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Bridging Technostress and AI Adoption in HR: A Moderated Mediation Study of Behavioural Intention and Support

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Abstract: The paper delves into the implications of various forms of technostress, i.e. complexity, insecurity, uncertainty, and overload, on the usage of AI-based recruitment systems in information technology firms. It also examines the mediating and moderating factors behind the relationship (behavioral intention and organizational support respectively). The information was gathered through snowball sampling technique and 273 useful answers were obtained. The required sample size was determined using a standard sample size determination formula. SPSS and the PROCESS macro were used to conduct the analysis, and the tests involved reliability, Exploratory Factor Analysis (EFA), descriptive statistics, mediation, and moderation analysis. The findings revealed that all the variables were reliable and were merged into seven valid factors. The results of mediation affirmed that behavioral intention is a significant predictor of the relationship between technostress and actual usage of AI systems. The moderation outcomes indicated that organizational support mitigates the adverse influence of technostress on actual usage. The study is of value to HR professionals and decision-makers. Better acceptance and utilization of AI tools can be observed in organizations where the support of the organization is enhanced and the stress of the employees related to the technology is minimized. Consequently, this may contribute to the ease of digitalization, enhanced hiring rates, and employee trust in AI-based procedures.

Keywords: Technostress, AI Adoption in HR, Behavioural Intention, Organizational Support, Employee Perception.

1. Introduction

AI tools are also becoming prevalent in the IT companies of India to assist in the recruitment process (Deshpande & Chakraborty, 2023; Sengupta *et al.,* 2025). Such tools are capable of screening resumes, scheduling interviews, and even estimating the suitability of a candidate to a job (Kaggwa *et al.,* 2024). Researchers observe that the efficiency of AI can hinge on how workers operate the tools rather than on the tools themselves (Bhatt & Shah, 2023; Hewage, 2023). Meanwhile, studies indicate that AI can influence psychological health and employment attitudes of workers (Liebherr *et al.,* 2025; Richa *et al.,* 2024; Soulami *et al.,* 2024). These ambivalent results indicate that the use of AI recruitment tools depends not only on the level of technological preparedness, but also on the emotional and mental experiences of HR professionals (Dima *et al.,* 2024).

When HR professionals are under pressure to quickly learn and use AI tools, or find the tools challenging, fear automation and have to deal with constant change, they may experience technostress. It is a state of distress that is directly related to the use of technology (Ramesh *et al.,* 2021). Technostress has been defined as a condition that arises when one fails to adapt to the modern digital devices in a healthy way (Ragu-Nathan *et al.,* 2008). Contemporary studies define technostress as a multidimensional concept with overload, complexity, insecurity, and uncertainty as its key factors (Wang *et al.,* 2022). The stressors are known to negatively affect performance, satisfaction and commitment in different workplaces such as IT and education sectors in India (Batta & Kar, 2023; Berger *et al.,* 2023; Chandra *et al.,* 2019; Rahmi *et al.,* 2025; Satpathy *et al.,* 2021). There is also evidence that technostress can reduce employee retention and increase turnover in the same sectors (Rajput & Sharma, 2024; Sharma *et al.,* 2024). This paper looks into the impacts of technostress on the HR professionals within Indian IT firms when they implement AI-based recruitment tools (Sengupta *et al.,* 2025).

We concentrate on four stress inducing factors overload, complexity, insecurity and uncertainty and track how each of them affects intention to use the tools and actual use. We also examine how the negative consequences of technostress can be reduced by the help of organizational support and how it can lead to its more successful adoption. According to previous research, technology stress may be less injury when staff is supported or feel more self-assured in AI (Chang *et al.,* 2024; Chuang *et al.,* 2025; Kim & Lee, 2024; Tu *et al.,* 2025). The research on human-AI collaboration also says that even technostress of the challenge type may stimulate users in favorable circumstances (Chang *et al.,* 2024; Li *et al.,* 2025; Xia, 2023). However, the majority of previous studies do not consider the issue of technostress in relation specifically to AI recruitment and HR work, where rapid updates, complex systems, and processes are common (Asif, 2024; Mori *et al.,* 2024; Nain & Shyam, 2024). Technostress in this aspect is significant to both researchers and practitioners. To researchers, the research fills a gap as it applies both technostress theory and technology acceptance models to real world adoption of HR tools (Islam *et al.,* 2024). The insights indicate to HR leaders that the solution to resistances is simple, through effective onboarding, clear communication and constant training, and thus gaining confidence (Domínguez *et al.,* 2025). Instead of presupposing the problem of resistance is caused by poor attitudes, organizations can act on the issues underlying the stress (Khalid *et al.,* 2025). It aligns with the recent studies in the area of human-centered AI adoption that indicate that user well-being and trust are the key factors to the long-time success (Alzeiby *et al.,* 2025; Kim & Lee, 2024; Litan, 2025; Sadeghi, 2024).

2. Literature Review

2.1 Theoretical Background

2.1.1 Overview of Technostress Theory

Technostress refers to the stress that individuals develop as a result of their failure to make good use of information and communication technologies (Chen, 2015; Kumar, 2024). A clear explanation of this idea was given by (Ragu-Nathan *et al.*, 2008; Tarafdar *et al.,* 2017) who came up with a tested model that illustrates what leads to technostress and what alleviates it. As per their research, the five primary causes of technostress are techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, and techno-invasion (Berger *et al.,* 2023; Jimmy *et al.,* 2023; Kim & Lee, 2021). These factors were first created to study everyday users of general IT systems, but later, they were also used in areas like healthcare (Kopuz & Aydın, 2020), education (Wang *et al.,* 2023), and more recently, in human resource management (Asif, 2024; Khalid *et al.,* 2025; Xia, 2023). The theory of technostress is rooted in transactional theory of stress (Saidy *et al.,* 2022; Wang & Li, 2019), which posits that when the demands that one perceives a technology to have and his/her resources to cope with them do not match, there is a psychological strain.

This has been justified empirically by (Ragu-Nathan *et al.,* 2008) who came up with a negative effect of technostress on user satisfaction, work performance and work commitment (Atrian & Ghobbeh, 2023; Hessari *et al.,* 2024; Pansini *et al.,* 2023; Ramakrishna *et al.,* 2011). The inventors of technostress do not rely only on the level of technology being utilized but rather on the perception of the individual regarding the complexity, pace of change and effect of the technology on job functions (Ibrahim *et al.,* 2021; Kumar, 2024). The concept of technostress can be applied to the situation with AI-driven recruitment tools because it will help one to realize the way HR professionals think about the new technologies as a burden instead of a resource (Khalid *et al.,* 2025; Xia, 2023). When tools are implemented without proper training, support or clarity, the stress that is caused can outweigh the advantages of adoption (Wójcik, 2025). The technostress framework therefore offers a basis of assessing why some HR professionals may resist or not use AI tools effectively even when the organization is interested or the tools are available (Asif, 2024).

2.1.2 UTAUT or Technology Adoption in HR Context

The Unified Theory of Acceptance and Use of Technology by (Venkatesh *et al.,* 2003) has been widely used in establishing the reasons why people accept and adopt the use of new technologies in different fields (Venkatesh, 2021). In this model, there are four key factors identified that influence the intention of an individual to use technology and the actual use of technology (Hewage, 2023). These include performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT has been adapted to examine the adoption of HR technologies although it was not initially designed to study this phenomenon, and it has been successfully applied in the context of HR professionals in emerging markets such as India where the rate of digitalization is high (Bhatt & Shah, 2023; Islam *et al.,* 2024; Jain *et al.,* 2022). In the HR field, AI tool adoption is not only dependent on its functionality but on how professionals view its usefulness, its usability, and the effects on their roles (Kalvakolanu et al., 2023; Wongras & Tanantong, 2023).

