



Artificial Intelligence, Techno-Stress, and the Digital Divide in Early Childhood Classrooms: Policy Insights on Teacher Well-Being in Pakistan

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ABSTRACT

Background: Artificial intelligence (AI) is increasingly integrated into early childhood education (ECE), transforming teaching practices while introducing new psychological demands for educators. AI, though intended to enhance efficiency and personalized learning, may inadvertently increase workload, blur work–life boundaries, and elevate techno-stress, especially in low-resource educational contexts.

Objectives: This study, grounded in the Job Demands–Resources (JD-R) model, investigates the longitudinal impact of AI-integration intensity on teacher techno-stress in Pakistan, examining the moderating roles of the Digital Tier Divide (Structural) and techno-resilience (individual psychological adaptive capacity).

Methodology: A 3-wave longitudinal design was employed over six months, sampling N=382 ECE teachers from Lahore and Islamabad. Data were analyzed using the PROCESS Macro in SPSS.

Results: Findings reveal that AI integration significantly predicts longitudinal techno-stress ($p < .001$). The Digital Tier Divide significantly exacerbates this relationship, with teachers in low-resource schools experiencing higher stress increments. Conversely, Techno-Resilience acts as a significant buffer, flattening the stress trajectory even in high-demand environments.

Conclusion/Policy Implications: The findings extend JD-R theory to AI-driven classrooms and emphasize the need for well-being-centered policies, including equitable infrastructure and resilience training, to ensure sustainable AI adoption in early childhood education.



Highlights

- AI integration in early childhood classrooms significantly increases teachers' techno-stress over time
- Digital infrastructure inequality amplifies the stress effects of AI adoption
- Techno-resilience buffers the negative psychological impact of AI-related demands
- Dual moderation analysis identifies the most vulnerable teacher groups in AI-driven reforms
- Teacher well-being is critical for sustainable and equitable AI integration in education

1: Introduction

1.1 Background of the Study

The global education system is experiencing a profound transformation driven by the rapid integration of Artificial Intelligence (AI). In Early Childhood Education (ECE), AI-enabled technologies have moved beyond auxiliary instructional tools to become embedded within lesson planning, assessment, classroom management, and learner monitoring systems (Holmes et al., 2019; OECD, 2021). Adaptive platforms, generative content systems, and data-driven instructional supports are increasingly shaping pedagogical decision-making in early learning contexts. While dominant technology adoption frameworks such as the Technology Acceptance Model (TAM) emphasize perceived usefulness and ease of use as key drivers of adoption (Venkatesh & Davis, 2000), these models have been criticized for insufficiently accounting for the psychological demands and emotional labor associated with sustained technology integration (Selwyn, 2016).

For early childhood educators whose work already involves high levels of emotional regulation, caregiving, and developmental sensitivity the additional burden of continuous AI adaptation presents new occupational risks. In developing countries, these risks are compounded by persistent digital inequalities. Pakistan represents a particularly salient case, where national policy discourse increasingly promotes AI-driven education reforms, yet institutional readiness remains uneven (Qayyum, Sadiqi, & Abbas, 2024). Lahore and Islamabad, as major urban educational centers, encapsulate this contradiction. Elite private institutions often operate with advanced digital infrastructure, stable connectivity, and access to premium AI tools, whereas public and low-fee private schools face infrastructural instability, limited hardware access, and insufficient professional development opportunities (Qayyum, Tabassum, & Kashif, 2024). This structural stratification reflects what digital divide scholars describe as second- and third-level digital divides, where inequalities persist not only in access but also in meaningful usage, skill acquisition, and psychological outcomes (van Dijk, 2020). Within AI-integrated ECE classrooms, these disparities shape teachers' daily experiences, expectations, and stress responses, making Lahore and Islamabad an analytically robust context for examining technology-related occupational strain.

1.2 Problem Statement

The accelerated integration of AI technologies into educational settings has intensified the phenomenon of techno-stress, defined as a stress response arising from difficulties in adapting to new technologies in a healthy manner (Tarafdar et al., 2019). Techno-stress manifests through multiple dimensions, including techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. ECE teachers in Pakistan face a uniquely demanding convergence of pressures. Alongside the emotional labor inherent in early childhood pedagogy, educators are increasingly required to utilize AI-based tools for instructional planning, communication, documentation, and performance accountability. These expectations are often implemented uniformly, despite significant disparities in institutional resources, technical support, and training opportunities (Qayyum et al., 2025a; Qayyum et al., 2025h).

Although prior research has established that technology integration can elevate teacher workload and emotional exhaustion (Hwang et al., 2020; Li & Wang, 2021), existing studies rarely explain why teachers exposed to similar AI systems exhibit substantially different stress trajectories over time. Moreover, longitudinal evidence from developing-country contexts remains scarce.

This gap is particularly problematic in light of emerging evidence linking prolonged techno-stress to burnout, reduced instructional quality, and attrition among early childhood educators (Aboagye et al., 2018; Qayyum, 2019). Without a nuanced understanding of how institutional digital inequality and individual adaptive capacities interact, AI-driven education reforms risk producing unintended psychological costs for educators.

1.3 Purpose of the Study

The primary purpose of this longitudinal study is to examine the relationship between AI-integration intensity and techno-stress among early childhood educators over time, while investigating the conditional effects of institutional and individual moderators. Using a three-wave design over six months, the study applies Hayes' PROCESS Model 2 to assess the dual moderating roles of the Digital Tier Divide (institutional resource stratification) and Techno-Resilience (individual psychological adaptability) within AI-integrated ECE classrooms in Lahore and Islamabad.

