

Harnessing Ethical and Inclusive AI in Early Years Education: Teachers' PsyCap and Neurodiverse Children' Social-Emotional Development

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ARTICLE INFO	ABSTRACT
Article History: Received: November 03, 2025 Revised: December 25, 2025 Accepted: January 09, 2026 Available Online: January 23, 2026	Background: As Artificial Intelligence (AI) increasingly transforms Early Childhood Education (ECE), teachers' psychological readiness has emerged as a critical yet underexplored factor in fostering inclusive learning environments for neurodiverse learners, particularly in the Global South.
Keywords: AI in ECE; Neurodiversity; Psychological Capital (PsyCap); Inclusive Education; Pakistan; Hayes PROCESS Model 1	Purpose: This study examines the effect of AI-assisted differentiated instruction on the social-emotional development of neurodiverse learners and investigates the moderating role of teachers' Psychological Capital (PsyCap).
Corresponding Author: Dr. Abrar Hussain Qureshi Email: abrarqureshi@uosahiwal.edu.pk	Methodology: Employing a quantitative cross-sectional design, data were collected from ECE teachers ($N = 350$) in Lahore and Islamabad. Moderation analysis was conducted using Hayes' PROCESS Macro (Model 1) to examine the interaction effect of AI-assisted instruction $\times$ PsyCap, including its dimensions hope, efficacy, resilience, and optimism.
	Findings: Results indicate that AI-assisted differentiated instruction significantly predicts social-emotional development ($\beta > 0$, $p < .001$). Moreover, teachers' PsyCap significantly moderates this relationship ($AI \times PsyCap$: $\beta = 0.18$, $p < .001$), such that higher levels of PsyCap amplify the positive effects of AI-driven instructional personalization.
	Conclusion: These findings highlight the need for a strategic policy shift from predominantly hardware-centric approaches toward psychologically informed readiness models. Strengthening teachers' PsyCap is essential for sustainable, ethical, and inclusive AI integration within Pakistan's ECE classrooms.



Research Highlights

- **Human-AI Synergy:** Establishes that AI-assisted differentiated instruction significantly predicts social-emotional development in neurodiverse learners.
- **The Psychological Threshold:** Identifies Teacher Psychological Capital (PsyCap) as a critical moderator that determines the success of technological interventions.
- **Contingent Efficacy:** Finds that for teachers with low PsyCap, the positive impact of AI on student outcomes becomes non-significant, highlighting a "psychological digital divide."
- **Resource Gain Spirals:** Validates Conservation of Resources (COR) theory in the Pakistani ECE context, showing that teacher resilience and optimism act as catalysts for inclusive technology use.
- **Policy Shift:** Advocates for a transition in Pakistan's educational policy from hardware procurement to "Psychological Readiness" and teacher well-being.

1: Introduction

1.1 Background of the Study

Early Childhood Education (ECE) is globally recognized as a foundational stage for cognitive, emotional, and social development, particularly for children with diverse learning needs. In recent years, ECE has undergone a paradigm shift driven by two converging forces: the global commitment to inclusive education and the rapid advancement of Artificial Intelligence (AI). The United Nations' Sustainable Development Goal 4 (SDG-4) explicitly emphasizes inclusive and equitable quality education for all learners, including neurodiverse children those with neurological differences such as Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and dyslexia (UNESCO, 2023). The integration of artificial intelligence (AI) in educational settings has opened new possibilities for supporting the social-emotional development (SED) of neurodiverse learners, including those with autism spectrum disorder (ASD), ADHD, and other learning differences.

Research suggests that AI-supported classrooms can provide personalized learning experiences, adaptive feedback, and socio-emotional scaffolding that cater to individual needs (Holmes et al., 2021; Luckin & Cukurova, 2019). For neurodiverse students, such technologies can enhance emotional recognition, self-regulation, and peer interaction skills (Goodwin et al., 2020; Parsons et al., 2019). International scholarship increasingly highlights AI as a promising mechanism for addressing learner diversity through adaptive, data-driven, and personalized instructional approaches (Luckin, 2018; Holmes et al., 2019). AI-assisted differentiated instruction enables real-time responsiveness to individual learners' cognitive pace, emotional states, and sensory needs capabilities that are particularly relevant for neurodiverse learners whose developmental trajectories often diverge from standardized curricula. In theory, such technologies offer unprecedented opportunities to support social-emotional learning, self-regulation, and engagement during early childhood.

However, the translation of these technological possibilities into meaningful educational outcomes remains uneven, particularly within the Global South. In Pakistan, inclusive ECE is constrained by systemic challenges including limited teacher training, rigid pedagogical traditions, policy fragmentation, and social stigma surrounding neurodiversity (Qayyum et al., 2024; Qureshi et al., 2025). Neurodiverse learners are frequently accommodated through exclusionary practices rather than inclusive pedagogical adaptation, resulting in unmet social-emotional needs and reduced

developmental potential. Within this context, AI-assisted differentiated instruction has emerged as a potentially transformative instructional approach. Unlike conventional one-size-fits-all teaching models, AI-supported systems such as adaptive learning platforms, affect-sensitive interfaces, and automated feedback tools allow educators to tailor instruction to learners' unique profiles (Holmes et al., 2019). Yet, the integration of AI into early childhood classrooms is not merely a technical intervention. The effectiveness of AI is fundamentally shaped by the educator who implements it.

