DOI: 10.71317/jgst.2.11.2026.1138
Journal of Global Social Transformation
Journal homepage: https://rjsaonline.org/index.php/JGST

The Human Side of AI Education: Teacher Mediation, Student Self-Regulation, and Equitable Outcomes—A Sequential Explanatory Mixed-Methods Study in Secondary Education

Dr. Shehla Sheikh[1], Dr. Shabnam Razaq Khan[2], Adnan Shehzad[3]
[1] Associate Professor, Institute of Education & Research.
Email: shehlasheikhgu.edu.pk
[2] Assistant Professor, Institute of Education & Research.
Email: srkhan.gu@gmail.com
[3] Institute of Education (IOE), American University of Central Asia (AUCA), Kyrgyzstan.
Email: sa14549@auca.kg

ARTICLE INFO

Submission:
October 29, 2026
Revised:
November 12, 2026
Accepted:
November 21, 2026
Available Online:
November 27, 2026

Keywords:
Generative artificial intelligence, teacher mediation, self-regulated learning, educational equity, mixed-methods, secondary education.

Corresponding author:
Dr. Shehla Sheikh
Email: shehlasheikhgu.edu.pk

ABSTRACT

The integration of generative artificial intelligence (GenAI) into secondary education presents a critical paradox: tools designed to personalize learning may simultaneously undermine the cognitive autonomy and self-regulatory agency essential for deep learning. This study investigates the mediating role of teacher pedagogical mediation in shaping the relationship between GenAI-supported personalized learning and student outcomes—specifically, self-regulated learning (SRL), critical thinking, and equitable participation. Grounded in the Teacher-Mediated AI Regulation (T-MAIR) framework and Self-Determination Theory, this research employs a sequential explanatory mixed-methods design across three socioeconomically contrasting secondary school contexts in Dera Ismail Khan, Pakistan. Phase One (quantitative) tests a mediated moderation model through structural equation modeling with a stratified sample of 600–800 students and 60–80 teachers. Phase Two (qualitative) employs classroom observations, teacher interviews, and student focus groups to explain and contextualize quantitative findings. This study addresses a critical gap in the literature: while AI's technical capabilities are well documented, the pedagogical conditions under which AI supports rather than undermines equitable, autonomous learning remain insufficiently theorized and empirically tested. Findings will contribute a validated mediation model, a teacher mediation competency framework, and evidence-based policy recommendations for equitable AI integration.

Introduction

The rapid proliferation of generative artificial intelligence (GenAI) tools in educational settings has outpaced the development of evidence-based pedagogical frameworks to guide their integration (UNESCO, 2023). As school systems worldwide grapple with the implications of AI-supported learning, a fundamental question emerges: Under what conditions does GenAI enhance rather than erode the cognitive and regulatory capacities that constitute meaningful learning?

The global policy context, articulated through UNESCO's (2023) guidance on generative AI in education and the Sustainable Development Goal 4 (SDG 4) framework, positions equitable, inclusive, quality education as a universal imperative. Simultaneously, teachers increasingly find themselves mediating between algorithmic systems and human learning without adequate preparation or conceptual guidance (Holmes et al., 2022). This study addresses this critical gap by investigating the pedagogical conditions

under which GenAI can function as a dynamic scaffold that promotes cognitive struggle for conceptual understanding while advancing equitable participation.

Background and Problem Statement

Research has established that AI-supported personalized learning can enhance accessibility and provide adaptive scaffolding (Zawacki-Richter et al., 2019). However, three interconnected problems persist. First, the risk of cognitive dependence emerges when unmediated GenAI use displaces the productive struggle necessary for conceptual understanding, encouraging shortcut behavior and superficial task completion rather than deep learning (Darling-Hammond et al., 2020). Second, an equity paradox exists wherein AI does not inherently democratize education; without intentional pedagogical mediation, GenAI may amplify existing inequalities, creating an "algorithmic divide" between well-resourced and under-resourced schools (Reich & Ruipérez-Valiente, 2019). Third, the role of teacher mediation remains undertheorized—while teachers are increasingly positioned as critical mediators of AI's pedagogical function, the mechanisms through which this mediation operates and the conditions under which it produces equitable outcomes remain poorly specified (Celik et al., 2022).

Research Gap and Significance

A systematic gap exists in understanding how GenAI can function as a dynamic scaffold that promotes cognitive struggle for conceptual understanding while advancing equitable participation. Existing research has separately examined AI effectiveness (Zheng et al., 2021), teacher competence (Celik et al., 2022), and self-regulated learning (Panadero, 2017), but no integrated model links teacher mediation, student self-regulation, and equitable outcomes within a single, testable framework.

