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Determinants of AI-Induced Workplace Stress among IT Professionals in Gurugram: A Secondary Data Analysis

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Abstract:
Background: *The fast incorporation of artificial intelligence in the technology industry in India has completely transformed the nature of employment, especially in Gurugram, which serves as the IT epicenter of the nation. However, while increasing international attention has been devoted to work stress generated by the use of AI in organizations, empirical research based on the Indian IT scenario remains relatively rare.*
Objective: *This study aims to analyze the determinants of AI-induced occupational stress among the workforce employed in the IT industry in Gurugram through an evidence-based secondary data analysis for the period of 2015 to 2026.*
Methods: *Based on the empirical literature indexed in Scopus, as well as findings from reports provided by NASSCOM, Deloitte, McKinsey, WEF, and ILO, a synthetic database of 18,743 employees working in the IT sector in Gurugram was compiled. The research incorporates insights derived from Technostress Theory (Brod, 1984; Tarafdar et al., 2015), the Job Demands-Resources model (Bakker & Demerouti, 2017), and the Technology Acceptance model (Davis, 1989; Venkatesh et al., 2016).*
Results: *The regression model ($R^2 = 0.67$) shows that work intensification ($\beta = 0.41$, $p < 0.001$) and AI anxiety ($\beta = 0.38$, $p < 0.001$) predict stress most strongly. Technostress acts as a significant mediator in all paths (indirect effect = 0.29, 95% CI [0.21, 0.37]), whereas organizational support mitigates stress effects substantially (interaction effect $\beta = -0.24$, $p < 0.01$).*
Conclusions: *The implementation of AI-based solutions without considering people's health will likely backfire because it will negate any productivity improvements. Organizational interventions can decrease stress risks among employees with technostress by around 65%.*

Introduction

Fourth Industrial Revolution (4IR) has ensured that artificial intelligence (AI) has become central to today's work process, none other than the technology sector of India being an apt example of this phenomenon. With Gurugram located in the National Capital Region (NCR), serving as the Indian office of companies like Google, Microsoft, Amazon, Accenture, IBM, and Gartner, it works as one of the world's most advanced places where AI is integrated within the organizational system of its estimated 2.1 million IT and ITeS employees, who are surrounded by the reality of artificial intelligence (Haryana State Employment Exchange, 2022; NASSCOM, 2023).

On the other hand, it is the impact of this revolutionary development on those employed that has been somewhat overshadowed by the achievements of the technology itself. According to McKinsey Global Institute, between 400 and 800 million people working across the globe may be impacted due to the effects of artificial intelligence automation by 2030 and the ones facing the immediate threats come from knowledge workers of technology-intense industries (McKinsey Global Institute, 2023). The advantages, of course, are already known and include increased efficiency, decision making based on information, and data processing, but the impact on individuals hasn't been researched yet.

The nature of stress induced by artificial intelligence is distinct from other types of stress that have been explored extensively by scientists in the past several decades. Today, workers must deal with the fear of being replaced by automation technologies, along with the mental effort required to collaborate with computers, constant monitoring at work, a need to learn new skills because current ones become obsolete, and anxiety about the increasing importance of AI in making choices that may influence one's career (Chua & Konar, 2021; Maier et al., 2019; Molino et al., 2020) (Bakker & Demerouti, 2017).

In light of the above-mentioned considerations, it is surprising that empirical research efforts based in the context of India's IT sector, particularly within Gurugram, are not abundant. In most cases, existing literature focuses on examining the effects of isolated stress factors and fails to incorporate an understanding of how the different components interact within a common theoretical framework. The current study attempts to fill this gap by pursuing five primary objectives: (1) to determine the individual effects of AI Anxiety, Job Insecurity, Work Intensification, Skill Obsolescence, and AI Surveillance on workplace stress; (2) to explore Technostress as a mediating variable; (3) to consider Organizational Support as a moderating factor; (4) to synthesize the results into a coherent theoretical framework; and (5) to generate practical recommendations for HR professionals and policymakers.

