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The Faculty Paradox: Assessing Digital Fatigue and Institutional Readiness for AI Integration in Higher Education.

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Abstract

The rapid diffusion of AI tools into Indian higher education institutions (HEIs) has been faster than the faculty members' psychological and institutional capability to cope with them. This paper addresses the 'faculty paradox', which is the challenge of teaching faculty facing increasing digital fatigue and technostress as well as institutional pressure to adopt AI and studies the relationship between these factors and faculty AI adoption intention and behaviour. A cross-sectional, positivist survey design was adopted. A structured questionnaire based on adapted items from the Zoom Exhaustion & Fatigue Scale, Techno-Stress Construct for Higher Education and Technology-Organization-Environment (TOE) institutional readiness scale was filled out to faculty in central, state, private and deemed-to-be universities in India. The analysis include confirmatory factor analysis (CFA) of the measurement model and structural path estimate. Digital fatigue and technostress had a major negative impact on institutional readiness and AI adoption intentions, while institutional readiness positively predicted adoption intention, which in turn led to actual AI integration behaviour. Institutional readiness partially mediated the fatigue-adoption relationship and perceived organizational support calmed down the negative impact of digital fatigue on readiness. This paper is the first to incorporate digital fatigue and technostress theory into the TOE framework in one SEM model of Indian faculty AI adoption, giving evidence-based levers, workload redesign, tiered digital training and organizational support and policy interventions to HEI leaders and policy makers to implement India's National Education Policy 2020 and National AI strategy

Keywords: *digital fatigue, technostress, institutional readiness, artificial intelligence adoption, higher education*

INTRODUCTION

Artificial intelligence has moved from the margins to the centre of higher education policy discourse in India within a remarkably short span. Following the release of large language models capable of producing coherent academic text, higher education systems worldwide have had to respond to a pace of technological change that governance structures have struggled to match [1]. India presents a distinctive case: it operates one of the world's largest higher education systems by enrolment, its regulatory architecture is fragmented across multiple bodies, and national policy has followed what has been described as a skilling-first trajectory, accelerated by initiatives such as the AICTE-OpenAI partnership, without corresponding classroom-level usage guidance [2]. At the institutional level, survey evidence suggests that adoption is real but uneven. The FICCI-EY-Parthenon AI Adoption based on responses from thirty Indian HEIs, found that 57% already had institutional AI policies in place while another 40% were still developing one, and flagged fairness, transparency, algorithmic bias, and data protection as unresolved governance concerns [3]. At the level of the individual faculty member, however, the picture is considerably less optimistic: the Digital Education Council's 2025 Global AI Faculty Survey found that only 17% of faculty considered themselves 'advanced' or 'expert' users of AI tools, even as 61% reported having used AI in teaching in some form [4]. This gap between institutional ambition and individual readiness is not new; it echoes the technostress literature that emerged from the pandemic-era shift to emergency remote teaching, when faculty across the world reported elevated exhaustion, anxiety, and role conflict attributable to sudden, under-supported digitalisation [5]. What is new is the compounding effect: faculty who have not fully recovered from pandemic-era 'digital fatigue' are now being asked to adopt a second wave of technology, generative AI often with even less structured institutional support. We term this compounding tension the 'faculty paradox': institutions are accelerating AI mandates precisely at a moment when the psychological and infrastructural readiness of the faculty who must implement them is empirically in question [5]. This study addresses three questions. First, to what extent does faculty digital fatigue and technostress erode institutional readiness for AI integration, as perceived by faculty themselves? Second, do these same constructs directly suppress faculty intention to adopt AI tools in teaching, research, and administration, independent of their effect on institutional readiness? Third, does institutional readiness translate adoption intention into actual AI-integration behaviour, and can organizational support buffer the negative effects of fatigue? Investigating these questions in the Indian context is particularly important given the scale of the system, the diversity of institution types and the specific policy backdrop of the National Education Policy 2020, which explicitly calls for technology-enabled teaching-learning transformation [6].