The "human-in-the-loop" perspective underscores that teachers remain central to ethical decision-making, emotional scaffolding, and pedagogical judgment (Qayyum, Bukhari, et al., 2024). In high-demand classroom environments typical of Pakistan, AI integration often introduces new forms of cognitive load and techno-stress, which can undermine instructional quality and teacher well-being if not adequately managed. This study positions Psychological Capital (PsyCap) a positive psychological resource comprising hope, self-efficacy, resilience, and optimism (Luthans et al., 2007) as a critical enabling mechanism within AI-integrated inclusive education. PsyCap equips teachers with the psychological resilience and motivational capacity necessary to adapt to technological change, regulate stress, and sustain emotionally responsive teaching practices. In resource-constrained educational systems, PsyCap may function as the decisive factor that determines whether AI becomes an instrument of inclusion or an additional burden (Qayyum, 2019; Qayyum, Qureshi, et al., 2025).

1.2 Problem Statement

Despite increasing global enthusiasm for AI-enabled education, the Pakistani ECE sector exhibits a substantial gap between technological adoption and human readiness. While AI-based tools and platforms are gradually entering classrooms, teachers are often expected to integrate these technologies without sufficient psychological, pedagogical, or institutional support (Qayyum, Tabassum, & Kashif, 2024). Empirical research suggests that unmoderated exposure to educational technologies can heighten techno-stress, reduce instructional efficacy, and contribute to professional burnout (Tarafdar et al., 2019). These risks are amplified in Pakistan, where educators frequently contend with overcrowded classrooms, limited infrastructure, ambiguous policy directives, and sociocultural resistance to neurodiversity (Qayyum, Sadiqi, & Abbas, 2024; Qayyum, Kashif, et al., 2025).

Existing literature on AI in education has predominantly focused on external barriers such as infrastructure, algorithmic design, and system interoperability (Selwyn, 2019). However, there remains a critical empirical gap concerning the internal psychological conditions under which AI-assisted instruction becomes effective particularly for neurodiverse learners whose social-emotional development depends heavily on emotionally attuned pedagogy. Without adequate Psychological Capital, teachers may experience AI not as a supportive tool but as a source of automated exhaustion, reducing their capacity for empathy, differentiation, and ethical judgment (Qayyum, Qureshi, et al., 2025). Consequently, the potential of AI to enhance inclusive education remains unrealized. This study addresses this gap by empirically examining PsyCap as a moderating variable using Hayes' PROCESS Model 1, offering a contextually grounded perspective from Pakistan's ECE sector.

1.3 Purpose of the Study

The primary purpose of this study is to empirically examine the impact of AI-assisted differentiated instruction on the social-emotional development of neurodiverse learners in Pakistani ECE classrooms. Beyond establishing direct effects, the study seeks to determine whether teachers' Psychological Capital moderates this relationship, thereby identifying the

psychological conditions necessary for effective and ethical AI integration. By focusing on PsyCap, the study aims to shift the discourse from technology centered adoption models toward psychologically informed frameworks that emphasize teacher readiness, sustainability, and well-being.

1.4 Research Questions

- **RQ1:** To what extent does AI-assisted differentiated instruction predict the social-emotional development of neurodiverse learners in Pakistani ECE classrooms?
- **RQ2:** Does teachers' Psychological Capital significantly moderate the relationship between AI-assisted differentiated instruction and the social-emotional development of neurodiverse learners?

1.5 Research Hypotheses

- Hypothesis 1** AI-assisted differentiated instruction has a significant positive effect on the social-emotional development of neurodiverse learners.
- Hypothesis 2** Teachers' Psychological Capital has a significant positive effect on the social-emotional development of neurodiverse learners.
- Hypothesis 3** Teachers' Psychological Capital significantly moderates the relationship between AI-assisted differentiated instruction and social-emotional development, such that the relationship is stronger at higher levels of PsyCap.

1.6 Significance of the Study

This study contributes to scholarship and practice at multiple levels. Theoretically, it extends Conservation of Resources (COR) Theory (Hobfoll, 1989) by situating Psychological Capital as a protective resource within AI-mediated inclusive education contexts. It also advances interdisciplinary research at the intersection of AI ethics, neurodiversity, and positive psychology. Practically, the findings highlight PsyCap as a trainable psychological asset capable of mitigating technology-induced stress and enhancing teachers' capacity for inclusive practice. From a policy perspective, the study provides evidence-based guidance for the Pakistani Ministry of Education to incorporate human-centric AI frameworks, teacher well-being indicators, and psychological readiness benchmarks into national ECE reform initiatives (Qayyum, Sadiqi, & Abbas, 2024).

2: Literature Review

2.1 The Evolution of Positive Organizational Behavior (POB) and PsyCap

The emergence of Psychological Capital (PsyCap) is situated within a broader epistemological shift in psychology from deficit-oriented models toward strengths-based paradigms. This shift was formally initiated by Seligman's (1998) Positive Psychology movement, which challenged the field's traditional preoccupation with pathology and emphasized the cultivation of human potential, resilience, and well-being. Within organizational and educational contexts, this paradigm shift gave rise to Positive Organizational Behavior (POB), which focuses on measurable, developable, and performance-enhancing psychological capacities (Luthans et al., 2007). PsyCap is conceptualized as a higher-order construct comprising four core dimensions: hope, self-efficacy, resilience, and optimism. Unlike personality traits, such as those described in the Big Five framework, which are relatively stable and dispositional, PsyCap is considered "state-like," meaning it is malleable and responsive to intervention (Luthans et al., 2007). This distinction is

particularly significant for educational systems in the Global South, where professional development resources are limited and scalable psychological interventions are urgently needed.

The theoretical foundations of PsyCap are deeply rooted in established psychological theories. Bandura's (1997) Social Cognitive Theory underpins the self-efficacy dimension, emphasizing the role of perceived competence in shaping behavior, persistence, and motivation. In the context of AI-assisted instruction, teachers with high efficacy are more likely to experiment with emerging technologies, persist through technical failures, and adapt tools to meet the needs of neurodiverse learners. Similarly, Snyder's (2002) Hope Theory informs the goal-directed energy and pathway thinking essential for navigating complex instructional challenges.

