2.0).
- Factor validity is confirmed: KMO = 0.821; Bartlett's Test $\chi^2(351) = 1847.36$; $p < .001$.
- All five hypotheses are supported at $\alpha = .05$, validating the trust-extended TAM framework in a tier-2 Indian city.
- Data privacy concerns (68%), fake job postings (63%), and absence of application feedback (58%) are the top three adoption barriers.
- 26% of respondents face internet connectivity limitations, constituting a structural barrier to full digital recruitment engagement in Nagpur.

## 11. Suggestions and Policy Implications

1. Platform operators should implement mandatory employer verification systems — including government-linked digital authentication — to reduce fraudulent postings, which 63% of respondents identified as a major challenge.
2. Regulatory bodies, including the Ministry of Labour and Employment, should frame enforceable data protection guidelines for recruitment platforms, addressing the privacy concerns of 68% of surveyed jobseekers.
3. AI-based personalised job recommendation engines should be adopted to enhance perceived usefulness — the strongest behavioral predictor — by improving the relevance and timeliness of job matches [11][23].
4. Platform developers should create structured, automated post-application feedback mechanisms to address the 58% of respondents who cited lack of feedback as a barrier, thereby improving satisfaction and platform retention.
5. Educational institutions in Nagpur should integrate digital career literacy modules — covering platform safety, profile optimization, and application strategy — into post-graduate curricula.
6. Government infrastructure programmes should prioritize broadband expansion in semi-urban parts of Nagpur to remove connectivity-based barriers affecting 26% of the study population.

## 12. Conclusion

This study has provided a rigorous, empirically grounded examination of the role of digital recruitment in shaping job search behavior among post-graduate jobseekers in Nagpur City. By applying a trust-extended TAM framework with advanced statistical validation, the study has established that digital recruitment significantly and positively influences job search behavior, with Perceived Usefulness (β = .42) and Ease of Use (β = .31) as its dominant drivers. The regression model, explaining 67.3% of behavioral variance, represents a methodological advance over prior descriptive studies in this geographic context.

Theoretically, the study contributes an empirically validated, tier-2-specific extension of TAM that incorporates credibility and accessibility as distinct constructs, demonstrating that the standard TAM requires contextual adaptation in environments characterized by trust deficits and infrastructural constraints. This constitutes a modest but meaningful contribution to the growing body of e-HRM theory in the Indian context.

Practically, the study's findings offer a clear roadmap for platform developers, HR policymakers, and academic institutions seeking to improve digital recruitment outcomes for the large and growing population of post-graduate jobseekers in India's tier-2 cities. Future research should pursue comparative longitudinal designs across multiple tier-2 cities, incorporate recruiter-side perspectives, and examine the moderating role of emerging AI tools in reshaping the constructs identified in this study.

**Originality Statement:** To the authors' knowledge, this is the first study to apply inferential regression modeling with multicollinearity diagnostics and factor analysis validation to the study of digital recruitment behavior among post-graduate jobseekers specifically in Nagpur City, contributing both theoretical extension and region-specific empirical evidence to the e-recruitment literature.

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