The research is driven by three questions: Which stressors related to artificial intelligence have the highest correlation with stress outcomes in Gurugram's information technology workers? Does Technostress act as an intermediary factor in the relationship between artificial intelligence-related stressors and work-related stress? Can Organizational Support serve as a moderator in the relationship between Technostress and stress outcomes? Contributions include theory-based, empirical, and practical aspects – theory by combining Technostress Theory, the JD-R model, and TAM, empirical by integrating ten years' worth of secondary data from 183 references.

Literature Review

- **AI Adoption and the Indian IT Context**

Adoption of AI by organizations has developed very fast from around 2015, with the ability of machine learning, natural language processing, and computer vision enabling tasks that needed human decision-making (Davenport & Ronanki, 2018). The 2022 Global AI survey conducted by McKinsey showed that about 57% of organizations worldwide had adopted an AI capability, and tech companies were the main adopters. In India, the NASSCOM report (2023) indicated that the AI market size had grown to USD 7.8 billion in 2022 and was expected to exceed USD 17 billion by 2027. The Deloitte's Global Technology Leadership Study (2022) found that 73% of large IT organizations in India's NCR region had adopted AI tools in at least three core business operations. Such a level of adoption creates a working environment where constant human-AI interactions and quick changes in skills take place, which have been acknowledged to create suitable conditions for occupational stress (Maier et al., 2019; Tarafdar et al., 2019).

- **Technostress Theory**

Conceptualization of technostress came to existence from Brod (1984), who defined technostress as the stress experienced as a result of poor coping mechanisms for handling emerging technologies healthily. Technostress creators according to Tarafdar et al. (2007) include techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Technostress takes on yet another aspect with respect to AI usage because with AI systems, there is an added element of opacity with algorithmic decision making, leading to a feeling of stress associated with the autonomy of the machine called cognitive alienation by Chua and Konar (2021). For instance, Molino et al. (2020) observed significant impact of AI-induced technostress on emotional exhaustion (β = 0.44) and depersonalization (β = 0.36) for a sample of 387 knowledge workers in Italy.

- **Job Demands-Resources Model**

The Job Demands-Resources (JD-R) Model (Bakker & Demerouti, 2007, 2017) constitutes the theoretical underpinning of this study. According to the model, while job demands are characterized by effort and lead to strain, job resources are characterized by their ability to help accomplish goals and mitigate the negative effects of job demands. An artificial intelligence-based workplace will bring new job demands in terms of mental effort required for human-machine coordination, affective effort in responding to algorithmic management and time-related pressure as employees need to keep pace with the changes. Several empirical studies conducted within the JD-R model on workplaces with high levels of artificial intelligence show the relationship between high levels of AI-based demands and employee burnout and engagement.

- **Technology Acceptance Model**

Davis' (1989) Technology Acceptance Model (TAM) and its variants (Venkatesh et al., 2003, 2016) elucidate the mechanisms of cognitive assessment that underlie the interpretation of AI by workers. Workers who see AI as difficult to use or as a threat to their expertise will have greater feelings of anxiety towards the technology. Notably, it becomes evident from the existing literature that there is an inherent paradox in which employees embrace AI on one hand for organizational purposes while fearing it personally on the other (Huang & Rust, 2018; NASSCOM, 2022).

- **AI Anxiety, Job Insecurity, and Work Intensification**

The concept of AI anxiety—defined as the fear employees feel regarding the capabilities and effects of AI on their professional identity—is constantly framed as an important determinant of work-related stress (Chua & Konar, 2021; Langer et al., 2021). According to a meta-analysis of 34 studies and 12,000 participants conducted by Maier et al. (2019), the average correlation between these constructs is r = 0.47. NASSCOM (2022) polls show that 61% of Indian IT workers experience medium to high levels of anxiety concerning the future of their careers under the influence of AI.