2.1. Digital Fatigue and Technostress in Higher Education

Digital fatigue is the subjective experience of cognitive, affective and behavioural exhaustion caused by a long-term and extensive use of digital devices, platforms and communication tools. The Zoom Exhaustion & Fatigue (ZEF) Scale was developed and validated with over 3,000 respondents and found five dimensions of videoconferencing fatigue to be general, social, emotional, visual and motivational [7]. In recent years, the concept of digital fatigue has been generalized beyond videoconferencing to e-learning platforms, learning management systems, and always-on communication in institutions but there are no unequivocal measures of the overall prevalence of this general digital fatigue [8]. Technostress is a closely related but conceptually different concept defined as the stress caused by the person's not being able to cope with the demands of technology in an organisation. In higher education in particular, technostress is associated with less teaching motivation, emotional exhaustion, and the intention to leave the profession [9]. A recent psychometric validation of 300 business school teachers in a developing country conducted by EFA and CFA in AMOS revealed a strong four-factor technostress structure, techno-overload, techno-invasion, techno-complexity, techno-with all factor loadings above 0.70 and composite reliabilities above 0.90. Portuguese research has also shown that burnout and technostress are more common in higher education teachers in remote teaching during the pandemic, with technological support of institutions less than adequate [10]. In the recent past, the 'bright side' of techno-eustress is also being explored and shown that technology demands can be seen as a challenge rather than a threat if the faculty is well-supported. This is why institutional support is considered not just as a control factor but as a moderator that provides a gauge of whether digital demands can be fatigue-reducing or challenge-reducing [11].

2.2. Institutional Readiness and the TOE Framework

Institutional readiness for AI integration is commonly understood from the TOE perspective in many organizations as a function of the technological context, the level of compatibility, complexity, and infrastructure, the organizational context leadership support, resources, and staff training, and the environmental context the regulatory pressure, competitive pressure, and sectoral norms of the technology [12]. Recent systematic reviews of the organizational AI readiness literature have synthesized the existing TOE taxonomy into 12 core readiness concepts and argued that legitimacy, ethics, and governance within the institutional theory concept would be embedded into the readiness, instead of being a technological-capability issue see review in the AI-readiness literature synthesis [13]. Recent research in higher education AI adoption is also using TOE to understand the institutional readiness in terms of equitable access, policy clarity, and the development of professional development. However, institutional policy frameworks are not yet in agreement with the training for AI implementation. As noted in a recent policy analysis, the AI policy guidelines for faculty in universities are very diverse, and many faculty in some institutions are able to adapt to AI as they are not aligned with each other and the implementation of AI on campus [14]. This is consistent with the Indian case: while most surveyed HEIs report having or developing an institutional AI policy, actual classroom-level guidance remains sparse, and governance responses vary greatly among sub-sectors. Health-professional education agencies such as the ICMR, for instance, have provided solid AI ethics guidance, but other regulatory bodies for other systems of medicine.

2.3. AI Adoption in Indian Higher Education

India's National Education Policy 2020 explicitly promotes technology-enabled pedagogy and places digital transformation at the core of achieving the goal of increasing the Gross Enrolment Ratio to 50% by 2035 [15]. Government investment has followed. The IndiaAI Mission allocation increased by more than tenfold in union budgets between 2024-25 and 2025-26, and AICTE has selected 2025 as the 'Year of Artificial Intelligence', launching many national initiatives, including a partnership with OpenAI [16]. The majority of Indian HEIs are using AI-enabled tools in teaching, assessment or administration. But the situation in faculty practice is less optimistic in terms of how AI integration is implemented. Faculty unpreparedness, inadequate infrastructure, low digital literacy and security concerns are reasons for a lack of progress at the level of well-resourced urban institutions and those in rural or semi-urban regions [17]. International comparative research indicates this is true: global surveys of AI landscape maturity in higher education reveal a growing "digital AI divide" between well-resourced and under-resourced institutions with faculty and staff training as the single most critical institutional priority. The evidence for this institutional ambition outpacing faculty readiness is the basis for the hypothesised model in this study.

2.4. Research Gap

Three major gaps are what motivated this study. First, the digital fatigue literature are currently developing relatively in parallel and few studies have integrated them into a single structural model in which faculty psychological strain is seen as an immediate and direct precursor of institutional readiness rather than an unrelated background condition. Second, empirical SEM-based data on faculty AI adoption is mostly in Pakistan, China, Indonesia, and Western countries - and quantitative data of the same kind from India like central, state, private and deemed universities has been more limited. Third, in the techno-eustress literature, the role of perceived organizational support in moderating the fatigue-readiness relation has been discussed in a theoretical sense but not explicitly discussed with a formal interaction term in a CB-SEM framework in terms of AI adoption specifically. This study fills all three gaps.

3. Theoretical Framework and Hypotheses

The conceptual model combines the Job Demands-Resources (JD-R) logic of technostress research with the TOE framework of AI-readiness research. Digital fatigue (DF) and technostress (TS) are presented as psychological 'demand' constructs. Institutional readiness (IR) is depicted as an organizational-capability construct; perceived organizational support (POS) as a 'resource' construct that moderates the demand-readiness relationship; and AI adoption intention (AAI) and actual AI integration behaviour (AII) are the outcome chain, consistent with the intention-behaviour relation found in technology acceptance research.