The recent research findings show that the perceived behavioral control, attitudes and enabling conditions still remain relevant in the implementation of HR tech (Kaggwa *et al.,* 2024). UTAUT, however, does not fully explain emotional or psychological barriers like fear, stress, or anxiety which are becoming more and more applicable when it comes to complex AI systems (Eftimov & Kitanovikj, 2023; Wolfe *et al.,* 2025). Therefore, the combination of UTAUT and technostress theory would give a more realistic perspective of HR technology adoption, as it incorporates both rational decision-making and emotional preparedness (Venkatesh, 2021). Such a combined perspective is required when examining the AI recruitment tools that can be viewed both as beneficial and a threat to the traditional HR decision-making autonomy (Asif, 2024; Nain & Shyam, 2024).

Conceptually, integrating UTAUT with technostress theory is not only additive but also addresses a theoretical tension (Alam *et al.,* 2020). UTAUT assumes that technology use is largely driven by rational appraisals that shape behavioural intention, whereas technostress reflects affective strain and coping appraisal, where perceived demands can disrupt or override rational evaluations (Islam *et al.,* 2024). Accordingly, technostress offers an explanatory mechanism for why favourable performance/effort expectations may not translate into intention or sustained use under conditions of strain (Zhang, 2024). In this study, behavioural intention represents the rational motivational pathway, while technostress creators represent an emotion- and stress-based resistance pathway; their joint consideration explains the intention–use gap in AI-enabled HR work (Hewage, 2023).

Although this study is empirically grounded in Indian IT firms, the phenomena of technostress and AI-enabled HRM are widely discussed in global scholarship (Abaza & Eltobgy, 2024). Cross-country research and synthesis studies show that technostress creators and their consequences are observed across diverse contexts, though effect magnitudes can vary depending on work systems, technology maturity, and institutional environments (Alam *et al.,* 2020). Likewise, global research on AI-enabled personnel selection highlights recurring concerns around trust, transparency, fairness, and algorithm aversion, indicating that adoption and sustained use depend not only on perceived utility but also on human and organisational conditions (Asif, 2024).

2.1.3 Integrating UTAUT and Technostress Theory and Rationale for Model Choice

UTAUT explains technology use primarily through a rational intention pathway (Theres & Strohmeier, 2023), whereby performance expectancy, effort expectancy, social influence, and facilitating conditions shape behavioural intention and subsequent use (Alam *et al.,* 2020; Venkatesh, 2021). Technostress theory complements this logic by explaining how technology-related demands create psychological strain that can reduce coping resources and trigger resistance or avoidance (Chang *et al.,* 2024; Chuang *et al.,* 2025; Khalid *et al.,* 2025). The intersection of these models therefore addresses a key conceptual gap in AI-enabled HR contexts: adoption decisions are not only utility-driven but also shaped by stress reactions that can weaken intention formation and/or prevent intention from translating into actual usage (Wongras & Tanantong, 2023; Xia, 2023; Zhang, 2024). Alternative frameworks such as Innovation Diffusion Theory and the Technology Readiness Index were considered; however, IDT primarily focuses on innovation attributes and diffusion patterns, while TRI emphasizes individual predispositions toward technology (Eftimov & Kitanovikj, 2023; Kalvakolanu *et al.,* 2023). In contrast, the present study required a framework that explicitly captures the intention-to-use mechanism and technology-induced strain and coping barriers that emerge during AI-enabled work, as well as the buffering role of organisational support. Therefore, UTAUT and technostress theory were selected as the most conceptually aligned foundations for the proposed model.

2.2 Technostress Creators

2.2.1 Techno-Overload

Techno-overload refers to a situation in which technology compels workers to work harder, faster, and longer to keep pace with its demands (Chuang *et al.,* 2025; Routray *et al.,* 2025). In the context of AI-based recruitment, HR professionals often become inundated with vast numbers of candidate applications and data points requiring review, where the apparent simplicity of AI masks increased cognitive and workload pressures (Asif, 2024; Hewage, 2023; Zheng *et al.,* 2025). Research indicates that such overload can lead to frustration, burnout, and job dissatisfaction (Khalid *et al.,* 2025; Wang *et al.,* 2022). The integration of AI tools often imposes additional pressure on HR teams, necessitating time-intensive maintenance to meet stringent deadlines (Domínguez *et al.,* 2025; Routray *et al.,* 2025).

The study by Wang (Wang *et al.,* 2022) further demonstrates that techno-overload negatively impacts employee well-being in digital workplaces, particularly when AI systems are deployed without adjusting existing workload expectations (Chang *et al.*, 2024). For HR professionals already managing multiple roles, navigating the tension between traditional and algorithm-driven processes proves cumbersome, often culminating in decision fatigue (Dima *et al.,* 2024; Khan *et al.,* 2025).

2.2.2 Techno-Complexity

Techno-complexity is a state whereby a user perceives a given technology as difficult to master, use, or adapt to their current workflow (Alsaif & Aksoy, 2023). In AI recruiting tools, the complexity may arise from the user interface, algorithm settings, or integration with other HR information systems (Islam *et al.,* 2024).

The platforms can be difficult for HR professionals without technical training to interpret, especially when systems lack transparency or offer little support documentation (Laurim *et al.,* 2021). (Berger *et al.*, 2023) stressed that complexity-related stress increases when the training is inadequate, the design of tools is not intuitive, or when employees have to work with several systems at the same time. It is not only operational but also cognitive stress: HR professionals may lack confidence in their capabilities to work in an AI-enriched environment (Khan *et al.,* 2025; Venugopal *et al.,* 2024). This doubt may cause avoidance behaviour or misuse of tools in the long run (Almeida *et al.,* 2025).

2.2.3 Techno-Insecurity

Techno-insecurity refers to the apprehension of job loss or diminished professional relevance arising from growing dependence on technology (Khalid *et al.,* 2025). In the HR context, particularly with the introduction of AI automating resume reviews, preliminary interviews, and predictive hiring decisions, professionals may feel that core aspects of their roles are being usurped by machines (Kutieshat *et al.,* 2025; Sharif *et al.,* 2025).

This fear is especially pronounced among mid-career HR professionals who have built careers on interpersonal and intuitive judgment skills (Fenwick *et al.,* 2024). Rajput and Sharma (Rajput & Sharma, 2024) noted that techno-insecurity directly impacts employee retention and job engagement, particularly in sectors aggressively promoting automation without adequate change management. In HR, the threat extends beyond job loss to erosion of decision-making power (Arslan *et al.,* 2021). With more evaluative tasks handled by AI, HR professionals may feel relegated to enablers rather than strategists, resulting in low morale and reduced adoption of new tools.

2.2.4 Techno-Uncertainty

Techno-uncertainty refers to a state of confusion or anxiety arising from continuous modifications to digital systems, frequent updates, or unclear future directions of technology (Chang *et al.,* 2024; Chuang *et al.*, 2025; Khalid *et al.*, 2025). In the context of AI-based recruitment platforms, particularly those delivered as software-as-a-service, systems are constantly updated with new features, algorithmic adjustments, and interface changes (Asif, 2024; Islam *et al.,* 2024; Venkatesh, 2021). These updates are often implemented without meaningful user involvement or adequate documentation, fostering uncertainty among HR professionals (Khan *et al.,* 2025; Rahmi *et al.,* 2025; Xia, 2023). As (Rahmi *et al.,* 2025) highlights, such rapid changes contribute to cognitive fatigue and digital strain by preventing employees from fully adjusting to technological shifts. In HR settings, this uncertainty is exacerbated by users' lack of control over updates, requiring constant adaptation regardless of individual readiness (Fan *et al.,* 2025; Khalid *et al.,* 2025; Nayak *et al.,* 2025).