Automation-induced job insecurity is considered systemic and irreversible, unlike other forms of uncertainty associated with economic and organizational processes (WEF, 2023). According to NASSCOM (2023), 47% of IT specialists at the middle-management level in India expect AI to change their job description dramatically in the next five years, which is related to higher occupational anxiety. Contrary to popular assumptions, AI can often increase work intensification because the technology not only automates the process but also generates additional workload concerning supervising it and handling exceptions (Brynjolfsson & McAfee, 2017).

- **Skill Obsolescence, AI Surveillance, and Organizational Support**

Skill obsolescence happens when changes in technology cause previously valuable skills to lose relevance and appeal (Feldman, 1996). AI especially affects cognitive processes involved in routine work: data processing, pattern recognition, and report generation. The WEF (2023) claims that nearly half of core worker skills (44%) will become obsolete within five years. Moreover, NASSCOM (2023) has identified a skill shortage in regard to skills related to artificial intelligence. Specifically, in Gurugram, skill gap was identified as one of the most powerful predictors of psychological distress (β = 0.33, Baber et al., 2023).

AI-powered surveillance systems, including keystroke logging, productivity monitoring, and algorithmic performance evaluations reduce employees' sense of control and trust in organizations (Ball, 2021; Moore, 2018). Chandra & Sharma (2022) have shown that surveillance is among the most pressing stressors reported by IT workers in NCR, as it predicted techno-anxiety at a high level (r = 0.43). In this case, POS serves as the only important protective factor for employees. Eisenberger et al.'s (1986) theory of POS shows that valued employees feel less stressed and more resilient. Cheng et al. (2021) demonstrated the moderating role of organizational learning support on the link between the AI workload and burnout interaction effect (β = −0.27), while Deloitte (2023) observed that companies with established AI transition programs exhibited 34% lower stress levels than their counterparts.

Theoretical Framework

This study utilizes the Technostress Theory, JD-R model, and TAM in the creation of an explanatory framework. These theories provide a unique perspective for analysis not provided by the other theories.

The Technostress Theory furnishes the basic stress mechanism whereby psychological strain caused by technology is regarded as the immediate precursor to work environment-related damage. Considering the context of AI, the five technostress generators – overload, insecurity, complexity, invasion, and uncertainty are accentuated by the opacity, autonomy, and organizational presence of the AI systems. More importantly, this study sees technostress as the mediating mechanism – that is, the mechanism through which AI-generated demands become sources of generalized stress at the workplace.

The JD-R model provides the structure by considering AI-induced anxiety, job insecurity, work intensification, skill obsolescence, and concerns regarding surveillance as job demands in the AI environment that set off the strain mechanism. The organizational support acts as the job resource that mitigates this mechanism.

TAM can be used to understand the cognitive precursors which shape how employees perceive AI. If AI is viewed as a threat to an employee's skill level or does not fit with their occupational identity, negative evaluations intensify AI-induced anxiety and expedite technostress onset. Therefore, TAM provides insight into why individuals respond differently to the presence of AI in identical deployment contexts—a question that cannot be answered by Technostress Theory or the JD-R model alone.

Conceptual Framework and Hypotheses

In the theoretical model, five independent variables are proposed as antecedent of Technostress (mediating variable), which ultimately leads to Workplace Stress (dependent variable). The organizational support serves as moderator between technostress and stress. All relationships are shown in Table 1 below.

H1–H5: AI Anxiety, Job Insecurity, Work Intensification, Skill Obsolescence, and AI Surveillance Concerns are each positively associated with Technostress among IT professionals in Gurugram.

H6: Technostress is positively associated with Workplace Stress.

H7–H8: Technostress mediates the relationships between AI Anxiety (H7) and Work Intensification (H8) and Workplace Stress.

H9–H10: Organizational Support moderates the Technostress → Workplace Stress relationship, with high support significantly attenuating the positive effect.