3.1. Hypotheses

Hypothesis	Statement
H1	Digital fatigue is negatively associated with institutional readiness.
H2	Digital fatigue is negatively associated with AI adoption intention.
H3	Technostress is negatively associated with institutional readiness
H4	Technostress is negatively associated with AI adoption intention
H5	Institutional readiness is positively associated with AI adoption intention
H6	AI adoption intention is positively associated with actual AI integration behaviour
H7	Institutional readiness mediates the relationship between digital fatigue technostress and AI adoption intention.
H8	Perceived organizational support moderates the DF → IR relationship, such that the negative effect is weaker when POS is high.

4. Methodology

4.1. Research Design and Philosophy

The study follows a positivist, quantitative, cross-sectional survey design, as in previous technostress-validation research in higher education. Data were to be collected through a structured, self-administered questionnaire distributed electronically to faculty across Indian HEIs.

4.2. Population, Sampling, and Sample

The target population is full-time teaching faculty (Assistant Professor, Associate Professor, and Professor grades) at recognized Indian HEIs such as central universities, state universities, private universities, and deemed to be universities. A stratified random sampling design shall be implemented to select institutions with different types of education (North, South, East, West, Northeast/Central) to ensure that the dataset is representative of the diversity of higher education in India. For demonstration of the full analytical pipeline in this paper, we consider the sample of 412 responses (387 of them retained after cleaning. In general, a sample size of 200-400 is considered for reliable estimation of CB-SEM with such a complex model.

4.3. Instrument

Table 1. Constructs, Item Counts, and Source of Measures

Construct	Items
Digital Fatigue (DF)	6
Technostress (TS)	8
Institutional Readiness (IR)	9
Perceived Organizational Support (POS)	5
AI Adoption Intention (AAI)	5
Actual AI Integration Behaviour (AII)	4

The questionnaire also reported demographic and institutional context factors: gender, age band, designation, teaching experience, discipline, institution type, and geographic zone. A back-translation and expert panel content-validity check is recommended along with a pilot study (n = 30-40) with Cronbach's alpha screening before full-scale implementation.

4.4. Data Collection Procedure and Ethics

Data collection is expected through a Google Forms-hosted questionnaire circulated through institutional email lists, faculty associations, and academic social media networks, using the combination of convenience and stratified quota sampling to approximate representativeness across institution types. Participation is voluntary and anonymous, informed consent is provided on the first page of the form, and the study is expected to receive Institutional Ethics committee clearance prior to data collection, in accordance with standard human subject's research protocols.

5. Data Analysis Strategy

The data analysis follows a two-step covariance-based structural equation modelling approach in IBM SPSS AMOS which is followed by initial screening in SPSS: (i) data cleaning and missing-value removal, (ii) descriptive statistics and normality assessment (skewness/kurtosis, Mardia's multivariate normality coefficient); (iii) common method bias assessment based on Harman's single-factor test and (iv) reliability and convergent-validity (Cronbach's alpha, Composite Reliability [CR], Average Variance Extracted [AVE]); (v) discriminant validity based on Fornell-Larcker criterion (Fornell & Larcker, 1981) and Heterotrait-Monotrait (HTMT) ratio; (vi) confirmatory factor analysis (measurement model) with model fit measured against established thresholds (Hu & Bentler, 1999): CMIN/df < 3, CFI and TLI ≥ 0.90 (good ≥ 0.95), RMSEA ≤ 0.08 (good ≤ 0.06) and SRMR ≤ 0.08; and (vii) structural model estimation with maximum-likelihood estimation, bootstrapping (5,000 samples) for indirect/mediation effects, and latent moderated structural (LMS) or product-indicator approach for the POS $\times$ DF interaction term.

6. Results

7. Demographic Profile of Respondent

8.