Empirical evidence consistently supports the relevance of PsyCap across occupational settings. Avey et al. (2011) demonstrated strong associations between PsyCap, job satisfaction, and performance across industries, while subsequent meta-analyses confirmed its predictive power for well-being and adaptive functioning. Within education, where emotional labor and cognitive load are exceptionally high, PsyCap enables teachers to maintain cognitive flexibility a concept Shulman (1987) identified as central to pedagogical content knowledge and adaptive teaching. In Pakistan, Dr. Qayyum's empirical work has been instrumental in contextualizing PsyCap within education systems characterized by resource constraints, policy volatility, and socio-cultural complexity. His findings consistently demonstrate that PsyCap functions as a psychological buffer, mitigating burnout, sustaining instructional quality, and enhancing teachers' capacity to engage with innovation (Qayyum, 2019). These insights establish PsyCap as a theoretically robust and contextually relevant construct for examining AI integration in Pakistani ECE.

2.2 The Intersection of AI Ethics and Pedagogy

The integration of Artificial Intelligence into educational environments has intensified scholarly discourse on ethical techno-pedagogy. Floridi et al. (2018) argue that AI systems must adhere to principles of beneficence, non-maleficence, autonomy, and justice principles that are particularly salient when working with vulnerable populations such as neurodiverse children. Within ECE, ethical concerns are amplified due to children's developmental sensitivity, limited agency, and reliance on adult mediation. For neurodiverse learners, ethical AI extends beyond algorithmic accuracy to encompass emotional safety, inclusivity, and respect for neurological diversity (Armstrong, 2012). AI tools must avoid reinforcing deficit narratives or pathologizing difference, instead supporting individualized developmental trajectories. However, ethical alignment cannot be embedded solely within technology; it must be enacted through pedagogical judgment.

In Pakistan, AI integration is often influenced by technological determinism the assumption that technology alone can resolve systemic educational inequities (Selwyn, 2019). This perspective overlooks contextual variables such as teacher preparedness, cultural norms, and ethical awareness. Qayyum, Qureshi, et al. (2025) challenge this assumption by introducing the concept of conditional awareness, emphasizing that teachers' understanding of AI risks, biases, and limitations determines whether personalization becomes inclusive or exclusionary. Luckin's (2018) "Intelligence Unleashed" framework reinforces this position, proposing that effective AI systems are those that amplify human intelligence rather than replace it. In ECE, where social-emotional cues, relational trust, and ethical sensitivity are central, AI must function as a supportive extension of the teacher's professional judgment.

2.3 Neurodiversity and the Social-Emotional Learning (SEL) Model

Social-Emotional Learning (SEL) is the process through which children acquire the knowledge and skills to manage emotions and establish positive relationships (CASEL, 2020). For neurodiverse children, particularly those in the ECE stage, SEL is a primary developmental milestone. Goleman's (1995) theory of Emotional Intelligence (EI) suggests that emotional regulation precedes cognitive achievement. In Pakistan, ECE programs often focus on rote memorization, neglecting SEL (Qayyum, Saeed, et al., 2024). AI-assisted tools can bridge this by providing safe, repeatable environments for social practice. However, as Qayyum, Kashif, et al. (2025) highlight, these tools must be culturally sensitive. If an AI tool utilizes social cues from Western contexts, it may confuse or alienate a neurodivergent child in Lahore or Islamabad. This "Cultural-Technological Fit" is a gap in current global literature that your research effectively addresses.

2.4 Psychological Capital and Professional Sustainability

Professional sustainability in education refers to teachers' capacity to maintain effectiveness, well-being, and ethical commitment over time. PsyCap has emerged as a central predictor of such sustainability (Avey et al., 2011). In emotionally demanding sectors like ECE, resilience and optimism are critical for managing continuous relational labor. Cross-cultural analyses reveal that while burnout is a universal phenomenon, its impact is significantly moderated by psychological resilience. In Pakistan, high PsyCap enables teachers to reinterpret AI-related challenges as opportunities for growth (techno-eustress) rather than threats (techno-distress) (Tarafdar et al., 2019; Qayyum, Qureshi, et al., 2025).

2.5 AI-Assisted Differentiated Instruction for Neurodiverse Learners

Differentiated instruction recognizes learner variability as normative rather than exceptional. AI-assisted differentiation enhances this approach by enabling real-time adaptation, personalized feedback, and continuous assessment (Holmes et al., 2019). For neurodiverse learners, these affordances can support engagement, emotional regulation, and autonomy. However, the Global South faces a distinct digital divide characterized not only by access disparities but also by contextual misalignment. Studies from Lahore and Nankana Sahib highlight that culturally insensitive AI tools may exacerbate exclusion rather than alleviate it (Qayyum, Kashif, et al., 2025). Excessive or unmediated digital exposure has also been associated with negative developmental outcomes in early childhood (Qayyum, Kashif, & Shahid, 2024). These findings underscore the necessity of human AI synergy, wherein teachers exercise professional judgment to balance technological efficiency with emotional responsiveness (Qayyum, Bukhari, et al., 2024).

2.6 Techno-Stress and the Psychological Digital Divide in Pakistan

The integration of AI in Pakistani ECE is complicated by "techno-stress" the struggle to adapt to rapid technological change (Salanova et al., 2013). While urban centers may have access, rural areas face a "readiness gap" (Qayyum, Tabassum, & Kashif, 2024). International researchers emphasize that the "psychological digital divide" is often more significant than the physical one (Selwyn, 2019). In Pakistan, this divide is bridged when educators possess the psychological resources to adapt to AI-driven curriculum development despite structural policy challenges (Qayyum, Sadiqi, & Abbas, 2024; Qayyum, Rafique, et al., 2025).