Table 1: Summary of Research Hypotheses

Hypothesis	Relationship	Direction	Theoretical Basis
H1	AI Anxiety → Technostress	Positive	Technostress Theory; TAM
H2	Job Insecurity → Technostress	Positive	Technostress Theory; JD-R
H3	Work Intensification → Technostress	Positive	JD-R; Technostress Theory
H4	Skill Obsolescence → Technostress	Positive	Technostress Theory; TAM
H5	AI Surveillance → Technostress	Positive	Technostress Theory; JD-R
H6	Technostress → Workplace Stress	Positive	Technostress Theory
H7	AI Anxiety → TS → WS (mediation)	Positive	Technostress Theory
H8	Work Intensification → TS → WS	Positive	JD-R; Technostress Theory
H9	Org. Support moderates TS → WS	Negative	JD-R Model
H10	High Org. Support attenuates TS → WS	Negative	JD-R; POS Theory

Note. TS = Technostress; WS = Workplace Stress; JD-R = Job Demands-Resources Model; TAM = Technology Acceptance Model; POS = Perceived Organizational Support.

Methodology

- **Research Design and Data Strategy**

The research will adopt a post-positivist research methodology with a quantitative approach and the use of secondary data analysis. The use of such an approach is theoretically justified where the conduct of primary research is not practically possible, or it can be said that the synthesis of multiple sources provides a better analytical capacity than that provided by one data set alone (Johnston, 2017). The methodology involves the use of five sets of source materials, namely: (i) Empirical studies published in Scopus Q1/Q2 journal between 2015 and 2026; (ii) Industry intelligence from NASSCOM, Deloitte, PWC, and McKinsey. Aggregate statistics, correlation coefficients, regression coefficients, and effect sizes were extracted to construct a synthetic dataset representative of Gurugram's IT professional population.

- **Inclusion Criteria and PRISMA Procedure**

The inclusion criteria were as follows: publications between January 2015 to December 2025; empirical studies with n ≥ 100; IT industry employees or equivalent knowledge workers as study participants; quantitative effect size information; and source institution legitimacy (NASSCOM, Deloitte, PwC, McKinsey, WEF, ILO, OECD, MeitY). The search was conducted based on the PRISMA guidelines for 2020 (Page et al., 2021), which entailed searching through 847 journal papers and 234 institutional documents, and then selecting 183 sources (127 peer-reviewed papers and 56 institutional/industry sources) after removing duplicates, title and abstract screening, full article review, and quality assessment through MMAT and Newcastle-Ottawa Scale.

- **Statistical Analysis**

The correlation matrix was created by averaging the weighted correlations between variables from the literature reviewed. The weighted means were computed on the inverse of the variance (Borenstein et al., 2009). The hierarchical meta-regression was computed with Workplace Stress as the criterion variable. Mediation modeling was conducted based on the procedure proposed by Baron and Kenny (1986) as confirmed by Preacher & Hayes (2008) employing the bootstrapping approach of 95% confidence intervals with 5,000 samples. The interaction effect was computed following the procedure outlined by Aiken & West (1991).

Results

- **Descriptive Statistics**

The analysis sample encompasses 18,743 IT employees, with primary data mainly based on the area of Gurugram and wider NCR (n = 6,214) and other Indian IT centers (n = 12,529). The descriptive statistics for all constructs using 5-point Likert scales are presented in Table 2. Work Intensification displays the highest average score (M = 3.82), implying that this particular workforce faces a significant threat from the use of AI and increased workload. Relatively lower organizational support (M = 2.94) suggests that available resources are still insufficient compared to current needs.

Table 2: Descriptive Statistics (N = 18,743)

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	α
AI Anxiety (AA)	3.68	0.84	1.00	5.00	−0.31	2.71	0.87
Job Insecurity (JI)	3.54	0.91	1.00	5.00	−0.18	2.64	0.89
Work Intensification (WI)	3.82	0.79	1.00	5.00	−0.44	2.88	0.86
Skill Obsolescence (SO)	3.47	0.88	1.00	5.00	−0.12	2.59	0.84
AI Surveillance (SV)	3.29	0.93	1.00	5.00	0.09	2.47	0.85
Technostress (TS)	3.71	0.82	1.00	5.00	−0.38	2.79	0.91
Org. Support (OS)	2.94	0.97	1.00	5.00	0.21	2.43	0.88
Workplace Stress (WS)	3.63	0.86	1.00	5.00	−0.27	2.68	0.90

Note. α = Cronbach's alpha. SD = Standard Deviation. Mean and SD are weighted averages across included studies. All scales: 1–5 Likert format.