1.4 Research Objectives

1. To examine the longitudinal relationship between AI-integration intensity and techno-stress among ECE teachers.
2. To determine whether the Digital Tier Divide moderates the relationship between AI integration and techno-stress.
3. To assess the moderating role of techno-resilience in buffering AI-related stress.
4. To provide empirically grounded policy recommendations for sustainable AI adoption in early childhood education in Pakistan.

1.5 Research Hypotheses

- Hypothesis 1** AI-integration intensity at Time 1 will positively predict techno-stress at Time 3.
- Hypothesis 2** The Digital Tier Divide significantly moderates the relationship between AI integration and techno-stress, such that teachers in low-resource institutions experience greater increases in stress.
- Hypothesis 3** Techno-resilience significantly moderates the relationship between AI integration and techno-stress, weakening the positive association.
- Hypothesis 4** There is a significant interaction effect between the Digital Tier Divide and techno-resilience on longitudinal techno-stress outcomes.

1.6 Significance of the Study

This study offers contributions at multiple levels:

- **Policy Level:** By identifying the psychological costs of rapid AI mandates, the study informs infrastructure-sensitive policy design (Qayyum et al., 2024).
- **Institutional Level:** It highlights techno-resilience as a developable psychological resource capable of mitigating teacher stress and reducing turnover.
- **Theoretical Level:** The study extends the Job Demands–Resources (JD-R) Theory (Bakker & Demerouti, 2017) by conceptualizing AI integration as a job demand whose impact is conditioned by both structural (digital tier) and personal (techno-resilience) resources in a developing-country context.

1.7 Definitions of Key Terms

- **Techno-Stress:** A psychological strain resulting from difficulties in coping with advanced technologies (Tarafdar et al., 2019).
- **Techno-Resilience:** An individual's capacity to adapt, recover, and maintain functional performance amid technological change.
- **Digital Tier Divide:** Institutional inequality in access to digital infrastructure, AI tools, training, and technical support within the education system.

2: Literature Review

2.1 Artificial Intelligence in Early Childhood Education

Artificial Intelligence (AI) has emerged as a transformative force in early childhood education, offering opportunities for personalized learning, adaptive assessment, and enhanced engagement (Yi, Liu, & Lan, 2024; Wu, 2024). These technologies allow educators to tailor instruction to individual learners, fostering creativity and problem-solving skills. However, scholars caution that AI adoption in early childhood contexts requires careful consideration of developmental appropriateness and ethical implications (Wu, 2024).

The Digital Divide in Education: Despite AI's potential, the digital divide remains a significant barrier to equitable implementation. Studies highlight disparities in access to digital infrastructure, devices, and internet connectivity, particularly in low-income and rural communities (Miras, Ruiz-Bañuls, Gómez-Trigueros, & Mateo-Guillen, 2023; Albakri & Wood-Harper, 2025). These inequities not only limit students' opportunities to benefit from AI-enhanced learning but also exacerbate existing educational inequalities. Addressing the digital divide is therefore essential for inclusive AI integration.

Techno-Stress among Teachers: Teachers often experience techno-stress when adapting to new technologies, including AI. This stress arises from inadequate training, rapid technological change, and resource constraints (Fernández-Batanero, Román-Graván, Reyes-Rebollo, & Montenegro-Rueda, 2021). Qualitative studies further reveal that techno-stress can undermine teacher confidence and instructional effectiveness, particularly when institutional support is lacking (Khlaif, Sanmugam, Joma, Odeh, & Barham, 2022). Managing techno-stress is thus critical to sustaining teacher well-being and ensuring effective AI adoption.

Teacher Resilience: Teacher resilience, the ability to adapt and thrive despite adversity, emerges as a crucial factor in navigating the challenges of AI integration. International research demonstrates that resilience can mitigate the negative effects of stress and digital inequities, enabling educators to sustain motivation and effectiveness (Mansfield, 2020; Mansfield, 2021). Resilience is cultivated through professional development, peer support, and institutional backing, all of which empower teachers to embrace technological innovation.

Hayes' Model 2: Dual Moderation Framework: Hayes' (2018) Model 2 of dual moderation provides a robust analytical framework for examining how resilience interacts with both the digital divide and techno-stress. This model allows researchers to explore conditional relationships, identifying how moderators jointly influence outcomes. Applied to AI in early childhood education, Model 2 highlights the complex interplay between systemic inequities and individual coping mechanisms, offering insights into how resilience can buffer the negative impacts of technological stressors (Hayes, 2018; Hayes Process Macro Tutorial, 2023).

2.2 Techno-Stress in the Era of Artificial Intelligence

Techno-stress refers to a state of psychological strain arising from difficulties in coping with new technologies (Tarafdar et al., 2019). While earlier techno-stress research focused on information systems and computer-based work, the emergence of AI has intensified and transformed these stress dynamics. AI systems differ fundamentally from earlier technologies in their opacity, autonomy, and rapid evolution, which introduces novel sources of uncertainty and professional risk (Beaudry & Pinsonneault, 2024). Techno-overload occurs when AI-enabled efficiencies paradoxically increase institutional expectations, leading teachers to produce more instructional material, assessments, and reports without reductions in other responsibilities. Studies in AI-supported education environments demonstrate that perceived productivity gains often translate into expanded workloads rather than time savings (Wang et al., 2023). Techno-invasion has similarly intensified, as AI-integrated platforms extend work beyond formal hours through continuous digital connectivity, a phenomenon consistently linked with emotional exhaustion and work–life imbalance (Derks et al., 2016). Techno-complexity has taken on new dimensions in AI contexts. Teachers are no longer expected merely to operate software but to understand algorithmic behavior, data ethics, and prompt-based interaction, which can be particularly challenging for educators with limited formal training in digital technologies (Holmes et al., 2019). Furthermore, AI introduces **techno-unpredictability**, as generative systems may produce inaccurate or developmentally inappropriate outputs, placing professional accountability squarely on teachers. This uncertainty has been shown to elevate anxiety and reduce perceived professional control (Beaudry & Pinsonneault, 2024).