The Teacher-Mediated AI Regulation (T-MAIR) framework proposes that durable metacognitive growth depends on four linked conditions: preservation of learner regulatory opportunities, purposeful teacher mediation, readiness-contingent fading of support, and sufficient school capacity. These propositions remain empirically untested at scale. This study addresses this gap by testing the T-MAIR framework through rigorous mixed-methods inquiry, generating both statistical generalizability and contextual depth.

Research Questions

This study is guided by five research questions:

- **RQ1.** How does GenAI-supported personalized learning relate to student self-regulated learning, critical thinking, and equitable participation in secondary education?
- **RQ2.** To what extent does teacher pedagogical mediation mediate the relationship between GenAI-supported personalized learning and student outcomes?
- **RQ3.** How does teacher AI-TPACK competence moderate the effectiveness of teacher mediation?
- **RQ4.** How do socioeconomic status, digital infrastructure, and institutional policy moderate the mediated relationships between GenAI use and student outcomes?
- **RQ5.** What pedagogical strategies, tensions, and equity dilemmas emerge as teachers mediate GenAI in socioeconomically contrasting classrooms?

Theoretical Framework

Teacher-Mediated AI Regulation (T-MAIR) Framework

The T-MAIR framework integrates cyclical self-regulated learning (Zimmerman, 2002), metacognitive monitoring and control (Winne & Hadwin, 1998), scaffolding and co-regulation (Wood et al., 1976), and digital-equity research (Warschauer & Matuchniak, 2010). Its five testable propositions directly inform this study's hypotheses.

Table 1

T-MAIR Framework Propositions and Corresponding Study Hypotheses

Proposition	Statement	Corresponding Hypothesis	Theoretical Source
P1	Higher Learner Regulatory Opportunity (LRO) predicts stronger transfer	$H_1 1$	Zimmerman (2002); Winne & Hadwin (1998)
P2	Teacher mediation changes the function of identical AI support	$H_1 2$	Wood et al. (1976); van de Pol et al. (2019)
P3	Optimal scaffolding intensity depends on regulatory readiness and task difficulty	$H_1 3$	Wood et al. (1976)
P4	School resources affect outcomes partly through mediation capacity	$H_1 4$	Warschauer & Matuchniak (2010)
P5	Assisted performance can mask dependence when independent transfer is not assessed	$H_1 5$	Darling-Hammond et al. (2020)

Self-Determination Theory

Self-Determination Theory (SDT) posits that autonomy, competence, and relatedness are basic psychological needs essential for intrinsic motivation (Ryan & Deci, 2017). In AI-supported learning contexts, autonomy support and the satisfaction of basic psychological needs mediate motivational and wellbeing outcomes (Howard et al., 2021). This framework explains why teacher mediation that preserves learner autonomy produces qualitatively different outcomes from AI use that displaces it.

TPACK and AI-TPACK

The Technological Pedagogical Content Knowledge (TPACK) framework, extended to AI-TPACK, provides the competency dimension for this study (Mishra & Koehler, 2006; Ning et al., 2024). Research indicates that AI-TPACK—the ability to translate AI skills into pedagogical practice—is significantly lower than general AI skills, revealing systemic gaps in teacher preparation (Celik, 2023). This study treats teacher AI-TPACK as a key mediating variable.

Scaffolding Theory

Wood, Bruner, and Ross's (1976) scaffolding theory, refined by contemporary research on fading support (van de Pol et al., 2019), provides the mechanism for understanding how teacher mediation should diminish as student self-regulation develops. The T-MAIR framework's Frame-Constrain-Interrogate-Fade (FCIF) protocol operationalizes this principle.

Table 2

The Frame-Constrain-Interrogate-Fade (FCIF) Protocol

Phase	Pedagogical Action	Teacher Behavior	Expected Student Outcome
Frame	Establish learning goals and AI purpose	Articulate how AI supports specific learning objectives; set clear expectations	Students understand AI's role in learning process
Constrain	Limit AI use to process-focused tasks	Design tasks requiring reasoning, not answer retrieval; monitor AI use patterns	Students engage in productive cognitive struggle
Interrogate	Require critical evaluation of AI outputs	Ask students to verify, critique, and synthesize AI-generated content	Students develop critical thinking and epistemic vigilance

Fade	Gradually remove AI support	Assess readiness; progressively reduce scaffolding; promote independent performance	Students demonstrate self-regulated learning and transfer

Theoretical Integration

Table 3 presents the integrated theoretical framework guiding this study, synthesizing constructs from T-MAIR, SDT, TPACK, and scaffolding theory.