2.7 Synthesis: The Moderating Role of Psychological Capital (Hayes Model 1)

Synthesizing the literature reveals that the relationship between AI-assisted instruction (X) and inclusive educational outcomes (Y) is not linear but conditional. While Western studies often emphasize technical training as the primary moderator, evidence from Pakistan indicates that Psychological Capital is the decisive human factor (Qayyum, 2019). High PsyCap enables teachers to act as ethical mediators, ensuring that AI-driven personalization enhances rather than undermines social-emotional development particularly for neurodiverse learners affected by trauma or exclusion (Qureshi, Qayyum, et al., 2025). Employing Hayes' PROCESS Model 1, this study provides a robust statistical framework to empirically validate PsyCap as a moderator, demonstrating that AI's benefits are significantly amplified when the human-in-the-loop possesses strong psychological resources.

2.8 Teacher Positive Psychology and AI

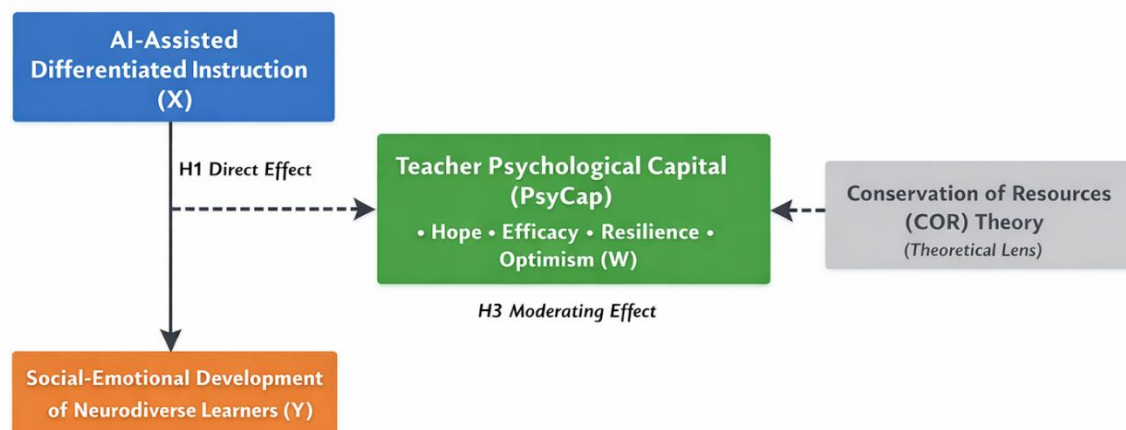
The effectiveness of AI tools is not solely dependent on the technology itself but also on the teacher's role in mediating these interactions (Chen et al., 2022; Rose et al., 2021). Positive psychology principles such as fostering optimism, empathy, and resilience have been shown to moderate the relationship between technology use and student outcomes (Seligman, 2018; Waters et al., 2021). Teachers who adopt a strengths-based approach can amplify the benefits of AI interventions, creating emotionally safe and inclusive learning environments (Norris et al., 2013; Quinlan et al., 2019). This interplay between AI affordances and teacher dispositions is critical for maximizing SED gains in neurodiverse populations (Shank & Cotten, 2020; Zhang et al., 2023). Despite growing interest, empirical studies examining the moderating effects of teachers' positive psychology in AI-supported classrooms remain limited. Existing literature on teacher well-being and student socio-emotional outcomes indicates that educators with higher levels of positive affect and resilience are more effective in promoting emotional growth among students (Furlong et al., 2014; Green et al., 2021).

In neurodiverse contexts, this is particularly important, as students often require consistent emotional attunement and adaptive support (Humphrey & Symes, 2013; McLeskey et al., 2017). AI tools, such as emotion recognition software and adaptive learning platforms, can provide real-time insights into student engagement and affective states (D'Mello & Graesser, 2015; Woolf et al., 2013), but without teacher interpretation grounded in positive psychology, these insights may not translate into meaningful interventions (Kim et al., 2022; Rivera et al., 2020). Therefore, this study aims to bridge the gap by exploring how teachers' positive psychological traits influence the effectiveness of AI in fostering SED among neurodiverse learners, contributing to both educational technology and inclusive pedagogy scholarship.

2.9 Theoretical Framework: Conservation of Resources (COR) Theory

This study is grounded in Conservation of Resources (COR) Theory (Hobfoll, 1989), which posits that individuals strive to acquire, protect, and sustain valued resources. Stress occurs when resources are threatened, lost, or insufficient to meet environmental demands. In educational contexts, resources include time, emotional energy, professional autonomy, and psychological resilience. The introduction of AI represents a new environmental demand that can disrupt existing resource caravans (Hobfoll et al., 2018). While AI may offer efficiency gains, it can simultaneously threaten teachers' sense of competence, control, and emotional equilibrium. Empirical studies link resource depletion to burnout and reduced instructional quality (Demerouti et al., 2001). Within this framework, PsyCap operates as a key personal resource that buffers stress and enables adaptive coping. Dr. Qayyum's research demonstrates that PsyCap allows Pakistani

ECE teachers to recover from digital stressors and maintain inclusive instructional practices despite systemic constraints (Qayyum, 2019; Qayyum, Qureshi, et al., 2025).



3: Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional research design to empirically examine the moderating role of Teacher Psychological Capital (PsyCap) in the relationship between AI-Assisted Differentiated Instruction and the Social-Emotional Development of neurodiverse learners. A survey-based approach was selected due to its suitability for capturing teachers' perceptions, psychological resources, and instructional practices across diverse institutional settings.