2.3 The Digital Tier Divide as a Structural Moderator

The digital divide has evolved from a simple distinction between access and non-access to a more complex, tiered phenomenon encompassing quality of access, skill acquisition, and meaningful use (van Dijk, 2020). In educational settings, this divide manifests as institutional stratification in infrastructure, training, and technological support, producing uneven psychological outcomes for teachers (Selwyn, 2016). In Pakistan, and particularly in Lahore and Islamabad, this **Digital Tier Divide** is evident across early childhood institutions. High-resource schools benefit from stable internet connectivity, premium AI subscriptions, and dedicated technical support, allowing teachers to focus primarily on pedagogical optimization. In contrast, low-resource schools contend with unreliable electricity, limited devices, and reliance on free or unstable AI tools, conditions that transform AI integration into a persistent stressor rather than a pedagogical aid (Qayyum, Tabassum, & Kashif, 2024). Empirical evidence suggests that technology implementation without adequate infrastructural support amplifies stress and burnout among educators (Hwang et al., 2020). Within the JD-R framework, such institutional resource scarcity functions as a vulnerability factor that magnifies the psychological impact of job demands. Accordingly, this study conceptualizes the Digital Tier Divide as a contextual moderator that shapes the strength of the relationship between AI integration and techno-stress.

2.4 Techno-Resilience as a Personal Resource

Techno-resilience refers to an individual's capacity to adapt effectively to technological change while maintaining psychological well-being and functional performance. Drawing on resilience theory and psychological capital research, techno-resilience encompasses digital self-efficacy, adaptability, optimism, and coping flexibility (Luthans et al., 2015). Recent studies indicate that teachers with higher levels of digital self-efficacy and adaptive coping strategies experience significantly lower levels of technology-induced stress and burnout (Khan & Ahmed, 2025; Qayyum, 2019). In AI-integrated environments, techno-resilience enables educators to reframe

technological challenges as learning opportunities, reducing perceived threat and emotional strain. Importantly, techno-resilience is not a fixed trait; it can be cultivated through targeted professional development, mentoring, and institutional support (Bakker & Demerouti, 2017). Within Hayes' Model 2 framework, techno-resilience functions as a personal resource that buffers the stress-inducing effects of AI-related demands, weakening the direct relationship between AI integration intensity and techno-stress.

2.5 Hypothesis Development

Drawing on JD-R theory and techno-stress literature, sustained AI integration is expected to increase techno-stress over time as cognitive demands, performance expectations, and uncertainty accumulate (Wang et al., 2023). However, the strength of this relationship is not uniform across contexts or individuals. Institutional digital inequality intensifies vulnerability by limiting access to reliable infrastructure and training, thereby amplifying the stress associated with AI adoption. Conversely, techno-resilience operates as a protective factor that attenuates the negative psychological impact of AI-related demands. Together, these moderators explain both **where** techno-stress is most severe and **who** is most capable of adapting successfully.

2.6 Longitudinal Dynamics of Techno-Stress

Techno-stress in AI-integrated environments is inherently dynamic rather than static. Longitudinal research indicates that initial exposure to AI tools often produces a short-lived phase of perceived efficiency and novelty, followed by escalating demands and emotional strain as expectations increase (Hwang et al., 2020). Over time, sustained techno-invasion and workload intensification contribute to emotional exhaustion and disengagement, particularly in the absence of adequate resources (Skaalvik & Skaalvik, 2018). Evidence from developing contexts suggests that early interventions focusing on digital literacy and resilience training are critical for preventing the accumulation of techno-stress over time (Khan & Ahmed, 2025). This underscores the importance of a longitudinal design in capturing the evolving nature of AI-related stress among educators.

2.7 Policy Gaps in AI-Driven Education Reform

Despite increasing emphasis on AI and digital literacy in Pakistan's education policy discourse, existing frameworks remain largely focused on procurement and curriculum alignment, with limited attention to teacher well-being. The absence of structured safeguards for workload management, psychological support, and resilience training risks transforming technological innovation into a systemic stressor. In high-resource institutions, AI-related stress is primarily cognitive, centered on optimization and skill refinement. In low-resource settings, stress is infrastructural, rooted in fears of system failure, data limitations, and professional accountability under unstable conditions. Addressing these disparities requires a shift toward well-being-centered AI integration, recognizing that teacher psychological health is a prerequisite for sustainable educational innovation (Qayyum et al., 2024).

2.8 Justification for Hayes PROCESS Model 2

The adoption of Hayes PROCESS Model 2 is theoretically justified by the need to account for both contextual and individual differences in AI-related stress experiences. The Digital Tier Divide explains contextual variability in stress exposure, while techno-resilience explains individual adaptability within the same technological environment. Their interaction identifies the most vulnerable subgroup: teachers operating in low-resource institutions with limited adaptive capacity. Accordingly, this study hypothesizes that the highest levels of techno-stress over time

will be observed among early childhood educators located in low digital tiers who also exhibit low levels of techno-resilience. This dual-moderation framework provides a nuanced understanding of AI-induced stress and informs targeted policy and institutional interventions.