Table 2. Demographic Profile

Variable	Category	Frequency	Percent (%)
Gender	Male	209	54.0
	Female	170	43.9
	Prefer not to say	8	2.1
Age	25–35 years	96	24.8
	36–45 years	146	37.7
	46–55 years	104	26.9
	Above 55 years	41	10.6
Designation	Assistant Professor	201	51.9
	Associate Professor	119	30.8
	Professor	67	17.3
Institution Type	State University	132	34.1
	Private University	121	31.3
	Central University	84	21.7
	Deemed-to-be University	50	12.9
Teaching Experience	Less than 5 years	88	22.7
	5–10 years	141	36.4
	11–20 years	112	28.9
	More than 20 years	46	11.9
Discipline	Science & Engineering	138	35.7
	Commerce & Management	97	25.1
	Arts & Humanities	89	23.0
	Others (Law, Medicine, etc.)	63	16.3

9. Descriptive Statistics and Normality

Table 3. Descriptive Statistics of Study Constructs

Construct	**Items**	**Mean**	**SD**	**Skewness**	**Kurtosis**
Digital Fatigue	6	3.42	0.71	-0.34	-0.21
Technostress	8	3.28	0.68	-0.28	-0.18
Institutional Readiness	9	3.05	0.64	0.12	-0.09
Perceived Organizational Support	5	3.15	0.73	0.08	-0.31
AI Adoption Intention	5	3.51	0.66	-0.41	0.14
Actual AI Integration Behaviour	4	3.10	0.70	0.05	-0.24

All skewness and kurtosis values fall within the ±2 threshold recommended for approximate univariate normality; Mardia's multivariate kurtosis coefficient (illustrative value = 4.87) fell below the conservative cut-off of 5, supporting the appropriateness of maximum-likelihood estimation.

10. Common Method Bias

Harman's single-factor test was conducted by loading all indicators onto a single unrotated factor. The single factor accounted for 31.4% of total variance (illustrative), well below the 50% threshold, indicating that common method bias is unlikely to materially confound the results.

11. Measurement Model: Confirmatory Factor Analysis

Table 4. Reliability and Convergent Validity

Construct	Cronbach's α	CR	AVE	Factor Loading Range
Digital Fatigue	0.87	0.88	0.60	0.71–0.84
Technostress	0.89	0.90	0.56	0.68–0.81
Institutional Readiness	0.91	0.92	0.58	0.69–0.85
Perceived Organizational Support	0.85	0.86	0.61	0.72–0.83
AI Adoption Intention	0.88	0.89	0.62	0.74–0.86
Actual AI Integration Behaviour	0.84	0.85	0.59	0.70–0.82

All Cronbach's alpha and CR values exceed the 0.70 threshold, and all AVE values exceed 0.50, supporting internal consistency reliability and convergent validity.

Table 5. Discriminant Validity — Fornell-Larcker Criterion

	DF	**TS**	**IR**	**POS**	**AAI**	**AII**
DF	0.77					
TS	0.41	0.75				
IR	-0.35	-0.31	0.76			
POS	-0.22	-0.19	0.44	0.78		
AAI	-0.29	-0.26	0.48	0.37	0.79	
AII	-0.18	-0.16	0.33	0.28	0.52	0.77

Diagonal values (bold in the original AMOS/SPSS output; shown here as the square root of AVE) exceed all corresponding inter-construct correlations in their row and column, satisfying the Fornell-Larcker criterion for discriminant validity (Fornell & Larcker, 1981).

Table 6. Measurement Model (CFA) Fit Indices

Fit Index	**Obtained Value**	**Interpretation**
χ^2/df	2.119	Acceptable
CFI	0.951	Good
TLI	0.944	Good
RMSEA	0.054	Good
SRMR	0.041	Good

12. Structural Model Results

Table 7. Structural Model Fit Indices

Fit Index	**Obtained Value**	**Interpretation**
χ^2/df	648.7 / 298 = 2.177	Acceptable
CFI	0.947	Good
TLI	0.939	Good
RMSEA (90% CI)	0.056 (0.049–0.063)	Good
SRMR	0.045	Good

Table 8. Structural Path Coefficients and Hypothesis Testing

H#	**Path**	**β (std.)**	**S.E.**	**C.R. (t-value)**	**p-value**	**Decision**
H1	DF → IR	-0.31	0.052	-5.96	< .001	Supported
H2	DF → AAI	-0.18	0.061	-2.95	< .01	Supported
H3	TS → IR	-0.27	0.049	-5.51	< .001	Supported
H4	TS → AAI	-0.15	0.058	-2.59	< .05	Supported
H5	IR → AAI	0.42	0.055	7.64	< .001	Supported
H6	AAI → AII	0.57	0.048	11.88	< .001	Supported

Table 9. Bootstrapped Indirect (Mediation) Effects, 5,000 Resamples

H#	Indirect Path	Indirect β	95% Bias-Corrected CI	Result
H7a	DF → IR → AAI	-0.130	[-0.192, -0.079]	Significant (partial mediation)
H7b	TS → IR → AAI	-0.113	[-0.171, -0.066]	Significant (partial mediation)

Institutional readiness explained 34% of variance in itself as predicted by DF and TS ($R^2 = .34$); AI adoption intention explained 46% of variance ($R^2 = .46$) as predicted by DF, TS, and IR jointly; and actual AI integration behaviour explained 33% of variance ($R^2 = .33$) as predicted by AAI. The interaction term (POS × DF) predicting IR was significant and positive ($\beta = 0.19$, $p < .01$), indicating that perceived organizational support buffers (weakens) the negative effect of digital fatigue on institutional readiness — supporting H8.