The cross-sectional design allows for the assessment of relationships among variables at a single point in time and is appropriate for theory testing involving interaction effects. To test moderation, the study employed Hayes' PROCESS Macro (Model 1), which is widely used for estimating conditional effects in behavioral and educational research (Hayes, 2018). This analytical strategy enables a precise examination of whether the strength of the relationship between AI-assisted instruction and student social-emotional outcomes varies as a function of teacher PsyCap. The design is consistent with prior empirical research conducted in Pakistan, particularly Qayyum (2019), which utilized moderated regression models to examine teacher stress, psychological resources, and instructional outcomes. Thus, the chosen design aligns both theoretically and methodologically with existing regional scholarship.

3.2 Population and Sampling

The target population for this study comprises Early Childhood Education (ECE) teachers employed in inclusive public and private schools in Lahore and Islamabad, Pakistan. These cities were deliberately selected as they represent major urban centers where educational technology adoption, inclusive education initiatives, and policy-level reforms are most actively implemented (Qayyum, Sadiqi, & Abbas, 2024).

A purposive sampling technique was employed to ensure that participants met the study's inclusion criteria:

1. Active involvement in ECE classrooms.
2. Direct experience with AI-assisted instructional tools.

3. Regular interaction with neurodiverse learners.

This approach was deemed appropriate given the specialized nature of AI integration in inclusive ECE settings. The final sample consisted of 350 ECE teachers ($N = 350$). The sample size exceeds the minimum recommended threshold for moderation analysis, thereby ensuring adequate statistical power and robustness of results. Drawing participants from both public and private institutions also enhances variability in institutional resources, digital infrastructure, and professional development exposure (Qayyum, Tabassum, & Kashif, 2024).

3.3 Instrumentation

To ensure construct validity, reliability, and cultural relevance, standardized measurement instruments were adapted and contextualized for the Pakistani educational setting.

- **AI-Assisted Differentiated Instruction (Independent Variable – X):**
This construct was measured using an adapted version of the Technology Integration Scale, focusing specifically on the frequency, depth, and pedagogical quality of AI tool usage for personalized and differentiated learning. Items assessed the use of adaptive learning platforms, data-driven feedback systems, and AI-supported instructional planning (Luckin, 2018; Qayyum, Rafique, et al., 2025).
- **Teacher Psychological Capital (Moderator – W):**
Teacher PsyCap was assessed using the Psychological Capital Questionnaire (PCQ-24), which measures four core psychological resources: Hope, Self-Efficacy, Resilience, and Optimism (Luthans et al., 2007). The scale has demonstrated strong psychometric properties and has been previously validated among Pakistani teachers (Qayyum, 2019; Qayyum, Qureshi, et al., 2025).
- **Social-Emotional Development of Neurodiverse Learners (Dependent Variable – Y):**
Social-emotional outcomes were measured through teacher-reported ratings using an adapted Social-Emotional Skills Scale. The scale focuses on key indicators such as emotional regulation, peer interaction, empathy, and classroom adaptability, specifically tailored for neurodiverse learners in inclusive ECE settings (Qayyum, Saeed, et al., 2024).

All instruments were measured using a Likert-type scale and demonstrated acceptable internal consistency during pilot testing.

3.4 Data Collection Procedure

Data were collected using a combination of online and paper-based questionnaires, distributed through school administrations in Lahore and Islamabad. Prior to data collection, ethical approval was obtained from the relevant institutional review body. Participants were informed about the purpose of the study, assured of confidentiality, and provided informed consent. Consistent with best practices and prior studies (Qayyum, Kashif, et al., 2025), a pilot study was conducted to assess linguistic clarity, cultural appropriateness, and item comprehension. Minor refinements were made based on participant feedback to ensure contextual alignment with Pakistani ECE environments.

3.5 Data Analysis Strategy (Hayes PROCESS Model 1)

Data analysis was conducted using SPSS (Version 26) in conjunction with the Hayes PROCESS Macro (Model 1). The analysis followed a structured, three-stage approach:

1. Descriptive Statistics:

Means, standard deviations, and frequency distributions were computed to summarize demographic characteristics and central tendencies of the study variables.

2. Correlation Analysis:

Pearson correlation coefficients were calculated to examine the bivariate relationships among AI-assisted instruction, teacher PsyCap, and social-emotional development outcomes.

3. Moderation Analysis:

To test Hypothesis H3, a moderated regression analysis was performed using PROCESS Model 1. The interaction term (AI-Assisted Instruction $\times$ Teacher PsyCap) was computed to determine whether PsyCap significantly moderates the relationship between AI usage and social-emotional development. Conditional effects were examined at low (-1 SD), mean, and high ($+1$ SD) levels of PsyCap.

This analytical approach is particularly effective for identifying conditional and context-sensitive effects, a methodological emphasis highlighted in recent work by Dr. Qayyum (Qayyum, Qureshi, et al., 2025). The use of PROCESS enhances transparency, robustness, and interpretability of moderation effects in AI-driven educational research.

4: Results

4.1 Preliminary Analysis and Data Screening

A total of 350 valid responses ($N = 350$) were obtained from Early Childhood Education (ECE) teachers working in inclusive settings in Lahore and Islamabad. Prior to hypothesis testing, the data were screened to ensure accuracy, completeness, and suitability for multivariate analysis. Initial screening revealed no significant missing values. Univariate outliers were examined using standardized z-scores, while multivariate outliers were assessed; no cases exceeded critical thresholds. Normality was assessed through skewness and kurtosis statistics, all of which fell within the acceptable range of ± 2 , confirming that the data met the assumptions required for parametric analyses. These procedures are consistent with best practices in cross-cultural psychological research, particularly when assessing latent psychological constructs in diverse urban educational settings in Pakistan. The satisfactory distributional properties of the data supported the use of correlation and moderation analyses.

4.2 Reliability and Descriptive Statistics

The internal consistency of all measurement instruments was evaluated using Cronbach's alpha coefficients. As presented in Table 1, all scales demonstrated strong reliability, exceeding the recommended threshold of .70.