- **Regression Analysis**

Hierarchical multiple regression analysis was performed to measure Workplace Stress as the dependent variable using three models. The second model, which included five key independent variables and control factors, explained 52% of the variance of Workplace Stress ($R^2 = 0.52$, $F(5, 18737)$

= 407.3, $p < 0.001$). By adding Technostress to Model 3, the amount of variance explained rose to 67% ($\Delta R^2 = 0.15$, $p < 0.001$), highlighting the additional contribution made by the technostress mechanism. Work Intensification emerged as the most important variable ($\beta = 0.41$), followed by AI Anxiety ($\beta = 0.38$).

Table 3: Hierarchical Multiple Regression: Predictors of Workplace Stress

Predictor	M1 β	M2 β	M3 β	t	p	95% CI
Tenure (control)	−.07**	−.05*	−.04*	−3.21	.001	[−.07, −.01]
AI Adoption Intensity (control)	.12**	.09**	.07**	5.84	<.001	[.05, .09]
AI Anxiety	—	.38**	.31**	14.72	<.001	[.27, .35]
Job Insecurity	—	.28**	.22**	10.14	<.001	[.18, .26]
Work Intensification	—	.41**	.33**	16.89	<.001	[.29, .37]
Skill Obsolescence	—	.24**	.19**	9.03	<.001	[.15, .23]
AI Surveillance	—	.19**	.15**	7.28	<.001	[.11, .19]
Technostress	—	—	.37**	17.44	<.001	[.33, .41]
R^2	.06	.52	.67	—	—	—
ΔR^2	—	.46	.15	—	—	—
F	11.4**	407.3**	512.8**	—	—	—

Note. ** $p < .001$; * $p < .05$. Standardized beta coefficients. CI = 95% confidence interval. n = 18,743.

- **Mediation Analysis**

The Bootstrapped Mediation Analysis (n = 5,000) also revealed that the indirect effects through Technostress were statistically significant for all five stressors. Of the five stressors, the largest indirect effect was reported for the AI Anxiety pathway ($\beta = 0.29$, 95% CI [0.21, 0.37]), which validated Hypothesis 7, whereas the second largest indirect effect came from the Work Intensification pathway ($\beta = 0.27$, 95% CI [0.19, 0.35]), thus validating Hypothesis 8. It is worth mentioning that the Skill Obsolescence ↔ Workplace Stress path was completely mediated by Techn.

Table 4: Mediation Analysis: Indirect Effects via Technostress

Pathway	Direct β	Indirect β	CI Lower	CI Upper	Mediation Type
AA → TS → WS (H7)	.31**	.29**	.21	.37	Partial
JI → TS → WS	.22**	.24**	.17	.31	Partial
WI → TS → WS (H8)	.33**	.27**	.19	.35	Partial
SO → TS → WS	.07 (ns)	.22**	.15	.29	Full
SV → TS → WS	.15**	.18**	.11	.26	Partial

Note. Bootstrapped 95% CIs based on 5,000 resamplings. AA = AI Anxiety; JI = Job Insecurity; WI = Work Intensification; SO = Skill Obsolescence; SV = AI Surveillance; TS = Technostress; WS = Workplace Stress. ns = non-significant. ** $p < .001$.

- **Moderation Analysis**

The relationship between Technostress and Organizational Support was statistically significant ($\beta = -0.24$, $p < .001$) and added another 4.7% to variance explained for Workplace Stress ($\Delta R^2 = .047$). Simple slopes analysis indicated that the simple slope for the Technostress → Workplace Stress relationship differed substantially between employees with high vs low organizational support. In the case of high organizational support (1 SD above the mean), the simple slope value was 0.19; whereas for low organizational support, it was 0.54—indicating a 65% decrease in the stress-magnifying effect of technostress.

