

Examining trust, transparency and AI adoption on LinkedIn : Evidence from an extended UTAUT framework

Chiragkumar B. Rathod [†]

Department of Business Management

Faculty of Management Studies

Smt. S. B. Patel Institute of Business Management

Sankalchand Patel University

Visnagar 384315

Gujarat

India

Vinitkumar M. Mistri ^{*}

Department of MBA

LDRP Institute of Technology & Research

Kadi Sarva Vishwavidyalaya

Gandhinagar 382015

Gujarat

India

Abhipsa Vagadia [§]

Department of MBA

Sunshine Group of Institutions

Affiliated with Gujarat Technological University

Rajkot 360005

Gujarat

India

[†] ORCID-ID: 0009-0007-3564-5887

^{*} ORCID-ID: 0009-0009-2413-8948

[§] ORCID-ID: 0009-0000-5477-6152

[†] E-mail: cbrathod.2018@gmail.com

^{*} E-mail: vinitmistri@gmail.com (Corresponding Author)

[§] E-mail: abhipsavagadia@gmail.com

Chirag Rasikbhai Patel [‡]

*Department of Business Management
Faculty of Management Studies
Sankalchand Patel College of Engineering
Sankalchand Patel University
Visnagar 384315
Gujarat
India*

Bhagvan M. Karnavat [@]

*Department of Management Studies
National Forensic Sciences University
Delhi Campus
Delhi 110085
India*

Abstract

This study examines how artificial intelligence (AI) features on LinkedIn—job matching, connection recommendations, and career suggestions—shape user satisfaction and engagement. Extending the Unified Theory of Acceptance and Use of Technology (UTAUT), we surveyed 300 active users, including HR professionals, job seekers, students, and recruiters. Perceived usefulness and accuracy positively predicted satisfaction and engagement, while transparency raised trust and privacy concerns lowered it. Trust partially mediated the usefulness–satisfaction link, and transparency strengthened that link. Recruiters rated AI effectiveness higher than general users did. The findings underscore the need for ethical, transparent AI integration in professional networking.

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Keywords: Artificial intelligence, LinkedIn, Professional networking, UTAUT, Algorithmic transparency, User trust, Recruitment technology.

1. Introduction

AI is transforming digital platforms from passive repositories into active agents that match, rank, and personalize. Professional networking sites, which underpin labor markets and talent mobility [18], illustrate this shift. LinkedIn, with over one billion members, applies graph neural

[‡] ORCID-ID: 0000-0003-4788-0749

[@] ORCID-ID: 0009-0005-8041-6464

[‡] E-mail: crpspce@gmail.com

[@] E-mail: bhagvan.karnavat@nfsu.ac.in

networks (GNNs) and large language models (LLMs) to job matching, relationship mapping, and content curation [6].

Engineering studies document these systems' technical design [6], yet little is known about how end-users and recruiters perceive them [7]. The gap matters because AI's efficiencies depend on acceptance, trust, and perceived fairness [3], [5], and opacity can suppress adoption [10]. Explainable AI (XAI) research shows that explanations build trust and reduce bias concerns [2], [15]. This study offers a user-centered test of an extended UTAUT model [12] with six objectives: (1) identify LinkedIn's core AI features; (2) gauge stakeholder awareness; (3) assess perceived usefulness, accuracy, transparency, privacy, and trust; (4) model their interrelationships; (5) compare user groups; and (6) derive theoretical and practical implications.

2. Literature Review and Hypotheses

2.1 AI in Professional Networking and Recruitment

AI supports candidate screening, job matching, and workforce planning through recommendation systems, natural language processing, and predictive analytics, shortening hiring time and improving matching accuracy [2]. Networking platforms extend these capabilities to individuals through personalized content, career guidance, and skill identification [6]. Concerns about bias, fairness, privacy, and transparency nonetheless persist and shape acceptance [5], [13].

2.2 UTAUT and AI Adoption

UTAUT holds that performance expectancy, effort expectancy, social influence, and facilitating conditions shape technology use [16], and it has been validated across consumer and AI contexts [17]. AI-focused extensions add trust, transparency, privacy concerns, and explainability, because AI systems make autonomous decisions that affect user outcomes [12]. Perceived usefulness remains a central driver of adoption, with trust and transparency strengthening acceptance [12].

2.3 Trust, Transparency, and Explainable AI

Trust is central to AI acceptance, particularly when decision logic is unclear and users expect fairness, accuracy, and ethical conduct [1], [14]; it consistently improves satisfaction and engagement [1], [8]. XAI renders algorithmic processes interpretable [14], [15], and explanations increase

trust and reduce uncertainty by clarifying why a job, candidate, or connection is suggested [2], [15]. Opacity, by contrast, erodes trust and engagement [9].