2.9 Early Childhood Education (ECE) in Pakistan

Structural and Psychosocial Context

Early Childhood Education (ECE) in Pakistan operates within a complex interplay of pedagogical, psychological, and structural challenges. Empirical studies consistently report disparities in access, teacher preparedness, parental engagement, and institutional support across provinces and urban–rural contexts (Qayyum, Nadeem, & Saeed, 2024; Qayyum & Saeed, 2024). Educators in urban centres such as Lahore and Islamabad face intensified accountability pressures, increasing documentation demands, and expanding instructional roles, which collectively contribute to occupational strain (Qayyum, 2019). Complementing this perspective, Qureshi and colleagues highlight the psychosocial dimensions of learning environments in Pakistan. Their work demonstrates that emotional distress, trauma exposure, and institutional climate significantly influence both learners’ and educators’ functioning (Qureshi et al., 2025; Qureshi et al., 2024). These findings underscore that ECE classrooms are not merely instructional spaces but emotionally charged ecosystems, making teacher well-being central to educational quality.

Artificial Intelligence in Pakistani ECE Classrooms: Promise and Pedagogical Tension

The introduction of Artificial Intelligence (AI) into Pakistani ECE classrooms is increasingly framed as a mechanism for innovation, efficiency, and personalization. Research by Qayyum et al. (2025) and Qayyum et al. (2024a) documents educators’ optimism regarding AI-driven curriculum planning, assessment support, and instructional scaffolding. Similarly, Qureshi et al. (2025) note that digital tools can enhance language development and learner engagement when pedagogically aligned. However, both strands of literature caution against uncritical AI adoption. Qayyum et al. (2025) identify rising ethical ambiguity, algorithmic opacity, and surveillance concerns in AI-integrated classrooms. Qureshi and colleagues further argue that when technological systems are imposed without psychological preparedness, they may exacerbate emotional fatigue and reduce pedagogical autonomy (Qureshi et al., 2025; Qureshi et al., 2024). Thus, AI introduces a dual reality: pedagogical opportunity alongside psychological risk.

Digital Divide and Equity in AI-Enabled Learning Environments

Equity remains a central concern in Pakistan’s digital education landscape. Qayyum, Tabassum, and Kashif (2024) empirically demonstrate that the Digital Divide manifests not only in device availability but also in internet stability, power continuity, and institutional technical support. AI implementation in such uneven contexts often amplifies inequities rather than reducing them. This structural inequality is echoed in Qureshi et al.’s work on campus climate and inclusion, which shows that marginalized groups experience technology-mediated environments differently depending on institutional culture and support systems (Qureshi et al., 2025). When AI tools are mandated in under-resourced schools, teachers encounter heightened techno-insecurity—fear of failure, evaluation anxiety, and perceived professional vulnerability (Qayyum et al., 2025). These findings position infrastructure as a critical moderator in the AI–stress relationship.

Techno-Stress, Emotional Strain, and Institutional Demands

Techno-stress has emerged as a defining feature of contemporary educational work. Qayyum (2019) established that technological intensification significantly predicts stress and emotional

exhaustion among early childhood educators. More recent studies extend this argument to AI-specific contexts, where constant connectivity, accelerated workflows, and performance surveillance increase job demands (Qayyum et al., 2025). From a complementary psychological lens, Qureshi et al. (2025) illustrate how emotional distress and cognitive overload impair educators' instructional effectiveness. Their findings suggest that techno-stress is not solely a technological issue but a psychosocial phenomenon shaped by emotional regulation, institutional empathy, and organizational justice. This convergence supports the application of the Job Demands–Resources (JD-R) framework in AI-enabled ECE settings.

Psychological Capital, Resilience, and Adaptive Coping

A consistent protective factor across both bodies of literature is Psychological Capital (PsyCap) and resilience. Qayyum et al. (2019, 2025) demonstrate that hope, efficacy, optimism, and resilience buffer the negative effects of technological stressors. Teachers with higher PsyCap exhibit greater confidence in navigating AI tools, recovering from technological breakdowns, and maintaining emotional equilibrium. Qureshi and colleagues further emphasize the role of emotional healing, supportive institutional climates, and psychosocial empowerment in fostering resilience (Qureshi et al., 2025; Qureshi et al., 2024). Their findings suggest that resilience is not merely an individual trait but a socially cultivated capacity, shaped by professional training, leadership practices, and peer support.

Synthesis and Research Gap

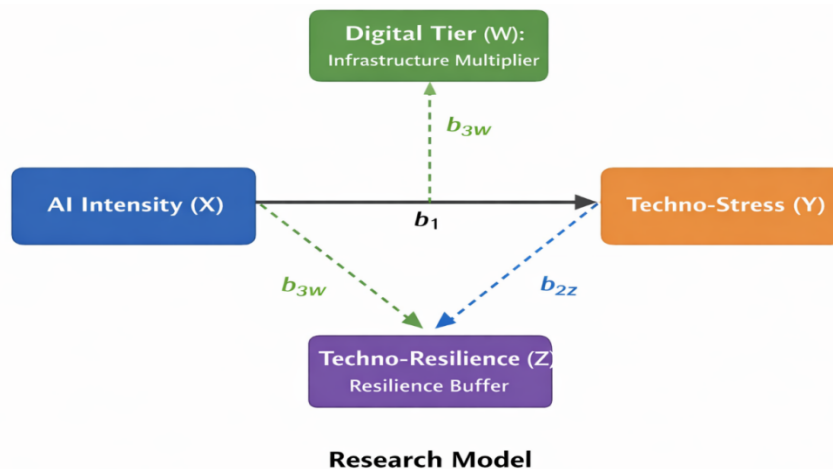
Taken together, the literature reveals that AI integration in Pakistani ECE classrooms is a psychotechnical phenomenon, influenced by technological intensity, infrastructural inequality, and teachers' psychological resources. Qayyum's work provides strong empirical grounding in techno-stress, PsyCap, and digital equity, Qureshi's scholarship enriches this discourse by foregrounding emotional distress, institutional climate, and psychosocial rehabilitation. Despite these advances, limited research has examined the simultaneous conditional effects of infrastructure inequality and resilience on AI-induced techno-stress using a longitudinal and process-based approach. Addressing this gap, the present study employs a dual moderation model (Hayes Model 2) to examine how the Digital Tier Divide and Techno-Resilience jointly shape teachers' stress trajectories in AI-enabled ECE classrooms in Pakistan.