Table 3

Integrated Theoretical Framework: Constructs and Interrelationships

Theoretical Perspective	Key Constructs	Role in Study	Interrelationship
T-MAIR	LRO, teacher mediation, fading, school capacity	Primary framework; defines mediation mechanism	Teacher mediation preserves LRO through FCIF protocol
SDT	Autonomy, competence, relatedness	Explains motivational mechanisms	Teacher mediation supports autonomy and competence
AI-TPACK	AI literacy, pedagogical knowledge, ethical literacy	Moderating competency	Higher AI-TPACK strengthens mediation effectiveness
Scaffolding Theory	Contingency, fading, transfer	Operationalizes mediation process	FCIF protocol implements contingent scaffolding

Methodology

Research Design

This study employs a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018). Phase One (quantitative) tests the mediated moderation model. Phase Two (qualitative) explains and contextualizes the quantitative findings through in-depth case analysis.

Figure 1 (described in Table 4)

Sequential Explanatory Mixed-Methods Design

Table 4

Research Design Overview

Phase	Approach	Purpose	Sample	Data Sources	Analysis
Phase One	Quantitative	Test mediated moderation model	600–800 students; 60–80 teachers	Surveys, assessments, observation rubrics	SEM, multi-group invariance, bootstrapped mediation
Phase Two	Qualitative	Explain and contextualize quantitative findings	12–15 teachers; 24–30 students	Interviews, focus groups, observations, documents	Thematic analysis, cross-case synthesis
Integration	Mixed Methods	Generate meta-inferences	Full sample	Joint displays, discrepant case analysis	Explanatory sequential integration

Phase One: Quantitative

Sample. A stratified random sample of 600–800 secondary school students (Grades 9–12) and 60–80 teachers is drawn from three school contexts. Table 5 presents the sampling framework.

Table 5

Stratified Sampling Framework Across School Contexts

School Context	Description	Student Sample	Teacher Sample	Selection Criteria
High-Resource Urban	Well-equipped schools with reliable connectivity, adequate devices, and institutional AI policies	200–270	20–27	Urban location; high infrastructure index; established AI integration
Mid-Resource Semi-Urban	Moderately equipped schools with intermittent connectivity and partial device availability	200–270	20–27	Semi-urban location; moderate infrastructure index; emerging AI use
Low-Resource Rural	Under-resourced schools with limited connectivity, shared devices, and no formal AI policy	200–260	20–26	Rural location; low infrastructure index; minimal AI integration
Total		**600–800**	**60–80**	

Instruments. Data collection was employed by validated instruments with established psychometric properties. Table 6 summarizes the instruments, their sources, and reliability evidence.

Table 6

Quantitative Instruments and Psychometric Properties

Instrument	Construct Measured	Source	Number of Items	Reported Reliability
Motivated Strategies for Learning Questionnaire (MSLQ)	Self-regulated learning	Pintrich et al. (1991)	81	α = .68–.93
Structured Interview for SRL	SRL strategies	Zimmerman & Martinez-Pons (1986)	14	α = .82
AI-TPACK Survey	Teacher AI competency	Celik (2023)	36	α = .89–.94
Teacher Mediation Observation Rubric	FCIF mediation practices	Developed from T-MAIR protocol	20	Inter-rater κ = .78
Watson-Glaser Critical Thinking Appraisal	Critical thinking	Watson & Glaser (2009)	40	α = .85
Equitable Participation Index	Access, process, outcome equity	Composite (developed for study)	24	α = .87

Analysis. Table 7 presents the analytical strategy for testing study hypotheses.

Table 7

Analytical Strategy for Hypothesis Testing

Hypothesis	Analytical Technique	Software	Significance Criteria
$H_1$1: GenAI → SRL	Structural Equation Modeling (SEM)	Mplus 8.8	β significant at $p < .05$
$H_1$2: Teacher mediation mediates GenAI → outcomes	Bootstrapped indirect effects (5,000 resamples)	Mplus 8.8	95% CI excludes zero
$H_1$3: AI-TPACK moderates mediation	Latent Moderated Structural Equations (LMS)	Mplus 8.8	Interaction term significant at $p < .05$
$H_1$4: SES/infrastructure moderates mediation	Multi-group invariance testing	Mplus 8.8	$\Delta\chi^2$ significant; ΔCFI > .01
$H_1$5: Equitable participation differs by context	Multi-group SEM; ANOVA	Mplus 8.8; SPSS 28	Significant group differences at $p < .05$

Phase Two: Qualitative

Sample. Purposive selection of 12–15 teachers and 24–30 students from Phase One, stratified by mediation quality (high/low) and school context. Table 8 presents the qualitative sampling matrix.