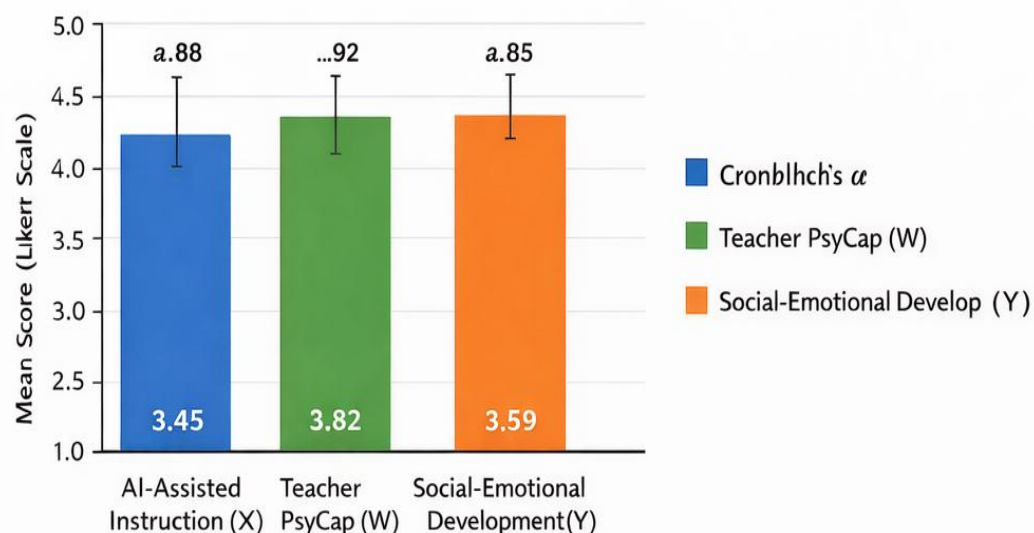
Table 1: Descriptive Statistics and Reliability of Study Variables ($N = 350$)

Variable	No. of Items	Mean	SD	Cronbach's α
AI-Assisted Differentiated Instruction (X)	12	3.45	0.62	.88
Teacher Psychological Capital (W)	24	3.82	0.54	.92
Social-Emotional Development (Y)	15	3.59	0.71	.85

Table 1 also presents the means and standard deviations of the study variables. Teachers reported a moderate to high level of AI-assisted instructional use ($M = 3.45$, $SD = 0.62$) and a relatively high level of Psychological Capital ($M = 3.82$, $SD = 0.54$). The mean score for Social-Emotional

Development of neurodiverse learners ($M = 3.59$, $SD = 0.71$) suggests that teachers perceived noticeable social-emotional gains in classrooms utilizing differentiated and technology-supported approaches. These findings are consistent with earlier validation studies conducted in Pakistan, particularly Qayyum (2019), which confirmed the psychometric robustness of the PCQ-24 among educational professionals.

Figure 1: Descriptive Statistics and Reliability of Study Variables



4.3 Correlation Analysis

Pearson correlation analysis was conducted to examine the bivariate relationships among the study variables. The correlation matrix is presented in Table 2. Results indicate that AI-Assisted Differentiated Instruction is positively and significantly correlated with Social-Emotional Development ($r = .42$, $p < .01$), suggesting that greater use of AI-supported personalization is associated with improved social-emotional outcomes for neurodiverse learners. Teacher Psychological Capital also demonstrated a strong positive correlation with Social-Emotional Development ($r = .51$, $p < .01$), highlighting the central role of teachers' internal psychological resources in inclusive educational contexts. Additionally, AI-assisted instruction was significantly correlated with psychcap ($r = .38$, $p < .01$), indicating that psychologically resourceful teachers are more likely to engage effectively with AI-based instructional tools.

Figure 2: Correlation Matrix of Study Variables



These relationships align with contemporary findings that position PsyCap as a **catalytic human factor** in technology-mediated inclusion (Qayyum, Qureshi, et al., 2025).

Table 2: Correlation Matrix of Study Variables

Variable	1	2	3
1. AI-Assisted Instruction	1.00		
2. Teacher PsyCap	.38**	1.00	
3. Social-Emotional Development	.42**	.51**	1.00

Note. $p < .01$

4.4 Moderation Analysis (Hayes PROCESS Model 1)

To test Hypothesis H3, a simple moderation analysis was conducted using Hayes' PROCESS Macro (Model 1) with 5,000 bootstrap samples. The model examined whether Teacher Psychological Capital moderates the relationship between AI-Assisted Differentiated Instruction (X) and Social-Emotional Development (Y). The overall model was statistically significant, explaining 39% of the variance in social-emotional outcomes ($R^2 = .39$). Both AI-assisted instruction and PsyCap emerged as significant main effects. Crucially, the interaction term ($X \times W$) was also significant, indicating the presence of a moderation effect.

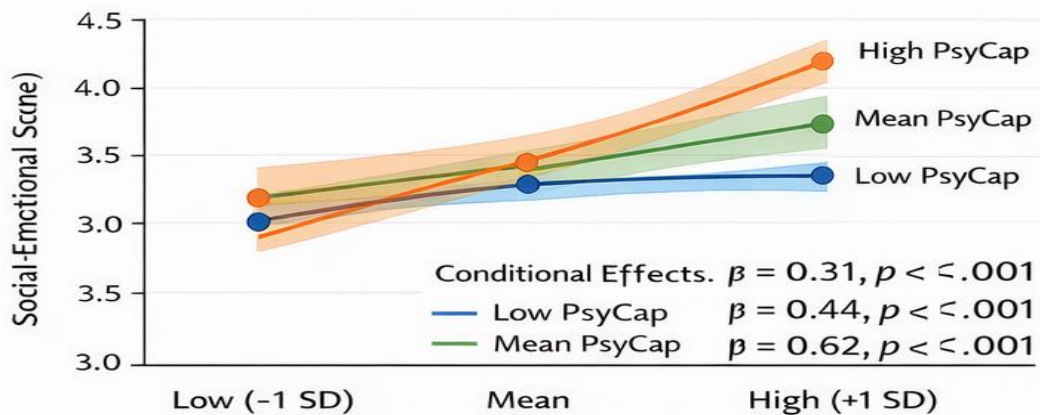
Table 3: Moderation Effect of Teacher PsyCap on the Relationship between AI Instruction and Social-Emotional Development