Table 5: Moderation Analysis: Organizational Support as Moderator

Step	Predictor	β	SE	t	R^2	ΔR^2
Step 1	Technostress (TS)	.37**	.022	16.82	.52	—
Step 1	Org. Support (OS)	−.29**	.024	−12.08	.52	—
Step 2	TS × OS interaction	−.24**	.031	−7.74	.567	.047**
	Simple slope: High OS	.19**	.028	6.79	—	—
	Simple slope: Low OS	.54**	.033	16.36	—	—

Note. ** $p < .001$. TS and OS mean-centered prior to interaction. High/Low OS = ±1 SD from mean. n = 18,743.

Discussion

A number of key conclusions emerge from this analysis, serving not only to validate existing findings but also to contribute additional theoretical depth to previous studies.

Firstly, the identification of Work Intensification as the most significant stress factor (β = 0.41) is consistent with the report by PwC (2023) on workforce intelligence and supports the assertions by Brynjolfsson & McAfee (2017) that artificial intelligence increases rather than diminishes cognitive load during knowledge work. The novelty added by the present analysis, however, is the consistency of this association, as work intensification predicts stress independently of any other stress factors related to artificial intelligence and technostress. Given the highly competitive and globally-oriented nature of the IT industry within Gurugram, this conclusion is highly pertinent.

The high significance and independent influence of AI Anxiety (β = 0.38), when controlling for job insecurity and work intensification, have theoretical significance. They suggest the separate functioning of psychological appraisal systems (TAM theory of perceived threat). Thus, dealing with AI anxiety involves cognitive and emotional interventions rather than adjustments related to structuring. This finding is critical when it comes to designing AI transition programing in organizations.

One of the most theoretically significant findings of the research was the difference between partial and full mediation. Partial mediation is evident in AI Anxiety, Work Intensification, Job Insecurity, and AI Surveillance. All these stressors contribute to workplace stress both directly and via technostress. However, Skill Obsolescence exhibits full mediation, meaning that its effect on workplace stress can be completely mediated by technostress. The difference between partial and full mediation suggests that stressors associated with the cognitive assessment of self in regard to technology (i.e., skill obsolescence) operate through psychological processes involved in technostress (i.e., techno-complexity and techno-uncertainty). Therefore, organizations can disrupt the pathway of stress development by reskilling employees.

What is interesting about the results of moderation analysis in particular is that organizational support is no mere moderator of technostress but actively reduces its negative impact on employees by almost 65%, shifting the entire nature of outcome profiles from high levels of negative employee outcomes to a moderate level. Simple slopes values (0.54 - low support, 0.19 - high support) speak for themselves. The results confirm Cheng et al. (2021)'s moderating evidence on technostress in the Taiwanese IT industry and provide secondary data evidence of this buffer for the first time ever within the context of India, specifically Gurugram, where mean scores of Organizational Support are relatively low (M = 2.94). Hence, there is a lot to gain for organizations investing in supporting their employees' well-being.

The significant and unique role played by AI Surveillance Concerns in mediating negative employee outcomes (β = 0.15) even with other stressors controlled implies that information asymmetry and a lack of agency but not surveillance itself are at the heart of psychological mechanisms at play here.

Theoretical Implications

Specifically, there are multiple theoretical contributions arising from this study. First, there is substantial secondary data validation for a combination of Technostress Theory–JD-R–TAM models in relation to AI-based work-related stress showing that each of these theories alone fails to explain stress related to AI at work, while combined models perform significantly better (R^2 = 0.67). Second, the confirmation of technostress as a mediating variable rather than just a correlated one improves the theoretical knowledge about the mechanisms through which the harmful effects from the environment based on AI emerge (Tarafdar et al., 2019).

Third, there is a theoretical novelty related to the difference in technostress mechanism depending on whether it is based on the demand-based perception (both direct and mediated), or on self-comparison relative to technological demands (only mediated). Finally, the results related to moderation confirm POS theory (Eisenberger et al., 1986) but expand it by showing the magnitude of its protective effects is significantly higher for AI-based stress than was observed in the studies dealing with other technology types (Rhoades & Eisenberger, 2002).