Consequently, it induces instability in work processes and heightens stress levels, even when updates represent technical improvements (Dima *et al.,* 2024; Litan, 2025; Zhang *et al.,* 2025). (Chandra *et al.,* 2019) further demonstrates that techno-uncertainty, as a key technostress creator, inhibits employee innovation and proactive tool usage; in unstable HR systems, this leads to ineffective communication, reactive rather than engaging behaviors, and diminished adoption (Chandra *et al.,* 2019; Chuang *et al.,* 2025). Ultimately, this ambiguity disrupts scheduling, erodes trust in digital systems, and impedes sustained use within time-sensitive recruitment environments (Asif, 2024; Chang *et al.,* 2024; Wang *et al.,* 2022).

2.3 Behavioral Intention and AI Tool Usage

Behavioral intention has been universally acknowledged as one of the major predictors of whether people will interact and use digital systems, including AI-based recruitment platforms (Alam *et al.,* 2020; Hmoud & Várallyai, 2020; Venkatesh, 2021; Wongras & Tanantong, 2023). Intention in the context of technology adoption models, especially UTAUT, is the conscious plan or motivation of a person to utilize a certain system in the future (Bhatt & Shah, 2023; Revillod, 2025; Tanantong & Wongras, 2024). In HR settings, behavioral intention to use AI depends on perceived usefulness of the system in enhancing recruitment quality and efficiency (Islam *et al.,* 2024; Zhang, 2024), the exertion of effort to use the system (Wongras & Tanantong, 2023), and the confidence of HR professionals in using the system (Wolfe *et al.,* 2025).

Nonetheless, the desire to use it successfully is not enough. According to many HR professionals, they are positive about AI tools and still do not use them because of stress or fear of making mistakes or simply do not feel comfortable with complicated user interfaces (Nain & Shyam, 2024; Wójcik, 2024, 2025). This disconnect between intention and use is particularly visible when the employees have to adopt new tools in their daily practice without sufficient time, resources, or training opportunities (Madanchian, 2024; Wang *et al.,* 2022). The workload that comes with the addition of AI to the current duties, particularly when working under strict deadlines, can diminish the real usage despite the good intentions (Jin *et al.,* 2026; Litan, 2025).

A number of recent studies have indicated that adoption of AI in HR is not determined by perceived usefulness alone (França *et al.,* 2023; Nawaz *et al.,* 2024). As an illustration, (Sadeghi, 2024) discovers that digital well-being and mental comfort play a pivotal role in the process of converting intention to action among employees. (Tu et al., 2025) also suggest that even strong behavioral intention can be defeated by psychological obstacles, including anxiety and self-doubt, in the case of AI tools that are not explainable or transparent. (Liebherr *et al.,* 2025) also mention that personal variables such as previous experience, familiarity with digital literacy, and cultural values affect the route between the intention and usage as well (Lu & Hu, 2025).

This gap highlights why an intention-based model alone is insufficient in AI recruitment contexts (Khalid *et al.,* 2025). Even when HR professionals recognise usefulness, technostress can reduce perceived coping resources and elevate avoidance, weakening intention formation and/or preventing intention from translating into actual usage (Chuang *et al*., 2025; Xia, 2023). Therefore, the present model treats technostress as a psychological barrier that interacts with the intention pathway proposed by UTAUT (Venkatesh, 2021).

In addition, research in real-world HR environments reveals that the use is most effective when employees perceive ownership and control of the tool, as opposed to being mere objects and recipients of technology foisted by top management (Rajput & Sharma, 2024; Alzeiby *et al.,* 2025). By involving HR professionals in the early stages of the selection, customization, or evaluation of AI tools, they will more effectively transfer their behavioral intention to the effective and consistent use of the tool. This underlines the significance of not only quantifying intention, but also of making the act of use feasible, risk-free, and professionally satisfying.

2.4 Organizational Support as a Moderator

Organizational support is the formal and informal structures that the employer introduces to assist the employees in the management of new systems (Budhwar *et al*., 2022). This can be training, user-friendly documentation, leadership support, peer learning, and responsive technical support in the case of AI adoption in recruitment (Fan *et al.,* 2025). In case of such support, stress linked to new technology is likely to be reduced, and behavioral intention is more likely to translate into actual usage of the system (Jabagi *et al.,* 2024; Pan *et al.,* 2021).

(Chang *et al.,* 2024) underline that the presence of supervisors and digital help systems allows employees to position technostress as a manageable challenge but not a threat (Prasad & De, 2024).

The ongoing support in the HR teams that employ AI-based recruitment technologies can assist people in keeping up with the high rates of change in the system, increasing workload, and interpreting algorithmic judgments better (Prikshat *et al.,* 2023). (Liebherr *et al.,* 2025) find that when left unsupported, even a minor difficulty can develop into long-term resistance or tool abandonment, especially when professionals are left alone to deal with new technologies (Benabou & Touhami, 2025). The self-efficacy or the confidence of the ability to work with technology is also built through organizational support (Madanchian & Taherdoost, 2025). As shown by (Kim & Lee, 2024), the increased self-efficacy leads to the direct increase in adoption rates, and it is enhanced when organizations provide onboarding, practice sessions, and feedback systems (Almeida *et al.,* 2025).

Moreover, (Rajput & Sharma, 2024) propose that the level of retention and engagement among HR professionals is more robust in companies that take the most active steps to mitigate tool-related stress by implementing leadership-initiated interventions and team-based learning activities (Benabou & Touhami, 2025). (Rahmi *et al.,* 2025) also affirm that support mechanisms are most successful when it is designed according to actual employee concerns as opposed to generic or one-off (Zhang *et al.,* 2025). This incorporates establishing psychological security, open communication concerning technology issues, and user input in upgrades of the platform. (Xia, 2023) also adds that such human interface as mentorship and peer support can be incorporated into a high-tech environment to minimize uncertainty and establish trust in AI tools.

However, the organizational support literature is not uniformly positive. Empirical work suggests that support may function as an enabler only when it is perceived as relevant, timely, and autonomy-preserving; symbolic support (e.g., generic communication without hands-on resources) may fail to reduce strain, and in some cases intensified 'support' through monitoring, mandatory training, or performance pressure can unintentionally heighten technostress by increasing perceived control and expectations. Moreover, access to support can be uneven across roles and teams, creating variability in how individuals experience the same technology implementation. These mixed findings indicate that organisational support is best understood as a boundary condition whose effectiveness depends on implementation quality and employee perceptions, which motivates its inclusion as a moderator in the present model.

2.5 Research Gap

Although there is an increased body of literature on technostress and the use of technology (Kumar, 2024), there exist observable gaps in terms of understanding the same in the HR specific context especially with regards to the use of AI-based recruitment tools in Indian IT firms (Batta & Kar, 2023; Kumar, 2025). The majority of the available literature has discussed technostress in the general fields of education, healthcare, and generic information technology jobs (Berger *et al.,* 2023; Rahmi *et al.,* 2025; Wang *et al.,* 2022; Wójcik, 2025). Though they can be of great help in understanding the psychological consequences of digital transformation (Khan *et al.,* 2025; Xia, 2023), they do not take into consideration the particular problems that HR professionals have to address (Dima *et al.,* 2024).

The administrative, interpersonal, and evaluative functions of HR are frequently intertwined, and the AI in hiring is more disruptive to these professions than in others (Kaaria, 2024). Specifically, the Indian IT sector offers a rapidly changing landscape within which digital maturity varies enormously across companies (Anjumanwarshaik *et al.,* 2025). In this case, recruitment tools based on AI are being implemented at a fast pace, however; there is minimal research on how HR professionals perceive this transformation (Nawaz *et al.,* 2024; Rukadikar & Khandelwal, 2025). As stressed by (Chandra *et al.,* 2019), employee innovation and the use of digital tools are susceptible to stress levels, and no research has directly explored the impact of technostress on behavior intention and real AI usage among HR professionals, in this regard (Islam *et al.,* 2024).