2.4 Privacy Concerns

Platforms collect extensive personal and professional data, creating risks of misuse, surveillance, and unauthorized access [8], [13]. Privacy concerns undermine trust and acceptance, especially when users do not understand how their data are used [8]; robust privacy governance is thus a prerequisite for sustained engagement.

2.5 Research Gap and Hypotheses

The conceptual framework, adapted from UTAUT [16], [17], AI-trust literature [1], [14], and XAI studies [2], [15], examines the relationships among usefulness, accuracy, transparency, privacy concerns, trust, satisfaction, engagement, and perceived AI effectiveness. It positions trust as a mediator of the usefulness–satisfaction relationship, transparency as a moderator that strengthens this relationship, and user role (recruiters vs. general users) as a factor influencing perceived AI effectiveness. Given limited research comparing user perceptions of AI-enabled networking platforms [6], [7], particularly across recruiters and general users with different objectives [3], the study tests seven hypotheses: H1, usefulness positively affects satisfaction; H2, accuracy positively affects engagement; H3, transparency positively affects trust; H4, privacy concerns negatively affect trust; H5, trust mediates the usefulness–satisfaction relationship; H6, recruiters perceive AI as more effective than general users; and H7, transparency strengthens the usefulness–satisfaction relationship. The proposed framework is presented in Figure 1.

3. Research Methodology

A quantitative cross-sectional survey assessed perceptions of LinkedIn's AI-enabled features among 300 active users, including HR professionals, job seekers, students, and recruiters. The sample met the recommended SEM requirement of 10–20 observations per estimated parameter [4]. AI awareness, usefulness, accuracy, transparency, privacy concerns, trust, engagement, and satisfaction were measured using 5-point Likert scales. Data were analyzed using SPSS 28 and AMOS through reliability testing, CFA, Pearson correlation, multiple regression and SEM

for H1–H4, PROCESS Model 4 for mediation (H5), interaction analysis for moderation (H7), and an independent-samples *t*-test with multigroup analysis for recruiter versus other users (H6).

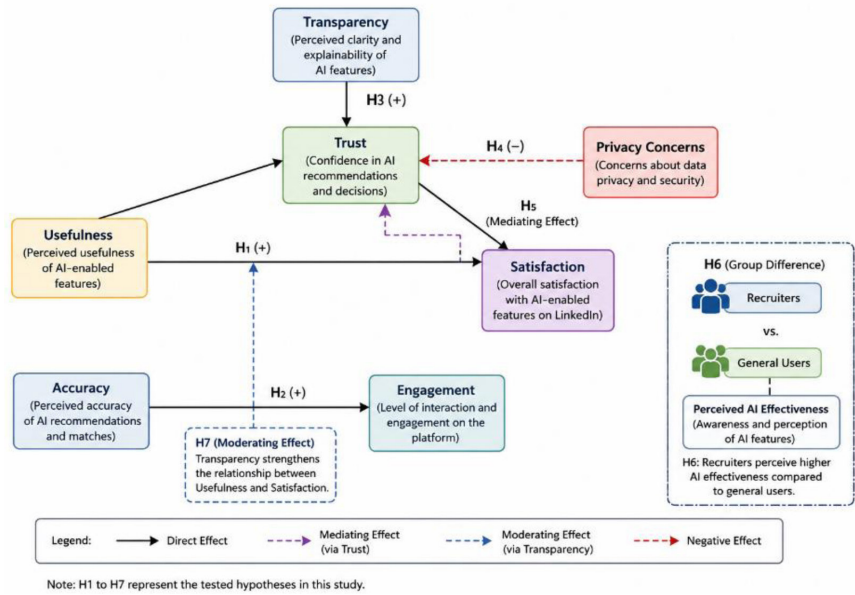


Figure 1

Conceptual Framework of AI Adoption and User Satisfaction on LinkedIn

Source: Developed by the authors based on UTAUT [16], UTAUT2 [17], AI trust literature [1], [14], and Explainable AI studies [2], [15].

4. Results

4.1 Measurement Quality

All scales exceeded the 0.70 reliability threshold (Table 1). CFA indicated acceptable fit ($\chi^2/df = 2.18$, CFI = .96, RMSEA = .06) [4]. Composite reliability exceeded .70 and average variance extracted exceeded .50 for every construct, and discriminant validity was supported by the Fornell–Larcker criterion and HTMT ratios below .85. Harman’s single-factor test showed that the first factor explained 34.7% of variance, below the 50% threshold, so common method bias is unlikely to distort the results [11]. Usefulness, accuracy, and satisfaction were rated highest, transparency lowest, and privacy concerns and trust fell in the middle.