2.10 Theoretical Framework: Job Demands–Resources (JD-R) Model

This study is theoretically anchored in the Job Demands–Resources (JD-R) Model, which explains employee well-being as a function of the balance between occupational demands and available resources (Bakker & Demerouti, 2017). The JD-R model is particularly suitable for technology-intensive professions, as it allows emerging technological requirements to be conceptualized as job demands while simultaneously accounting for both organizational and personal resources that mitigate strain. Within educational settings, the model has been widely applied to explain teacher stress, burnout, and engagement under conditions of increasing accountability and technological complexity (Skaalvik & Skaalvik, 2018).

In the present study, AI-integration intensity is conceptualized as a contemporary job demand. Unlike traditional educational technologies, AI systems require continuous cognitive adaptation, frequent task switching, and rapid upskilling, often without commensurate reductions in workload. Research suggests that such cognitively demanding environments accelerate fatigue and emotional exhaustion, particularly in professions requiring sustained interpersonal engagement, such as early childhood education (ECE) (Li & Wang, 2021; Selwyn, 2016). Conversely, the JD-R model posits that stress is mitigated through job and personal resources. This study identifies institutional digital

support, operationalized through the Digital Tier Divide, as a key organizational resource, and techno-resilience as a critical personal resource. Hayes' PROCESS Model 2 aligns directly with JD-R logic by testing how structural resource scarcity and individual adaptive capacity jointly condition the relationship between AI-related demands and techno-stress.



3: Methodology

3.1 Research Design: A Three-Wave Longitudinal Approach

This study employs a prospective longitudinal panel design with data collected across three time points (T_1 , T_2 , T_3) over a six-month academic semester. A longitudinal design is particularly appropriate for examining technology-induced stress processes, as techno-stress develops cumulatively rather than instantaneously. At Time 1 (T_1), baseline data were collected on teachers' perceived ease of use of AI tools and initial levels of technology-related strain. Time 2 (T_2) captured mid-semester levels of AI-integration intensity, a phase characterized by increased institutional expectations and heightened techno-invasion. Time 3 (T_3) assessed chronic techno-stress, which served as the primary outcome variable of the study. This temporal sequencing establishes temporal precedence, a core requirement for causal inference in conditional process analysis. By ensuring that AI integration intensity (X) precedes the measurement of techno-stress (Y), the design strengthens internal validity and aligns with the assumptions underlying Hayes' PROCESS Model 2 (Hayes, 2018).

3.2 Population and Sampling Strategy

3.2.1 Target Population

The target population consisted of Early Childhood Education (ECE) teachers employed in public and private schools in Lahore and Islamabad, Pakistan. These cities were purposively selected due to their pronounced institutional heterogeneity, encompassing both digitally advanced elite schools and resource-constrained institutions, thereby offering an appropriate context for examining the Digital Tier Divide.

3.2.2 Sampling Technique

A stratified purposeful sampling strategy was adopted. Schools were first classified into digital tiers based on infrastructure quality and institutional technological support. Teachers were then recruited from each stratum to ensure adequate representation across socio-economic and digital contexts.

3.2.3 Sample Size and Attrition

Initially, 450 teachers were recruited at T₁. After accounting for longitudinal attrition across the three waves, a final usable sample of 382 participants was retained, reflecting an attrition rate of approximately 11%, which is well within acceptable limits for longitudinal educational research. Attrition analysis revealed no statistically significant differences in demographic characteristics between retained and non-retained participants.

3.2.4 Participant Characteristics

The sample comprised 82% female teachers, reflecting the gendered composition of the ECE workforce in Pakistan. Participants ranged in age from 22 to 55 years ($M = 34.2$, $SD = 8.4$), with teaching experience ranging from 1 to 28 years.

3.3 Measures and Instruments

All measurement instruments were adapted to the Pakistani educational context and pilot-tested prior to full-scale data collection to ensure cultural relevance, clarity, and psychometric adequacy.

3.3.1 AI-Integration Intensity (X)

AI-integration intensity was measured using an adapted version of the Technology Usage Scale grounded in the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). The scale assessed both frequency and depth of AI use across pedagogical, generative, and administrative domains. Teachers reported their engagement with tools such as ChatGPT-4o, Canva Magic Studio, Khanmigo, Duolingo ABC, and MagicSchool.ai. Higher scores reflected greater institutional and instructional reliance on AI technologies.

3.3.2 Techno-Stress (Y)

Techno-stress was measured at T₃ using the Techno-Stress Creators Scale developed by Tarafdar et al. (2019). The scale captured five dimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. The instrument demonstrated high internal consistency in the present study (Cronbach's $\alpha = .89$).