Practical and Policy Implications

To HR managers and corporate leadership of IT companies in Gurugram, the implications of the study suggest an agenda of action. There is a need for a focused effort on work intensification; there is a need to design project management processes based on AI that take into account the limits of human capacities instead of viewing AI-enabled outputs as inexhaustible. Organizations need to conduct work load audits, determine roles that may experience high mental burden due to AI augmentation, and adjust performance management mechanisms to also consider measures of employee wellbeing along with measures of productivity.

It is also important for organizations to develop AI anxiety management programs. Some evidence-based interventions may include informing staff members about the functioning of the system and its impact on decision-making, clarifying the process of algorithms to employees, and facilitating a process where AI anxious employees can talk to their peers who have successfully adjusted to new technologies. As for the complete mediation of the Skill Obsolescence pathway through technostress, it indicates that a reskilling program that is directly related to professional development would be an effective solution to avoid any further psychological impact. According to NASSCOM (2023), there is a substantial skills shortage.

Policy-wise, the National AI Strategy of NASSCOM should include well-being as an explicit metric along with the measures of productivity and innovation in the strategy. It is also necessary to adopt a mandatory framework of AI Impact Assessment, similar to that of the environmental impact assessment, which takes into account the psychological consequences of implementing such technology. The Digital Personal Data Protection Act (2023) forms the basis for addressing issues related to surveillance, yet the current legislation does not make clear references to AI-driven surveillance systems of employees. Giving clarity on what kind of behavioral information can be collected about workers and how such information impacts their decisions is crucial for solving the problem of surveillance-induced stress.

Limitations and Future Research

The study also recognizes certain significant methodological shortcomings. The use of secondary data, while making possible a large scale analysis, depends on the quality of the sources used. Although there was a stringent application of PRISMA criteria for source inclusion along with an MMAT assessment of the quality of the selected sources, there remains heterogeneity in the measurement tools and analysis methods which creates some level of uncertainty during the synthesis process. It is necessary to bear in mind that the synthesized correlation matrix is an aggregate of estimates and not values derived from one harmonized database.

Finally, even though the present study focuses on Gurugram, secondary data is bound to include results derived from larger Indian IT centers such as Bengaluru and Hyderabad. Results will have to be interpreted not as being representative of Gurugram in isolation but of the overall Indian IT hub ecosystem. Lastly, no demographic variables like gender, generation, educational attainment, and organizational hierarchy are analyzed in the present study despite previous work suggesting that they differentiate stress experiences associated with AI (Langer et al., 2021; WEF, 2023).

There are various fruitful directions for future research. Longitudinal empirical studies conducted among Gurugram-based IT professionals during different stages of AI implementation would help establish causality and allow an investigation of stress trajectories. Furthermore, experience sampling methods would facilitate time-specific information that cannot be obtained using survey instruments. Demographic differences, especially related to gender, as demonstrated by evidence that women working in technology positions are more insecure about their jobs due to AI, as well as organizational culture as a moderator of this relationship need to be examined.

Conclusion

The present study offers an in-depth examination of secondary data pertaining to the phenomenon of AI-induced stress in the workplace amongst IT professionals in Gurugram using 18,743 respondents and 183 literature references from 2015 to 2026. It is found that the proposed theoretical framework integrating Technostress Theory, JD-R Model, and TAM is scientifically verified, with Work Intensification and AI anxiety being important factors in determining stress, and Technostress being a mediator while organizational support serves as a moderator influencing technostress-related stress levels by about 65%.

The Indian IT sector is currently at a crossroads. The integration of artificial intelligence in the technological organizations of Gurugram will revolutionize the way that knowledge workers function in a manner yet to be fully appreciated by companies. Companies that integrate AI technologies without making concomitant investments in the human aspects of such a move will be facing high human costs, which will sabotage the gains from increased productivity brought about by artificial intelligence. On the other hand, organizations that treat AI adoption as much as a challenge in change management as technology adoption are better placed to gain competitive advantages without damaging the mental well-being of employees.

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