Moreover, although UTAUT-based models provide adoption behavior by explaining it with rational determinants (Wolfe *et al.,* 2025), they do not always take into account emotional and psychological obstacles such as stress, fear, or overload (Chang *et al.,* 2024). This introduces an explanatory gap that restricts the explanatory potential of the traditional adoption models to high-stakes HR choices (Khalid *et al.,* 2025; Negt & Haunschild, 2024). Finally, organizational support as a moderator of technostress during the adoption of AI in recruitment has not been studied empirically, even though it has been theorized (Fan *et al.,* 2025; Kim & Lee, 2024; Tu *et al.,* 2025). The proposed study will address these gaps by investigating the interaction between technostress makers and AI adopters, mediated by behavioral intention, and moderated by organizational support in the HR department of Indian IT companies (Goswami et al., 2023).

2.6. Proposed Research Model

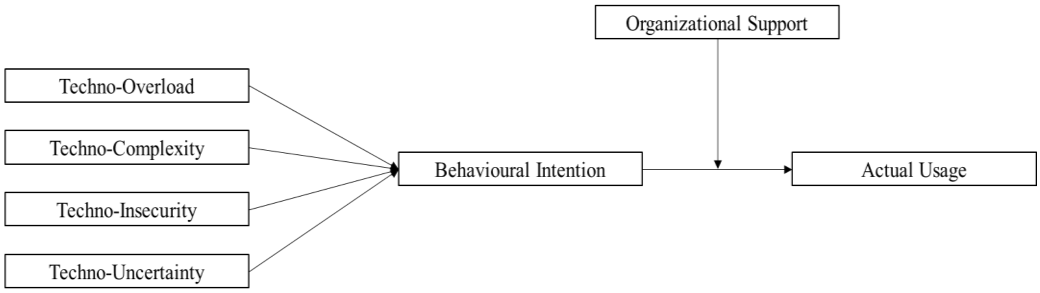

Figure 1. Proposed conceptual model

3. Research Methodology

3.1 Research Design

This research uses a quantitative method and follows a cross-sectional survey design. It studies how technostress affects the use of AI by HR professionals working in IT companies in India. The study is based on two well-known models: the technostress model by Ragu-Nathan *et al.* (2008) and the technology acceptance model by Venkatesh *et al.* (2003). It also includes organizational support as a factor that may change how technostress influences AI use. This research design was chosen because it helps to study the connections between different factors using real data collected at one point in time.

3.2 Population and Sampling

The population of this study will be the HR professionals in the recruitment department of Indian IT firms, especially those who are using or exposed to AI-driven recruitment platforms. The relevance of these professionals is that they directly interact with the systems that automate the screening, shortlisting, or selection process and will be the ones likely to experience the benefits and stress of AI tools.

Snowball sampling was used in the study because of the nature of the target group as it was a specialized group. The sampling started with known HR professionals in academic, LinkedIn, and corporate networks and then asked to share the survey with other qualified respondents in their networks. This method is appropriate when examining a specialized population of professionals who are hard to reach or a niche population. It also enables organic growth of the sample as a result of trust-based referrals, which makes it more likely that the respondents tell the truth.

3.3 Sample Size

In this study, the final sample consisted of 273 HR professionals who work in the recruiting department of different Indian IT companies. This sample size was arrived at by taking into consideration the Cochran sample size formula as a guiding benchmark, but also taking into consideration the practical limitation of reaching a specialized population by use of non-probability snowball sampling.

Because the sample under study is a niche population, i.e., HR professionals working with AI-based recruitment, one could not employ the probability sampling techniques since the sampling frame is not well distinguished. Thus, snowball sampling was employed to reach the target population. Nevertheless, to make sure that the sample size was statistically adequate to allow reliable analysis, particularly Structural Equation Modeling (SEM), Cochran formula was used to determine the minimum sample size that would be acceptable.

The formula employed is:

$$n_0 = \frac{Z^2 \cdot p\,(1-p)}{e^2} \tag{1}$$

Where:

1.96 (at a 95 percent confidence level)

p=0.5 (max variability)

e=0.06 (desired margin of error)

$$n_0 = \frac{(1.96)^2 \cdot 0.5 \cdot (1-0.5)}{(0.06)^2} \tag{2}$$

$$n_0 = \frac{3.8416 \cdot 0.25}{0.0036} = \frac{0.9604}{0.0036} \approx 267 \tag{3}$$

This calculation shows that at least 267 responses are needed to have a general confidence in the findings. The total number of 273 valid responses is above this threshold, which indicates that the sample size is sufficient in terms of statistical planning.

Cochran formula is traditionally applied to probability sampling techniques, but it is commonly accepted in studies in social sciences as a help in determining the adequate sample size, even in such non-probability sampling types as snowball sampling. This is especially prevalent where the population is specialized, difficult to access, or does not have a clear sampling frame - which is the case in this study.

Moreover, the selected sample size is methodologically appropriate to conduct Structural Equation Modeling (SEM). The study model will have 7 latent variables, with each latent variable consisting of 5 observed variables, making 35 observed variables. According to the commonly adopted SEM standards (Hair *et al.,* 2013), model stability and validity demand the presence of a recommended range of 7 to 10 responses per observed item.

$$Sample\ Size\ Ratio = \frac{273}{35} \approx 7.8\ responses\ per\ item \tag{4}$$

The ratio establishes that the sample is sufficient to make an analysis using SEM, and of particular significance is the fact that there are validated scales and a clear definition of the measurement model. Geographical, organizational size, and the extent of AI exposure among the HR professionals also lends credibility to the sample.

3.4 Collection of Data

The questionnaire was sent out via Google Forms. This was through professional networks (LinkedIn, HR WhatsApp groups, email lists). The respondents were guaranteed confidentiality and participation was optional. The data collection took place during four weeks. Automatic recording of responses and exporting of responses into SPSS and AMOS were done.

3.5 Ethical Considerations

Each of the participants was informed of the intention of the study and that they could keep their answers to themselves and that the answers would only be used academically. There was no collection of personal identifying information. The participants were allowed to withdraw whenever they wanted. The study is not a physical or psychological risk, and thus no formal institutional review board approval was necessary; however, ethical procedures were observed throughout the study.

4. Interpretation and Analysis

Inference: Table 1 presents the demographic profile of the 273 HR professionals who participated in the study.

Table 1. Demographic Profile of Respondents

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	118	43.2%
	Female	152	55.7%
	Prefer Not to Say	3	1.1%
Age Group	20–25 Years	38	13.9%
	26–30 Years	89	32.6%
	31–35 Years	84	30.8%
	36–40 Years	42	15.4%
	Above 40 Years	20	7.3%
Work Experience	Less Than 1 Year	18	6.6%
	1–3 Years	67	24.5%
	4–6 Years	88	32.2%
	7–10 Years	62	22.7%
	More Than 10 Years	38	13.9%
Education Level	Bachelor's Degree	98	35.9%
	Master's Degree (MBA / MSc)	148	54.2%
	Postgraduate Diploma in HR	19	7%
	Doctorate / PhD	8	2.9%
Company Size	Small (< 500)	42	15.4%
	Medium (500–2,000)	79	28.9%
	Large (2,001–10,000)	96	35.2%
	Very Large (> 10,000)	56	20.5%
Designation / Role	HR Executive / HR Associate	72	26.4%
	Senior HR Executive	58	21.2%
	HR Manager	74	27.1%
	Senior HR Manager / HR Lead	43	15.8%
	HR Business Partner / HR Head	26	9.5%

Source: Author's Calculations (Primary Data, N = 273)

With respect to gender, the sample was predominantly female (55.7%), followed by male respondents (43.2%), which is broadly consistent with the feminisation of HR roles observed in the Indian IT sector. In terms of age, the majority of respondents fell within the 26–30 years (32.6%) and 31–35 years (30.8%) brackets, indicating that the sample largely comprised early to mid-career professionals — a cohort that is particularly relevant to the study given their direct and ongoing exposure to AI-driven recruitment tools. Regarding work experience, the largest proportion reported 4–6 years of experience (32.2%), suggesting that most respondents possess sufficient professional background to meaningfully evaluate technostress and AI adoption in their roles. In terms of educational qualification, over half the respondents held a Master's degree or MBA (54.2%), followed by Bachelor's degree holders (35.9%), reflecting the high educational attainment typical of HR professionals in the Indian IT industry. The distribution of respondents across company sizes was balanced, with a slight concentration in large firms employing 2,001–10,000 employees (35.2%), ensuring that the findings capture experiences from organisations with varying levels of technological infrastructure and AI maturity. Finally, in terms of job designation, HR Managers (27.1%) and HR Executives (26.4%) constituted the core of the sample, with Senior HR Managers, HR Business Partners, and HR Heads also represented, lending both operational and strategic perspectives to the data.