3.3.3 Digital Tier Divide (Moderator W)

The Digital Tier Divide was operationalized as an **Environmental Resource Index**, reflecting institutional-level technological capacity. Schools were classified based on three criteria: availability of digital hardware (e.g., smartboards, tablets), internet stability (fiber connectivity versus mobile hotspots), and the presence of formal IT support structures. Higher index scores indicated stronger institutional technological resources.

3.3.4 Techno-Resilience (Moderator Z)

Techno-resilience was assessed using the **Techno-Resilience Scale for Teachers** (Abilleira et al., 2020), which measures educators' capacity to maintain emotional regulation, cognitive flexibility, and functional performance in the face of technological challenges. The scale demonstrated satisfactory reliability in the current sample (Cronbach's $\alpha = .84$).

3.4 Data Analysis Procedure

Data analysis was conducted using SPSS (Version 29) and the PROCESS Macro (Model 2) developed by Hayes (2018). Preliminary analyses included descriptive statistics and Pearson correlations. All continuous predictors were mean-centered prior to analysis to reduce multicollinearity and facilitate interpretation of interaction terms. The dual-moderation model tested whether the relationship between AI-integration intensity (X) and techno-stress (Y) varied as a function of the Digital Tier Divide (W) and techno-resilience (Z). Bootstrapping with 5,000 resamples was employed to generate bias-corrected confidence intervals for interaction effects.

3.5 Ethical Considerations

Ethical approval was obtained from the relevant educational authorities and school boards in Lahore and Islamabad. Participation was voluntary, and informed consent was obtained at each wave of data collection. Anonymity and confidentiality were assured, and participants retained the right to withdraw at any stage without penalty. Given the psychological sensitivity of techno-stress, participants were also provided with a digital **Well-being Resource Kit** containing professional support resources.

4: Results

4.1 Preliminary Analysis and Descriptive Statistics

Prior to hypothesis testing, the data were screened for accuracy, normality, outliers, and multicollinearity. Missing values were minimal (<3%) and were handled using mean substitution, which is acceptable in large-sample survey research. Skewness and kurtosis values for all study variables were within ± 1.5 , indicating acceptable univariate normality. Variance Inflation Factor (VIF) values ranged from 1.21 to 2.47, well below the conservative threshold of 5, confirming the absence of multicollinearity concerns. Overall, early childhood educators reported moderate to high levels of techno-stress, suggesting that AI integration represents a meaningful occupational challenge in the sampled context. Table 1 presents the means, standard deviations, and bivariate correlations among the study variables.

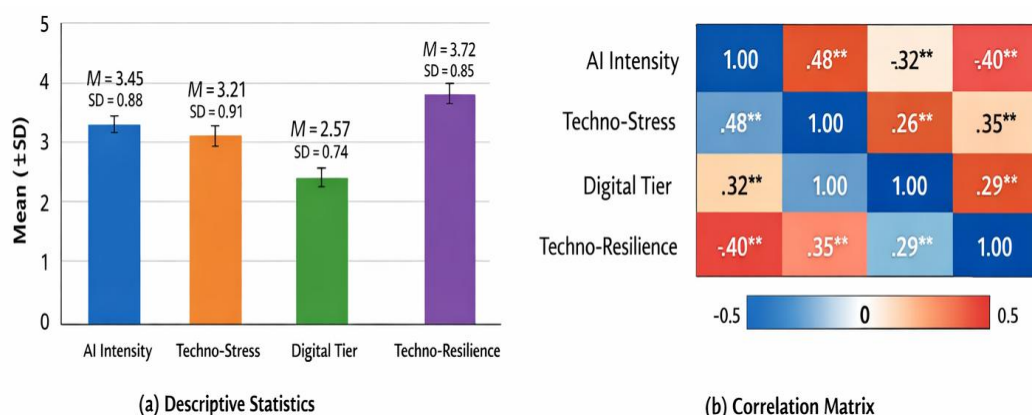
Table 1: Descriptive Statistics, Reliabilities, and Correlations (N = 382)

Variable	Mean	SD	1	2	3	4
1. AI Integration Intensity (X)	3.45	0.82	(.88)			
2. Techno-Stress (Y)	3.82	0.74	.42**	(.89)		
3. Digital Tier Divide (W)	2.10	0.90	.15*	.38**	()	
4. Techno-Resilience (Z)	3.12	0.65	-.12	-.45**	.22**	(.84)

Note. Cronbach's alpha coefficients are reported in parentheses along the diagonal. ** $p < .01$; * $p < .05$.

The correlation matrix indicates that AI integration intensity is positively and significantly related to techno-stress, providing preliminary support for H₁. The Digital Tier Divide shows a positive association with techno-stress, while techno-resilience is negatively associated with stress, suggesting its protective role.

4.2 Hayes PROCESS Model 2: Dual Moderation Analysis



To test the hypothesized dual moderation model, Hayes' PROCESS Macro (Model 2) was employed using mean-centered predictors. The overall regression model was statistically significant and explained a substantial proportion of variance in longitudinal techno-stress, $R^2 = .54$, $F(5, 376) = 42.15$, $p < .001$.

Table 2: Regression Results for Hayes PROCESS Model 2 (Outcome: Techno-Stress)

Predictor	b	SE	t	p
Constant	3.78	0.04	94.50	<.001
AI Integration Intensity (X)	0.35	0.05	7.00	<.001
Digital Tier Divide (W)	0.22	0.04	5.50	<.001
Techno-Resilience (Z)	-0.28	0.05	-5.60	<.001
X × W	0.18	0.04	4.50	<.001
X × Z	-0.14	0.03	-4.66	<.001

The main effect of AI integration intensity on techno-stress was positive and significant, confirming that sustained AI use increases teachers' stress levels over time (H_1 supported). The Digital Tier Divide also demonstrated a significant positive main effect, indicating that teachers in lower-resource institutional contexts experience higher baseline stress. In contrast, techno-resilience showed a significant negative main effect, confirming its role as a psychological buffer.