Table 1
Reliability, Validity, and Descriptive Statistics

Construct	M	SD	Cronbach's α	CR	AVE
Awareness	4.25	0.71	.86	.90	.64
Engagement	4.45	0.87	.87	.97	.61
Usefulness	4.15	0.92	.90	.91	.67
Accuracy	4.05	0.98	.89	.90	.65
Transparency	2.72	1.22	.85	.87	.59
Privacy concerns	3.28	1.12	.83	.85	.56
Trust	3.58	1.02	.88	.89	.63
Satisfaction	4.10	0.94	.92	.92	.71

Note. CR = composite reliability; AVE = average variance extracted.

4.2 Hypothesis Testing

All seven hypotheses were supported (Table 2). Usefulness predicted satisfaction ($\beta = .48$) and accuracy predicted engagement ($\beta = .41$). Transparency increased trust ($\beta = .35$), whereas privacy concerns reduced it ($\beta = -.32$). Trust partially mediated the usefulness–satisfaction relationship (direct $\beta = .35$, $p < .001$; indirect $\beta = .14$, 95% CI [.05, .23]). Transparency moderated this relationship ($\beta = .25$, $p < .01$), with a steeper simple slope at high (.68, $p < .001$) than at low transparency (.32, $p < .01$). Recruiters rated AI effectiveness higher than general users, $t(298) = 4.12$, $p < .001$, mean difference = .42, $d = .58$. Multigroup analysis showed stronger usefulness–satisfaction ($p < .01$) and accuracy–engagement paths for recruiters, with better model fit (CFI = .97 vs. .95).

Table 2
Summary of Hypothesis Tests

Hyp.	Path	Estimate	p	Result
H1	Usefulness $\rightarrow$ Satisfaction	$\beta = .48$	$< .001$	Supported
H2	Accuracy $\rightarrow$ Engagement	$\beta = .41$	$< .001$	Supported
H3	Transparency $\rightarrow$ Trust	$\beta = .35$	$< .01$	Supported
H4	Privacy concerns $\rightarrow$ Trust	$\beta = -.32$	$< .01$	Supported
H5	Trust mediates Usefulness $\rightarrow$ Satisfaction	Indirect $\beta = .14$ [.05, .23]	$< .01$	Supported

Contd....

H6	Recruiters > general users (AI effectiveness)	$t(298) = 4.12$; diff = .42	< .001	Supported
H7	Transparency moderates Usefulness → Satisfaction	$\beta = .25$	< .01	Supported

5. Discussion

Usefulness and accuracy were the main drivers of satisfaction and engagement, consistent with UTAUT performance expectancy [16] and evidence of AI improving HR efficiency [2], positioning LinkedIn as an AI-enabled talent marketplace [6], [14]. However, transparency was the lowest-rated factor, reflecting concerns about black-box AI models [5], [10], while privacy concerns reduced trust and may reinforce discrimination risks [5], [13]. Partial mediation indicates that AI usefulness does not fully translate into satisfaction without trust [8], [14]. Moreover, transparency strengthened the effect of usefulness, creating a “transparency premium” in which explainability supports algorithmic legitimacy and procedural fairness; tools such as SHAP and LIME can improve understanding of AI decisions in recruitment [9], [14], [2], [15].

Recruiters perceived AI as more effective because tools such as LinkedIn Recruiter prioritize speed and cost efficiency [3], while general users are more sensitive to trust and privacy concerns [6], [7], supporting role-based moderation in UTAUT [12]. Thus, recruiters may tolerate limited transparency when benefits are measurable, whereas general users require greater algorithmic legitimacy. The findings extend UTAUT by introducing algorithmic legitimacy—combining procedural justice and explainable AI (XAI)—as a boundary condition of performance expectancy [12], [14]. Practically, LinkedIn should provide matching-criteria dashboards and XAI tools [2], [15], adopt privacy-preserving methods such as federated learning [18], and implement granular data opt-ins and differential privacy to strengthen transparency, fairness, and user trust [10], [13], [18].

6. Conclusion

Perceived usefulness and accuracy improve LinkedIn users’ satisfaction and engagement, while transparency and privacy influence trust, which partially mediates the usefulness–satisfaction relationship; transparency further strengthens this effect. Ethical AI adoption requires XAI, privacy protection, transparent data practices, and bias audits [2], [9],

[14], [15], with efficiency-focused tools for recruiters and greater explainability for general users. Trustworthy AI can enhance loyalty, reduce regulatory risk, and support an inclusive digital labor market where AI complements human networking [12].

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