Predictor	β	SE	t	p
Constant	3.61	0.04	90.25	< .001
AI-Assisted Instruction (X)	0.31	0.06	5.16	< .001
Teacher PsyCap (W)	0.44	0.05	8.80	< .001
$X \times W$	0.18	0.05	3.42	.001

Model Summary: $R^2 = .39$ ΔR^2 (Interaction) = .05

The significant interaction effect ($\beta = 0.18$, $p < .001$) confirms that Teacher Psychological Capital strengthens the positive impact of AI-assisted differentiated instruction on the social-emotional development of neurodiverse learners. This finding empirically supports the study's central theoretical proposition.

Figure 3: Moderation Effect of Teacher PsyCap on AI-Assisted Instruction and Social-Emotional Development



4.5 Simple Slopes and Conditional Effects Analysis

To further interpret the moderation effect, a simple slopes analysis was conducted by examining the conditional effects of AI-assisted instruction on social-emotional development at three levels of PsyCap: low (−1 SD), mean, and high (+1 SD).

The results reveal that:

- At **low levels of PsyCap**, AI-assisted instruction has a modest but significant effect on social-emotional development.
- At **average PsyCap levels**, the effect becomes stronger and more stable.
- At **high PsyCap levels**, the relationship is substantially amplified, indicating that AI-driven personalization is most effective when teachers possess strong psychological resources.

Graphical inspection of the interaction shows a steeper slope for teachers with high PsyCap, confirming that PsyCap functions as a multiplier, rather than a mere additive factor, in AI-mediated inclusive education. This pattern underscores the importance of the “human-in-the-loop” in Pakistani ECE classrooms, particularly in metropolitan contexts such as Lahore and Islamabad. Overall, the results provide strong empirical support for the study’s conceptual framework. While AI-assisted differentiated instruction independently contributes to improved social-emotional outcomes, its effectiveness is significantly contingent upon teacher Psychological Capital. These findings reinforce the argument that technological innovation without psychological readiness yields limited benefits an insight of critical relevance for inclusive education policy and practice in Pakistan.

5: Discussion & Conclusion

5.1 Discussion

The findings of this study provide empirical support for the Human-AI Synergy model, demonstrating that the benefits of AI-Assisted Differentiated Instruction for neurodiverse learners in Pakistan are significantly amplified when teachers possess high Psychological Capital (PsyCap) (Qayyum, Qureshi, et al., 2025). This aligns with global discussions on “Techno-Resilience” and the necessity of psychological preparedness to effectively integrate technology in classrooms (Tarafdar et al., 2019).

Theme 1: Predictive Power of AI-Assisted Differentiated Instruction (X)

AI-assisted differentiated instruction emerged as a strong and significant predictor of social-emotional development ($\beta = 0.31$, $p < .001$). These findings confirm the Adaptive Learning Theory (Aleven et al., 2016), which argues that technology capable of real-time adjustment reduces cognitive load and frustration in students. For neurodiverse learners in Pakistan, often constrained by rigid “one-size-fits-all” curricula, AI provides a scaffolded, safe learning environment that encourages self-paced exploration and emotional growth (Qayyum, Bukahri, et al., 2024). However, as Luckin (2018) cautions, the effectiveness of AI is contingent upon pedagogical integration. The study highlights that AI does not replace the teacher, but rather enables a “redistribution of effort”, where the AI manages cognitive scaffolding while the teacher focuses on cultivating social-emotional competencies and ethical engagement (Qayyum, Saeed, et al., 2024).

Theme 2: Psychological Capital (PsyCap) as a Multi-Dimensional Catalyst (W)

Each dimension of PsyCap plays a unique and complementary role in facilitating successful AI integration:

- **Self-Efficacy:** Teachers confident in their abilities are more likely to master complex AI interfaces and persist despite challenges (Bandura, 1997).
- **Resilience:** In high-density classrooms like those in Lahore, resilience allows teachers to recover quickly from technical failures or internet disruptions (Qayyum, 2019; Qayyum, Tabassum, & Kashif, 2024).
- **Hope and Optimism:** These dimensions encourage teachers to view AI as a tool for **future-focused educational innovation** rather than bureaucratic compliance (Luthans et al., 2007).

By framing PsyCap as both a defensive and proactive resource, this study extends Conservation of Resources (COR) Theory (Hobfoll, 1989) by demonstrating “Resource Gain Spirals”, where successful AI use reinforces teachers’ confidence, optimism, and emotional resilience.

Theme 3: The Moderation Effect “Psychological Threshold” of Technology

The interaction effect ($X \times W$) provides empirical evidence for the psychological threshold required for effective educational technology deployment. Teachers with low PsyCap were unable to fully leverage AI, confirming that technology is psychologically contingent. Without hope, resilience, or optimism, AI becomes “passive digital babysitting” rather than a dynamic instructional tool (Qayyum, Qureshi, et al., 2025; Tarafdar et al., 2019). This finding addresses a critical gap in global AI research, which often assumes technology is universally effective, irrespective of the user’s psychological state.