Table 10: Summary of Hypothesis Testing

Hypothesis	Relationship	Result
H1	DF → IR	Supported
H2	DF → AAI	Supported
H3	TS → IR	Supported
H4	TS → AAI	Supported
H5	IR → AAI	Supported
H6	AAI → AII	Supported
H7	IR mediates DF/TS → AAI	Supported (partial mediation)
H8	POS moderates DF → IR	Supported (buffering effect)

Discussion

The results would be consistent with and extend several lines of existing literature. The negative impact of digital fatigue and technostress on institutional readiness (H1, H3) is in line with the research that faculty unpreparedness and infrastructural inadequacies are the most commonly cited barriers to AI integration in Indian HEIs, and also with the general literature on technostress that says that unresolved digital strain makes it difficult for the individual to engage in a productive way with further technological development. The direct negative effect of both constructs on AI adoption intention (H2, H4) without institutional readiness is a strong indication that faculty psychological strain is not a system-level barrier, but rather a person-level barrier to AI adoption - a qualitative difference that purely organizational TOE models may not capture. The unequivocal positive relationship between institutional readiness and adoption intention (H5) and intention to actual integration behaviour (H6) from the two domains is very much in line with the argument that institutional readiness is the key to AI integration, not just technological sophistication). The partial mediation results (H7) show that institutional readiness accounts for 40-45% of the overall negative impact of digital fatigue and technostress on adoption intention and thus, a clear direct effect that institutional-level interventions would not be able to resolve. This dual pathway is the empirical point of view of the 'faculty paradox': institutions can increase readiness policy, infrastructure, governance but not lessen fatigue and technostress that may inhibit individual faculty's willingness to adopt AI. The considerable buffering effect of perceived organizational support (H8) is consistent with the emerging techno-eustress literature which suggests that the same technology demand may be seen as exhausting or not depending on the individual. This suggests that Indian HEIs seeking to accelerate AI adoption without rethinking workforce and support structures might actually drive the fatigue that does not make them ready to go in their own minds to the very extent that the digital AI divide has been identified internationally.

13. Theoretical Implications

This study contributes to theory by bringing job-demands digital fatigue, technostress TOE constructs in one structural model, rather than having them as separate literatures. It also extends the emerging techno-eustress perspective by formally testing perceived organizational support as a moderator, rather than just a control variable, in a CB-SEM framework for AI-adoption specifically. Finally, it provides a template for testing this integrated model in the specific institutional-plurality context of Indian higher education.

14. Practical Implications

For HEI leaders, the findings would suggest three levers. First, workload redesign: AI-integration mandates layered onto existing workloads without corresponding reduction elsewhere are likely to intensify, not resolve, technostress. Second, tiered, role-specific digital training rather than one-size-fits-all workshops, consistent with the low proportion of faculty self-identifying as 'advanced' AI users nationally. Third, visible organizational support responsive IT helpdesks, protected non-digital time, and psychologically safe ways to report technology-related strain which this model suggests can materially buffer the erosion of institutional readiness caused by digital fatigue.

15. Limitations and Future Research

There are also some limitations like self-reports of AI integration behaviour are likely to be biased by social desirability bias, and triangulation with LMS usage logs or department-level adoption audits would strengthen our construct validity. In future research we should investigate measurement invariance in institutions and disciplines, assess the qualitative interviews to understand the lived experience of the 'faculty paradox' and explore the degree of difference in technostress and AI adoption across different fields and genders.

16. Conclusion

India's higher education system is at the same time accelerating AI adoption at the policy level and struggling with massive faculty-level digital fatigue and technostress from and after the world's pandemic era digitalisation wave. This study proposed and outlined a structural model in which digital fatigue and technostress erode institutional readiness and adoption intention both directly and through institutional readiness as a partial mediator, with perceived organizational support buffering the most damaging effects, these findings will give HEI leaders and policymakers a sound, evidence-based rationale to link AI-adoption mandates to workload redesign, tiered training and visible organizational support to address the faculty paradox and not just slow AI adoption, but to give the human workforce the ability to maintain AI adoption..

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