4.1 Descriptive Constructs of Statistics (N = 273)

Inference: Descriptive statistics were calculated as shown in table 2 to determine the central tendencies and dispersion of each construct in the model. The constructs consisted of five items each rated on a 5-point Likert-scale and the sum of each construct was taken. All variables had mean values of between 17.73 and 18.07, which means that there was a moderately positive response on all dimensions. The standard deviations ranged between 4.34 to 4.58 indicating a steady range of responses that were not extreme.

These findings give the initial estimations that the respondents experienced moderate to high perceived technostress, and a reasonable intention and reported use of AI tools, and that they perceived organizational support as present.

Table 2. Descriptive statistics

Construct	Min	Max	Mean	Std. Deviation
Organizational Support	7.00	24.00	17.95	4.34
Techno-Complexity	6.00	24.00	18.00	4.58
Techno-Insecurity	6.00	24.00	17.76	4.42
Techno-Uncertainty	7.00	25.00	17.91	4.45
Techno-Overload	6.00	24.00	18.07	4.52
Behavioral Intention	6.00	25.00	17.73	4.50

Source: Author's Calculation

4.2 Reliability Test

Table 3. Reliability (Cronbach's alpha)

Construct	No. of Items	Cronbach's Alpha
Techno-Overload	5	0.834
Techno-Complexity	5	0.843
Techno-Insecurity	5	0.829
Techno-Uncertainty	5	0.832
Behavioral Intention	5	0.840
Organizational Support	5	0.819
Actual Usage	5	0.819

Source: Author's Calculation

Inference: Table 3 shows that to ascertain the internal consistency of the constructs employed in the research, the reliability analysis using Cronbach alpha was done on all the seven variables, which were measured using five items on a 5-point Likert scale. The alpha coefficients were 0.819 to 0.843, which means that all constructs had good internal consistency, according to the accepted standard of 0.7 (Hair *et al.,* 2013).

In particular, the greatest reliability was demonstrated by Techno-Complexity (alpha = 0.843), followed by Behavioral Intention (alpha = 0.840) and Techno-Overload (alpha = 0.834). Other constructs like Techno-Uncertainty, Techno-Insecurity, Actual AI Tool Usage, and Organizational Support had a good level of reliability with alpha values of over 0.81. These findings indicate that the scales of measurement used were statistically sound, and could be used in further analysis.

4.3 Factor Analysis

Inference: The Kaiser-Meyer-Olkin (KMO) value is 0.977, which is much higher than the minimum required value of 0.70 from table 4. This shows that the data is suitable for factor analysis. Also, the Bartlett's Test of Sphericity is significant ($p < 0.001$), meaning the variables are related to each other well enough to do factor analysis. Together, these two results confirm that the sample size is good and the variables are connected, so it is possible to identify hidden patterns using Exploratory Factor Analysis (EFA).

Table 4. KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.977
Bartlett's Test of Sphericity	Approx. Chi-Square	6092.243
	df	595
	Sig.	.000

4.4 Mediation Analysis

Table 5. Mediation results

Technostress Variable	Direct Effect (X→Y)	Indirect Effect (X→M→Y)	Total Effect (X→Y)	Direct Effect Sig.	Indirect 95% CI (LLCI - ULCI)	Mediation Type
Techo Complexity	0.4259	0.3704	0.7963	p < .001	0.2834 - 0.4532	Partial
Techo Insecurity	0.5085	0.3372	0.8457	p < .001	0.2563 - 0.4228	Partial
Techo Uncertainty	0.4355	0.3829	0.8184	p < .001	0.2938 - 0.4758	Partial
Techo Overload	0.4721	0.3467	0.8188	p < .001	0.2636 - 0.4322	Partial

Source: Author's Calculation

Inference: The mediation results for behavioural intention are summarized in Table 5. The findings indicate that behavioral intention has a partial role in the relationship between the four forms of technostress (techno-complexity, insecurity, uncertainty, and overload) and the actual utilization of AI tools. The direct and indirect effects are both statistically meaningful, and the results are significantly not equal to zero. It implies that technostress has a direct negative impact on the use of AI tools and the intention to use them. Intent, however, is relevant. Even in situations where HR professionals are experiencing stress, their use of AI can be enhanced when they have an intention to use it.

4.5 Moderation Analysis

Table 6–9. Moderation regression coefficients, Moderation regression coefficients for organizational support are reported in Tables 6–9.

Table 6. Techno Overload x Organizational Support

Variable	B	SE	t	LLCI	ULCI
Constant	-12.6491	2.1453	-5.8962	-16.8728	-8.4254
Techno Overload	1.5218	0.156	9.7574	1.2147	1.8289
Organizational Support	1.4808	0.1626	9.1064	1.1606	1.8009
Techno Overload x Organizational Support	-0.0688	0.0099	-6.9677	-0.0882	-0.0494