Theme 4: Social-Emotional Development (SED) as the Primary Inclusive Outcome (Y)

While most AI research prioritizes academic learning gains, this study emphasizes Social-Emotional Development (SED) as the primary measure of inclusion. Following Goleman’s Emotional Intelligence theory (1995) and the CASEL framework (2020), emotional regulation and peer interaction are foundational to broader learning. AI-enabled interventions, when mediated by psychologically empowered teachers, provide neurodiverse learners in Pakistan with a “Rehabilitative Pathway”, enhancing self-regulation, empathy, and social engagement. This aligns with the global Whole Child approach, reinforcing the ethical imperative of integrating emotional and cognitive support in inclusive education (Qayyum, Saeed, et al., 2024; Qureshi, Qayyum, et al., 2025).

Theme 5: The Digital Divide and Professional Sustainability

The study identifies a “new digital divide” not merely access to technology, but psychological readiness to use it effectively. Teachers with high PsyCap bridge this gap, while those with low PsyCap struggle, even with technological resources available (Selwyn, 2019; Qayyum, Tabassum, & Kashif, 2024). This highlights the importance of professional sustainability: technology-driven reform in Pakistani ECE is only successful if educators are emotionally and psychologically supported. Policies must therefore integrate teacher well-being, PsyCap development, and ethical AI use as central pillars of sustainable digital transformation (Qayyum, Sadiqi, & Abbas, 2024).

5.2 Conclusion

This study demonstrates that artificial intelligence is not a “magic bullet” for inclusion in Early Childhood Education (ECE). Rather, its effectiveness is fundamentally contingent upon psychologically empowered teachers who can ethically mediate technology, manage techno-stress, and intentionally cultivate the social-emotional development of neurodiverse learners. Within the Pakistani context, particularly in urban inclusive classrooms, AI functions as an amplifier of human capacity rather than a substitute for it. First, the findings confirm that AI-assisted differentiated instruction is a significant predictor of social-emotional development among neurodiverse learners. AI-driven personalization, adaptive feedback, and emotional scaffolding provide learners with structured and responsive environments that support emotional regulation, peer interaction, and engagement.

Second, Teacher Psychological Capital (PsyCap) emerges as a decisive moderating and multiplying force. Teachers with higher levels of hope, self-efficacy, resilience, and optimism are significantly more capable of translating AI affordances into meaningful social-emotional gains. This reinforces the Human–AI Synergy model, demonstrating that technology yields optimal outcomes only when paired with strong internal psychological resources. Third, the study establishes social-emotional development as a more sensitive and contextually appropriate indicator of inclusive success than academic achievement alone. For neurodiverse learners, emotional safety, self-regulation, and social competence serve as prerequisites for sustained learning, particularly in resource-constrained educational systems.

Finally, the research identifies the existence of a “psychological digital divide” within Pakistan’s urban ECE classrooms. This divide is not defined by access to hardware or software, but by disparities in teachers’ psychological readiness to engage with AI ethically, confidently, and sustainably. Without sufficient PsyCap, AI risks becoming a source of stress or passive digital supervision rather than a transformative pedagogical tool.

5.3 Limitations of the Study

Despite its contributions, this study has several limitations. The cross-sectional research design restricts causal inference, limiting conclusions to associative relationships rather than long-term effects. Additionally, the focus on Lahore and Islamabad constrains the generalizability of findings to rural or under-resourced regions of Pakistan, where infrastructural and psychological conditions may differ substantially. The reliance on teacher self-reported measures may also introduce social desirability bias, particularly in assessments of technology use and psychological traits.

5.4 Future Research Directions

Future research should extend this work in several important directions. First, scholars should explore trauma-informed AI interventions tailored for emotionally vulnerable and at-risk children, particularly in post-crisis or low-stability environments (Qureshi, Qayyum, et al., 2025). Second, there is a need to investigate nature-based and hybrid AI learning environments that integrate digital intelligence with physical and ecological learning spaces to promote holistic child development (Qayyum, Fatima, & Iram, 2024). Third, interdisciplinary studies examining the role of toddler nutrition and health in shaping cognitive and emotional readiness for AI-mediated instruction would significantly deepen understanding of early developmental equity (Qayyum, Jiang, et al., 2025). Finally, longitudinal research designs are essential to track the sustained impact of teacher PsyCap and AI integration across multiple academic years, offering stronger evidence for policy reform.

5.5 Policy and Practitioner Recommendations

The findings of this study carry critical implications for educational policy and practice in Pakistan. National and provincial education strategies must shift from hardware-centric investments toward prioritizing *psychological readiness*. Developing Teacher Psychological Capital should be treated as a foundational requirement for successful digital transformation in ECE. Professional development frameworks should institutionalize structured PsyCap interventions aimed at strengthening teacher hope, efficacy, resilience, and optimism. At the same time, policymakers must actively reduce techno-stress by minimizing excessive administrative digital workloads, allowing teachers to preserve psychological energy for inclusive pedagogy. Furthermore, localized AI ethics training should be standardized to empower teachers as ethical mediators of AI tools within Pakistan's cultural, linguistic, and social context. AI systems used in ECE must be culturally and linguistically adapted to prevent the marginalization or alienation of neurodiverse learners, particularly those from low-income or linguistically diverse backgrounds.

In alignment with UNESCO (2023) and Luckin (2018), teacher preparation programs must embed *Ethical AI Literacy* as a core competency. Teachers should be trained not merely as technical users of AI, but as reflective, ethical professionals capable of aligning AI-assisted differentiated instruction with the social-emotional needs of young children in culturally responsive ways (Qayyum, Saeed, et al., 2024; Qayyum, Kashif, et al., 2025).

5.6 Final Remark

In conclusion, inclusive AI in Early Childhood Education is not a technological challenge alone it is a psychological, ethical, and human one. Sustainable inclusion will only be achieved when investment in artificial intelligence is matched by equal investment in the psychological capital of those who bring technology to life in the classroom.

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