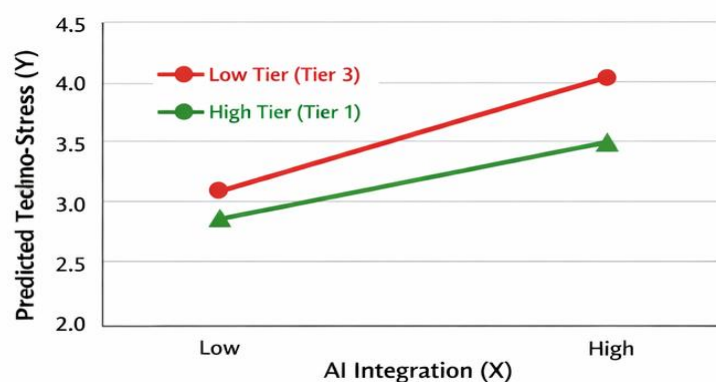


Figure 2. Digital Tier Divide: Moderation Effect of Digital Tier (W)

4.3 Interpretation of Interaction Effects and Conditional Patterns

Both interaction terms were statistically significant, confirming the presence of dual moderation effects. The AI Integration $\times$ Digital Tier Divide interaction was positive, indicating that the stress-inducing effect of AI integration becomes significantly stronger as institutional resources decline. Teachers working in low-resource schools experienced a sharper increase in techno-stress as AI demands intensified, supporting H₂. Conversely, the AI Integration $\times$ Techno-Resilience interaction was negative, demonstrating that teachers with higher techno-resilience were substantially protected against the stress effects of increased AI usage. Even at high levels of AI integration, resilient teachers reported comparatively lower stress, supporting H₃. To synthesize these effects, conditional patterns were examined by comparing extreme groups.

Table 3: Conditional Patterns of Techno-Stress across Contextual and Personal Conditions

Condition	Observed Stress Pattern
Low Digital Tier + Low Techno-Resilience	Highest techno-stress; steep stress escalation
Low Digital Tier + High Techno-Resilience	Moderate stress; resilience partially offsets infrastructural strain
High Digital Tier + Low Techno-Resilience	Moderate stress; infrastructure buffers some demands
High Digital Tier + High Techno-Resilience	Lowest stress; strongest protective configuration

These conditional patterns confirm H₄ and illustrate that the most vulnerable group consists of teachers operating in low-resource institutional environments who also lack sufficient techno-resilience. Conversely, the combination of strong institutional support and high personal resilience produces the most adaptive outcomes.

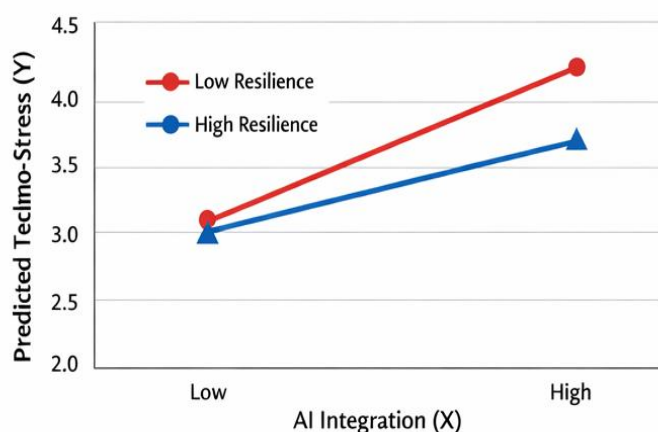


Figure 3. Resilience Buffer: Moderation Effect of Techno-Resilience (Z)

Table 4: Summary of Hypothesis Testing

Hypothesis	Statement	Result
H ₁	AI integration intensity positively predicts techno-stress	Supported
H ₂	Digital Tier Divide moderates the AI–techno-stress relationship	Supported
H ₃	Techno-resilience moderates the AI–techno-stress relationship	Supported
H ₄	Combined effects of Digital Tier Divide and techno-resilience produce differential stress outcomes	Supported

Overall, the results provide strong empirical support for the JD–R–informed dual moderation framework and validate the use of Hayes PROCESS Model 2 for understanding longitudinal techno-stress in AI-integrated early childhood education contexts.

5: Discussion, Policy Implications, and Conclusion

5.1 Discussion of Findings

This study set out to examine how AI integration influences techno-stress among early childhood educators in Pakistan, and how this relationship is shaped by structural and personal resources. Using a three-wave longitudinal design and Hayes’ PROCESS Model 2, the findings provide robust empirical support for the Job Demands–Resources (JD-R) framework in AI-integrated educational environments.

5.1.1 AI Integration as a Job Demand: The AI–Stress Paradox

The findings demonstrate that AI-integration intensity at Time 1 significantly predicts increased techno-stress at Time 3. This result confirms Hypothesis 1 and supports JD-R theory, which posits that stress emerges when job demands exceed available resources (Bakker & Demerouti, 2017). Although AI technologies are often promoted as efficiency-enhancing tools, the results indicate that, in practice, they are currently functioning primarily as *job demands* for ECE teachers rather than as job resources. This phenomenon reflects what may be described as an AI–stress paradox. While AI tools streamline lesson planning, assessment design, and administrative tasks, the time saved is rapidly reabsorbed by heightened institutional expectations. Similar findings have been reported in AI-enabled work environments, where technological efficiency leads to work intensification rather than workload reduction (Wang et al., 2023; Selwyn, 2016). In the competitive educational ecosystems of Lahore and Islamabad, AI adoption appears to have created a “productivity treadmill,” wherein teachers must continuously produce more sophisticated outputs to remain professionally viable.