Source: Author's Calculation

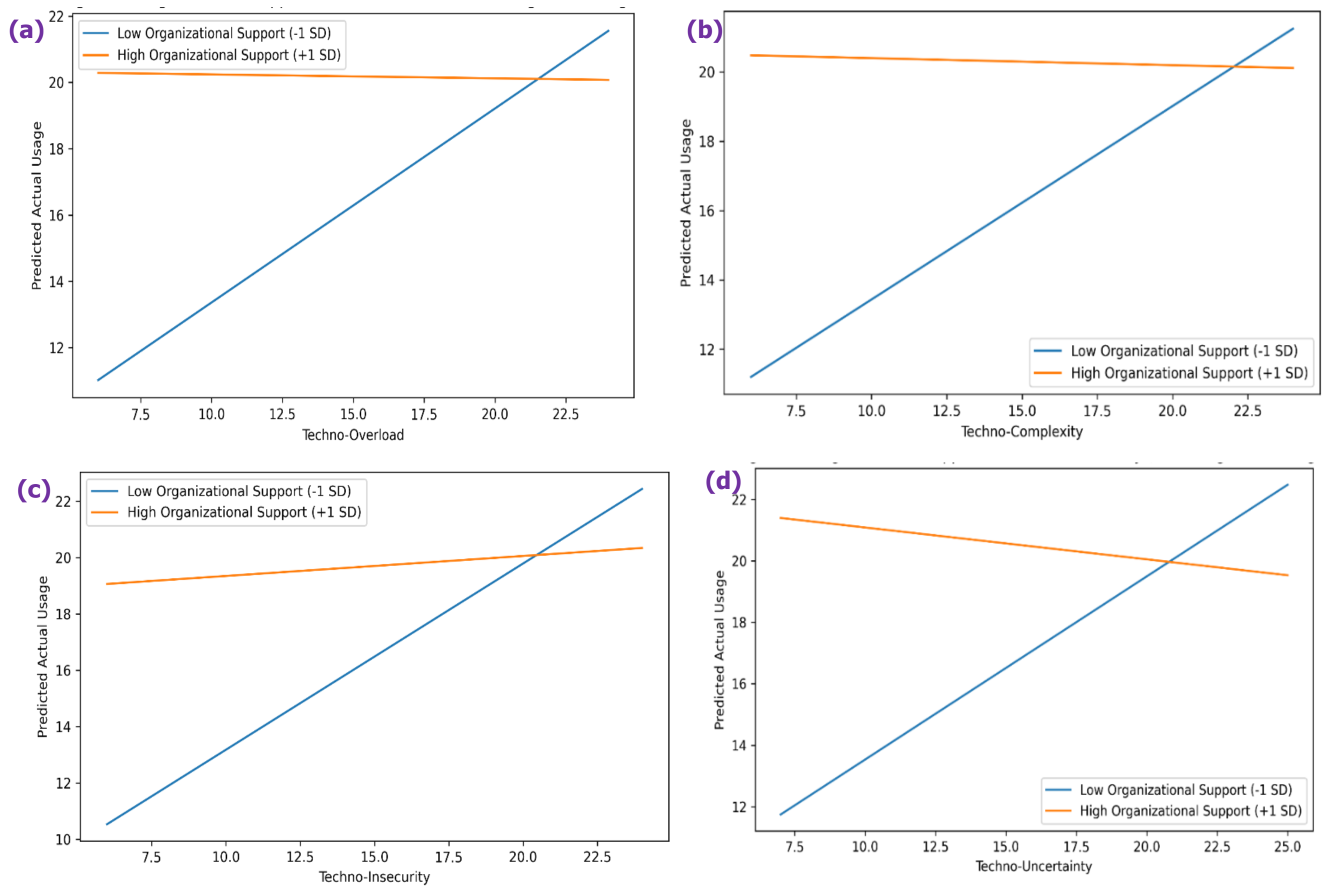

Figure 3a. Moderating Effect of Organizational Support on the Relationship between Techno-Overload and Actual Usage (Simple Slopes at ±1 SD of Organizational Support), **Figure 3b,** Moderating Effect of Organizational Support on the Relationship between Techno-Complexity and Actual Usage (Simple Slopes at ±1 SD of Organizational Support). **Figure 3c.** Moderating Effect of Organizational Support on the Relationship between Techno-Insecurity and Actual Usage (Simple Slopes at ±1 SD of Organizational Support). **Figure 3d.** Moderating Effect of Organizational Support on the Relationship between Techno-Uncertainty and Actual Usage (Simple Slopes at ±1 SD of Organizational Support).

Table 7. Techno Complexity x Organizational Support

Variable	B	SE	t	LLCI	ULCI
Constant	-12.1581	2.0264	-5.9998	-16.1477	-8.1684
Techno Complexity	1.4663	0.1495	9.8069	1.172	1.7607
Organizational Support	1.4699	0.15	9.7963	1.1745	1.7653
Techno Complexity x Organizational Support	-0.0667	0.0092	-7.2252	-0.0848	-0.0485

Source: Author's Calculation

Inference: The interaction effect is negative and significant (B = -0.0688, $p < 0.01$), which means that organizational support prevents negative influences of techno-overload on actual use. Simply put, when the HR professionals feel overloaded with the task related to AI, the powerful organizational (i.e., training or leadership) support will prevent the tendency to abandon the tool.

Inference: This finding also exhibits a strong negative interaction (B = -0.0667), which means that organizational support mitigates the detrimental nature of perceived complexity in AI tools. In the cases when systems are too technical or confusing, support structures such as training and peer mentoring enable HR professionals to keep on using the tools efficiently.

Inference: In this case, the moderation effect is once again negative and statistically significant (B = -0.068), indicating that organization support can make employees feel more secure about their jobs, even in the case of automation of key HR functions by AI tools. This minimises fear-related opposition to technology.

Table 8. Techno Insecurity x Organizational Support

Variable	B	SE	t	LLCI	ULCI
Constant	-12.3634	1.9673	-6.2844	-16.2367	-8.4901
Techno Insecurity	1.5867	0.15	10.576	1.2913	1.8821
Organizational Support	1.3907	0.1458	9.5413	1.1037	1.6776
Techno Insecurity x Organizational Support	-0.068	0.0091	-7.471	-0.086	-0.0501

Source: Author's Calculation

Table 9. Techno Uncertainty x Organizational Support

Variable	B	SE	t	LLCI	ULCI
Constant	-15.2351	2.1316	-7.1471	-19.4319	-11.0383
Techno Uncertainty	1.693	0.1578	10.7304	1.3824	2.0036
Organizational Support	1.6758	0.1568	10.6858	1.367	1.9845
Techno Uncertainty x Organizational Support	-0.0806	0.0098	-8.213	-0.0999	-0.0613

Source: Author's Calculation

Inference: The strongest negative interaction is observed here (B = -0.0806) indicating that organizational support is especially beneficial in situations where employees are uncertain about AI systems that are often updated or changed. Such support mechanisms as constant communication, clear policies, and guidance can decrease this uncertainty to a great extent.

4.6 Model Fit Indices Summary

To strengthen confidence in the stability of the findings, indirect effects were evaluated using bootstrapped confidence intervals (Table 5). In addition, the proposed relationships were examined using complementary analytical approaches: conditional process (PROCESS) estimates are reported alongside SEM model fit evidence (Table 10) as convergent support for the overall model structure. Future research may extend these robustness assessments by re-estimating interaction models using alternative scaling/standardization choices and additional resampling checks. Figure 4 and 5 shows the SEM model 1 and 2 respectively.

Table 10. SEM model fit indices

Fit Index	Criteria/Threshold	Default Model Value
CMIN/DF	< 3 (good fit)	1.128
GFI	> 0.90	0.996
AGFI	> 0.90	0.971
RMR	< 0.08	0.072
NFI	> 0.90	0.998
CFI	> 0.95	1.000
RMSEA	< 0.06 (good); < 0.08 (acceptable)	0.022
HOELTER (.05)	> 200	629

Source: Author's Calculations

5. Findings

The main aim of this study was to understand how different types of technostress affect the use of AI tools in hiring by HR managers working in Indian IT companies. To do this, a detailed statistical analysis was used to study the relationship between different technostress factors, such as overload, complexity, insecurity, and uncertainty. behavioural intention, actual usage, and the moderating effect of organizational support. Descriptive statistics showed that the HR professionals indicated moderate levels of technostress in all four dimensions. The average scores of each construct were between 17.73 and 18.07, which indicated that stress caused by AI tools was generally experienced. Meanwhile, the behavioural intention to use AI tools was not too low, which means that although HR professionals are stressed, they are willing to use AI.

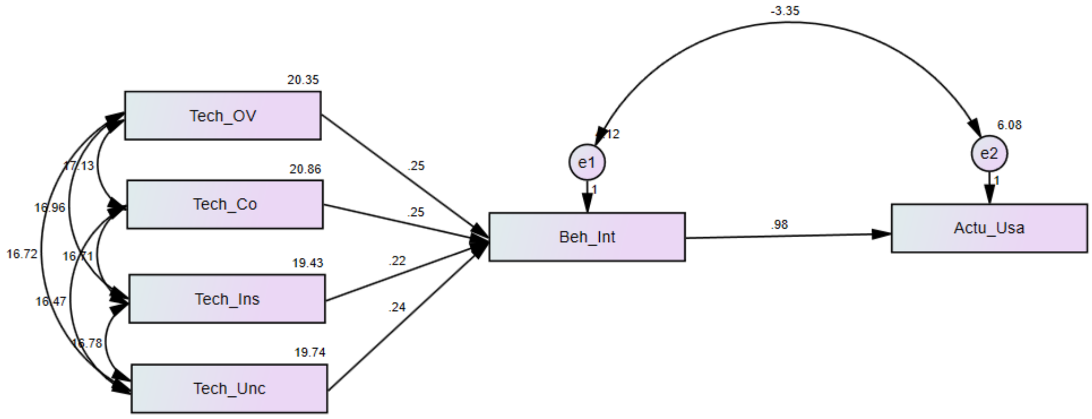

Figure 4. SEM Model 1

Source: Author's Calculations

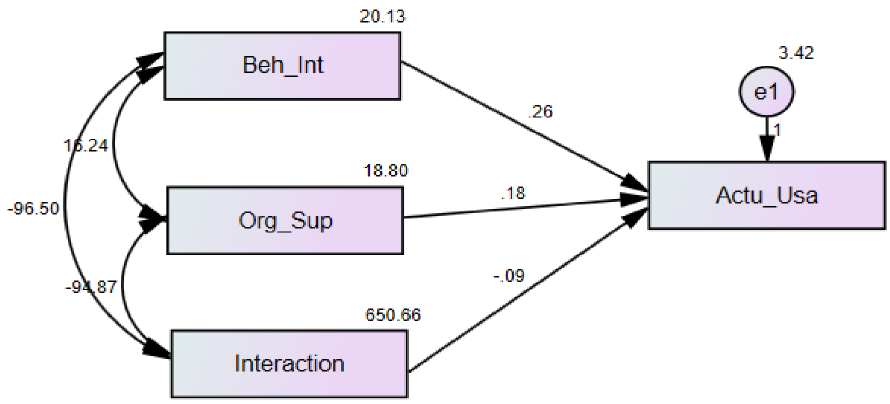

Figure 5. SEM Model 2

Source: Author's Calculations

The reliability test based on Cronbach Alpha indicated that there was a high reliability of all constructs as the values ranged between 0.81 and 0.99. This proves that the questionnaire was reliable and the information gathered was reliable to be used in further analysis. The factor analysis indicated a high level of sampling adequacy (KMO = 0.977) and significant Bartlett Test ($p < 0.001$), which suggested that the data was fit to be used in structural analysis.

The mediation analysis indicates that behavioural intention partly mediates the correlation among all four technostress creators and the actual usage of the AI tools. This implies that when HR professionals are stressed (because of overload, insecurity, etc.), their intention to use the tools continues to impact the use of the tools. The stress decreases that intention. It follows that behavioural intention mediates the relationship between technostress and actual usage. In addition to significance testing, the mediation results are reported with bootstrapped confidence intervals for indirect effects (Table 5), and moderation effects are reported with confidence intervals (Tables 6–9). The explanatory power of the model is summarized using variance explained (R^2): the model explains $R^2 = 0.52$ of variance in behavioural intention and $R^2 = 0.28$ of variance in actual AI tool usage. From a practical significance perspective, the buffering effect of organisational support is most pronounced under techno-uncertainty (Figure 3d), indicating that support interventions are likely to yield the greatest behavioural benefit in high-change AI environments

Organizational support is relevant as the moderation analysis has shown. The negative interaction effects in all the four cases indicate that when the employees are assisted by their organizations in terms of training, clear directions, or leadership support, the negative effect of technostress is lessened. As an example, respondents who feel overburdened or insecure by the use of AI tools are more willing to continue using the tools when they feel supported. Uncertainty was the most significant type of stress when it comes to moderation, i.e. support is particularly crucial when employees feel uncertain or confused about the AI updates and system changes. To aid interpretation, we plotted the interaction at ±1 SD of organisational support. Figures 3a–3d show that the slope between technostress and actual usage is steeper under low organisational support and flatter under high organisational support, indicating a buffering effect.

These findings were also corroborated by the findings of the Structural Equation Modeling (SEM) model where the model fit indices were within the acceptable limits (e.g., RMSEA = 0.022, CFI = 1.000, GFI = 0.996) which demonstrated that the proposed model fits the observed data very well. On the whole, the results show that technostress can decrease the use of the AI tool in HR, but the impact can be mitigated when the behavioural intention is high and when the organizational support is provided. This implies that businesses have to proactively engage effective mechanisms to assist HR personnel to deal with AI-related stress and to improve the effectiveness of AI adoption in recruiting activities.

6. Discussion

This study proposed (Figure 1) that technostress creators influence AI-based recruitment tool usage through both a motivational pathway (via behavioural intention) and a contextual pathway (via organizational support as a buffer). Consistent with the conceptual model, the findings show that technostress experienced by HR professionals—particularly overload, complexity, insecurity, and uncertainty—reduces willingness to engage with AI tools and constrains sustained use. The results indicate that higher technostress is associated with weaker behavioural intention, suggesting that even when AI tools are seen as useful, stressors linked to learning burden, pace of work, automation concerns, and system changes can undermine motivational readiness to adopt AI in recruitment tasks.

Behavioural intention remains an important predictor of continued AI use, indicating that motivational readiness can partially sustain usage even under stressful conditions. This supports the model's positioning of intention as a key mechanism connecting workplace experiences to post-adoption behaviour. Mediation results show that behavioural intention partially transmits the effects of all four technostress creators to actual usage, implying that technostress influences usage both indirectly (by weakening intention) and directly (through strain-based constraints). The moderation analysis demonstrates that organizational support reduces the adverse influence of technostress on actual usage. Practically, when organizations provide training, clear guidance, and accessible technical support, the technostress–usage relationship becomes less severe. This buffering pattern is visually evident in the interaction plots (Figures 3a–3d), where slopes are steeper under low support and flatter under high support. Taken together, the discussion returns to the proposed model by demonstrating that AI adoption in HR is shaped not only by intention but also by stress-based resistance, and that supportive organizational conditions meaningfully change whether technostress translates into reduced use. This model-level interpretation explains why AI implementation may succeed in some organizations but stall in others experiencing similar technologies but lower support capacity.

These patterns converge with Technostress Theory by reinforcing that technology-related demands (e.g., overload, complexity, insecurity, and uncertainty) can trigger strain-based resistance and reduce engagement with digital tools. At the same time, the findings extend intention-based adoption logic (UTAUT) in digital HR contexts by showing that behavioural intention alone may be insufficient when stressors are high, helping explain the intention–usage gap in AI-enabled recruitment. Thus, the study advances an integrative perspective in which adoption is shaped jointly by rational appraisal (intention formation) and stress-based constraints, with organisational support acting as a key boundary condition that weakens the negative stress–usage link

7. Suggestions

According to the results, there are a number of useful recommendations that can be offered to organizations to minimize technostress and promote the use of AI in the recruitment process. To start with, organizations are supposed to offer clear and consistent training opportunities to enhance the digital competency of HR specialists. This can minimize the complexity and confusion over AI tools. Second, HR employees should be engaged in the process of implementing AI systems. When employees know why a new system is being employed and how this new system will benefit them, they tend to embrace it and make it very effective.

Third, organizations are supposed to develop an open communication culture where employees can voice their concerns regarding technology, particularly the aspects of job security and work roles change. Managers must be able to articulate that AI is not supposed to do human jobs instead. Fourth, they can provide help desks or tech support teams that will help mitigate uncertainty and build confidence with AI tools. All the HR staff should have easy access to these services.

Given that the buffering effect of organizational support was strongest for techno-uncertainty (interaction B = -0.0806), organisations should prioritise structured change-management practices for AI updates—advance communication of system changes, short refresh trainings, and clear usage policies—to reduce uncertainty-driven disengagement.