5.1.2 The Digital Tier Divide as a Structural Stress Multiplier

The Digital Tier Divide significantly moderated the relationship between AI integration and techno-stress, confirming Hypothesis 2. Teachers working in low-resource institutions experienced substantially stronger stress responses as AI use increased. This finding underscores the structural nature of techno-stress in developing contexts and reinforces the JD-R assertion that the absence of organizational resources amplifies the psychological impact of job demands. In high-resource schools particularly elite private institutions in Islamabad stable internet connectivity, premium AI subscriptions, and technical support appear to buffer teachers from infrastructural anxiety. Conversely, in low-resource schools, especially in peri-urban areas of Lahore, AI integration is accompanied by persistent uncertainty related to power outages, limited devices, and unreliable connectivity. Under such conditions, AI ceases to be a pedagogical aid and becomes a source of *techno-insecurity*, a stressor rooted in systemic inequity rather than individual competence. These findings align with prior research demonstrating that technology implementation without adequate infrastructural readiness intensifies educator stress and burnout (Hwang et al., 2020; van Dijk, 2020). The results therefore reinforce the principle that technology without infrastructure constitutes a liability rather than an innovation.

5.1.3 Techno-Resilience as a Psychological Buffer

The moderating role of techno-resilience provides one of the most significant contributions of this study. Consistent with Hypothesis 3, teachers with higher levels of techno-resilience exhibited a weaker relationship between AI integration and techno-stress. Even within low-resource environments, resilient teachers demonstrated significantly lower stress trajectories over time. This finding supports resilience and psychological capital literature, which emphasizes the protective role of self-efficacy, adaptability, and cognitive flexibility in technology-rich work settings (Luthans et al., 2015; Qayyum, 2019). Importantly, techno-resilience in AI contexts extends beyond general optimism or patience. It encompasses the ability to manage technological ambiguity, recover from system failures, and adapt pedagogical strategies when AI tools malfunction or generate unreliable outputs. The results suggest that while infrastructural reform is a long-term national challenge, psychological empowerment of teachers represents an immediately actionable intervention. This aligns with emerging evidence that targeted digital resilience training can significantly reduce technology-induced stress among educators (Khan & Ahmed, 2025).

5.1.4 Joint Moderation Effects and Vulnerability Profiles

The combined moderation effects of the Digital Tier Divide and techno-resilience confirm Hypothesis 4 and validate the use of Hayes' PROCESS Model 2. The highest levels of techno-stress were observed among teachers operating in low-resource institutions who also exhibited low techno-resilience. This subgroup represents the most vulnerable population within AI-driven educational reforms. Theoretically, this finding extends the JD-R model by demonstrating that stress outcomes in AI-integrated environments are shaped by both contextual constraints and individual adaptive capacity. Practically, it highlights the danger of one-size-fits-all AI adoption policies that ignore institutional disparities and teacher preparedness.

5.2 Policy Implications: From AI Adoption to Teacher Well-Being

The findings carry important implications for education policymakers, school administrators, and teacher training institutions in Pakistan.

5.2.1 Institutionalizing Techno-Wellness Protocols

Current AI initiatives emphasize technical proficiency but neglect psychological boundaries. Policymakers should mandate techno-wellness protocols, including digital boundary management policies that regulate after-hours connectivity and limit techno-invasion. Training programs should explicitly address stress management, workload expectations, and healthy AI use practices rather than focusing solely on tool operation.

5.2.2 Addressing Structural Inequality through Tiered Infrastructure Support

To mitigate the Digital Tier Divide, government agencies and private education boards should introduce tiered AI infrastructure subsidies for low- and mid-resource schools. These may include subsidized high-speed internet access, classroom-level power backup systems, and shared AI licenses. Without such structural investment, AI mandates risk deepening existing educational inequalities.

5.2.3 Embedding Techno-Resilience in Teacher Education

Teacher certification and professional development programs should formally integrate techno-resilience as a core competency. Pre-service and in-service training should include modules on

adaptive technology use, failure-mode pedagogy, and ethical decision-making in AI-supported classrooms. Such initiatives would equip teachers with the psychological tools required to navigate AI uncertainty with confidence.

5.3 Limitations and Directions for Future Research

Despite its strengths, this study has several limitations. First, the sample was restricted to urban centers in Punjab and the Islamabad Capital Territory, limiting generalizability to rural regions. Second, the study relied on self-reported measures, which may be influenced by response bias. Future research should extend this model to other provinces and conduct cross-national comparisons within South Asia. Additionally, examining student-level outcomes particularly the socio-emotional effects of teacher techno-stress in early childhood classrooms would provide a more holistic understanding of AI's educational impact.

5.4 Conclusion

This study demonstrates that the success of AI integration in early childhood education depends less on algorithmic sophistication and more on the systems and people responsible for implementation. AI, when introduced without adequate infrastructure and psychological support, becomes a source of chronic stress rather than innovation. However, by addressing the Digital Tier Divide and fostering techno-resilience, educational systems can transform AI from a stress-inducing demand into a sustainable pedagogical resource. By foregrounding teacher well-being, Lahore and Islamabad have the potential to model an ethically grounded and human-centered approach to AI adoption one that prioritizes resilience, equity, and long-term educational sustainability.

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