Because significant negative interactions were also observed for techno-complexity (interaction B = -0.0667) and techno-overload (interaction B = -0.0688), organisations should combine role-based training and workflow redesign (e.g., reducing parallel manual steps, allocating dedicated time for tool learning, and peer mentoring) to prevent perceived burden from translating into reduced usage

8. Limitations of the Study

This research provides valuable information regarding the impact of technostress on the application of AI in the recruitment process, yet there are certain limitations. One, the information was gathered by surveying only HR professionals in IT firms in a single region, thus making the findings not applicable in other industries or regions. The opinions and experiences of people who work in non-IT industries or in other regions might be different. Because the sample is drawn from Indian IT firms, the findings may reflect context-specific conditions such as rapid digitalisation, relatively high exposure to AI tools, and organisational norms around technology-driven performance. In other national or sectoral contexts, cultural values (e.g., uncertainty avoidance), infrastructural readiness (availability of reliable HR-tech ecosystems and support resources), and institutional factors (labour regulation, data governance, and automation discourse) may shift the strength of technostress effects or the buffering role of organisational support. Future work should test the model across countries and sectors to examine whether these contextual conditions moderate the observed relationships. Future work can explicitly compare regions (e.g., Europe, East Asia, North America) to test whether differences in institutional governance, AI maturity, and labour-market narratives shift the strength of technostress pathways and support effects.

As participant recruitment used snowball sampling distributed through professional networks, it was not possible to determine a precise response rate or a complete sampling frame. Consequently, standard non-response bias diagnostics (e.g., wave analysis using early vs. late respondents) and comparisons against population-level norms could not be implemented with full rigor. This constraint should be considered when interpreting the generalizability of the findings, and future studies employing probabilistic sampling frames are encouraged to replicate the model and formally test non-response effects.

Second, self-report questionnaires were utilized in the study. Although a certain attempt was provided to obtain the truthful answers, there is always a possibility that not all responses were completely unbiased or misinterpreted, and this aspect can influence the validity of the findings.

Third, only four technostress factors were studied, that is, complexity, overload, insecurity, and uncertainty. There were other significant reasons, which were not mentioned, including resistance to change or mistrust of AI.

Lastly, this study had a cross-sectional design that is, it involved examining only a single period of time. Therefore, it is not able to indicate how things could be different in the future. A longitudinal study would have given more in-depth information on the way the perception and usage changes with the experience. Finally, the research employed the UTAUT-based model and did not compare it with other behavioural models, which could have offered alternative insights.

9. Future scope for the study

The research presents a number of opportunities in future research. Among the aspects that should be addressed is to expand the study to other industries. In the future, the manufacturing, healthcare, education, and other industries can be included to compare the effects of technostress on AI adoption in the sectors. This would give a better picture of the workplace context in the acceptance of technology.

The other direction is to investigate other factors that could affect the AI adoption. As an example, one can examine such variables as organizational culture, leadership support, digital literacy, and the fear of job replacement to observe their effects in combination with technostress. In addition, more complicated models are available to future researchers by employing various behavioral theories to compare the results, e.g. Technology Readiness Index or the Innovation Diffusion Theory.

Additionally, it would be beneficial to use a longitudinal study to monitor the changes in employee attitudes over time as they become more acquainted with AI tools. This would help in tracking the long term consequences of technostress and organizational support. The qualitative tools, including interviews or focus groups, can also be used to obtain more detailed data on the personal experience of AI in the workplace.

Lastly, the stress management practices, training, or digital wellness policies may be created and tried to diminish the technostress and to increase the AI readiness of the employees. The practical contributions can assist the HR teams and managers to apply AI tools in real world contexts more efficiently.

9.1 Theoretical Contributions and Advancement

This study contributes to technostress theory by extending technostress creators (overload, complexity, insecurity, and uncertainty) to the specific context of AI-enabled HR recruitment work, where rapid system updates and automation concerns intensify strain and shape post-adoption behaviour. It also contributes to AI–HR adoption research by demonstrating a process mechanism in which behavioural intention partially mediates the relationship between technostress and actual usage, thereby explaining why adoption may not translate into sustained use under stress. Finally, the findings highlight organizational support as a boundary condition that buffers the technostress–usage relationship, indicating that adoption outcomes depend not only on individual readiness but also on organizational enabling conditions.

9.2 Managerial Implications

The findings of this research provide significant implications to managers and HR professionals of the IT industry. It shows that different types of technostress such as overload, complexity, insecurity, and uncertainty can negatively affect the readiness of employees to accept and use AI tools. Nevertheless, technostress can be mitigated by the existence of high organizational support that will make employees more confident and motivated to use AI-based systems.

Managers need to realize that mere introduction of AI is not sufficient. They must make sure that employees are prepared to utilize it in mind and heart. It can be implemented through adequate training, eliminating unneeded workload, and effectively clarifying the motive and use of AI implementation. Employees will be more open to using AI tools when they know how they will simplify their work and not jeopardize their employment.

The organizations must also aim at creating a healthy working environment. Technostress may be lessened by regular feedback and communication, counseling, and technology onboarding programs. Employee involvement in the choice and implementation of new AI systems should also be promoted by managers so that employees feel more involved and less anxious.

Lastly, internal surveys will also allow organizations to quantify the amount of technostress and behavioral intentions at regular intervals to take early measures to avoid the occurrence of resistance to digital changes. Such proactive steps may result in the ease of AI implementation, enhanced employee performance, and success in the long-term digital transformation initiatives.

Table 11. Technostress-to-Intervention Framework for AI-enabled Recruitment

Technostress type	Underlying mechanism in AI-enabled recruitment	Recommended organisational interventions	Expected behavioural outcome
Techno-overload	AI tools increase task pace/volume; parallel manual + AI workflows create time pressure and fatigue	Workflow redesign (reduce duplicate steps), allocate protected time for tool use, staffing support during peak hiring cycles, micro-learning support	Reduced overload-driven avoidance; improved sustained usage
Techno-complexity	Perceived difficulty in learning/using AI tools reduces confidence and increases errors/frustration	Role-based training, guided walkthroughs, peer mentoring, helpdesk/knowledge base, "sandbox" practice environment	Higher ease/confidence; stronger intention and continued use
Techno-insecurity	Fear of replacement or evaluation by algorithms reduces trust and increases resistance	Transparent communication on role augmentation, reskilling pathways, job-security messaging, human-in-the-loop decision policy	Lower resistance; increased willingness to use AI tools
Techno-uncertainty	Frequent updates/unclear rules create ambiguity; users disengage due to unpredictability	Change-management communication (advance update alerts), refresh trainings, clear usage SOPs, update logs, dedicated support during rollouts	Reduced uncertainty-driven disengagement; stable adoption and usage

To enhance managerial applicability, Table 11 provides a structured framework linking each technostress type to its core mechanism, recommended organisational interventions, and expected behavioural outcomes in terms of behavioural intention and sustained AI tool usage.

10. Conclusion

This paper has examined the impact of various types of technostress on employee readiness to embrace AI technologies in the work place, particularly in the IT industry. It considered four primary technostress drivers; technological overload, complexity, insecurity, and uncertainty and how they affect the actual use of AI both directly and through the mediating role of behavioral intention. The negative impacts of these technostress factors were also examined with the help of moderation analysis on how such impacts can be mitigated through organizational support.

The results supported the expectation that technostress exerts a negative and significant influence on behavioral intention and actual use of AI. These negative effects are however minimized when the employees are properly supported by their organizations through training, communication and direction. Behavioral intention was also found to be significant, as in case the employees believe they are competent and willing, they are more likely to apply AI tools even in stressful conditions. While this evidence is grounded in Indian IT firms, the framework is transferable to other settings where AI is introduced into HR workflows. However, cross-national and cross-sector validation is needed because cultural and institutional conditions may alter how technostress translates into intention and use, and how organisational support is enacted.

The paper brings out the importance of both technology and people in the implementation of AI. Although AI systems have a variety of advantages, their effectiveness is determined by the level of comfort and support that the users experience. In general, the study emphasises that a balanced policy that incorporates digital innovation and the well-being of employees is necessary to achieve successful and sustainable adoption of AI.

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