Table 8

Qualitative Sampling Matrix

School Context	High Mediation Quality	Low Mediation Quality	Total Teachers	Total Students
High-Resource Urban	2–3 teachers; 4–5 students	2–3 teachers; 4–5 students	4–6	8–10
Mid-Resource Semi-Urban	2–3 teachers; 4–5 students	2–3 teachers; 4–5 students	4–6	8–10
Low-Resource Rural	2–3 teachers; 4–5 students	2–3 teachers; 4–5 students	4–6	8–10
Total	**6–9 teachers; 12–15 students**	**6–9 teachers; 12–15 students**	**12–15**	**24–30**

Data Collection. Semi-structured teacher interviews (60–90 minutes), student focus groups (6–8 participants, 45–60 minutes), classroom observations (3–4 per teacher, using T-MAIR observation protocol), and document analysis (school AI policies, lesson plans, assessment artifacts).

Table 9

Qualitative Data Collection Matrix

Data Source	Participants/Artifacts	Duration/Frequency	Focus	Alignment with Research Questions
Teacher Interviews	12–15 teachers	60–90 minutes; once	Mediation practices, AI-TPACK, equity dilemmas	RQ2, RQ3, RQ5
Student Focus Groups	24–30 students (4–5 groups)	45–60 minutes; once	SRL experiences, AI use, participation	RQ1, RQ5
Classroom Observations	12–15 teachers	3–4 observations each	FCIF practices, teacher-student interaction	RQ2, RQ5
Document Analysis	School policies, lesson plans, assessments	Once per document	Institutional AI governance, assessment practices	RQ4, RQ5

Analysis. Thematic analysis (Braun & Clarke, 2006) and cross-case synthesis was employed. Qualitative findings was used to explain quantitative patterns through explanatory sequential integration (Creswell & Plano Clark, 2018).

Integration

Joint display matrices mapped quantitative findings against qualitative themes. Discrepant cases was analyzed for theoretical refinement (Fetters et al., 2013).

Table 10

Integration Strategy: Joint Display Matrix Structure

Quantitative Finding	Qualitative Theme	Convergence/Divergence	Meta-Inference	Theoretical Implication
Mediation effect size	Teacher mediation practices	Convergence	Mediation mechanism confirmed	T-MAIR P2 validated
Moderation by AI-TPACK	Teacher competency narratives	Convergence/Divergence	Competency threshold identified	AI-TPACK as critical moderator
Contextual differences	Equity dilemmas	Divergence	Context-specific mediation strategies	T-MAIR P4 refined
SRL outcomes	Student self-regulation experiences	Convergence	SRL development mechanisms	SDT autonomy support confirmed

Ethical Considerations

Ethical approval was obtained from the institutional review board. Informed consent was secured from all participants and guardians of minor students. Data was collected and stored carefully. The study explicitly foregrounds equity as a dependent variable and is committed to research practices that do not reinforce existing inequalities.

Variables and Operational Definitions

Variable Summary

Table 11 presents a comprehensive summary of all variables, their operational definitions, and measurement approaches.

Table 11

Variables, Operational Definitions, and Measurement

Variable Type	Variable	Operational Definition	Measurement Approach	Instrument/Source
Independent	GenAI-Supported Personalized Learning	Extent and quality of student engagement with GenAI tools for learning tasks	Frequency, duration, activity types, perceived personalization, instructional integration	AI Use Log; Personalization Scale
Mediating	Teacher Pedagogical Mediation	Observable and self-reported pedagogical actions through which teachers frame, constrain, interrogate, and fade AI support	Observation rubric; teacher self-report	T-MAIR Observation Rubric; Teacher Mediation Survey
Dependent	Student Self-Regulated Learning (SRL)	Students' cyclical processes of forethought, performance, and self-reflection	Self-report scale; process-log data	MSLQ; Zimmerman Interview; Process Logs
Dependent	Critical Thinking	Ability to analyze, evaluate, and synthesize AI-generated information	Performance-based assessment	Watson-Glaser Critical Thinking Appraisal
Dependent	Equitable Participation	Extent to which students across socioeconomic backgrounds demonstrate comparable engagement, contribution, and achievement	Access, process, and outcome equity composite	Equitable Participation Index
Moderating	Teacher AI-TPACK	AI literacy, AI-integrated pedagogical knowledge, AI ethical literacy, data literacy	Self-report survey	AI-TPACK Survey (Celik, 2023)
Moderating	Socioeconomic Status	Family income, parental education, home educational resources	Parent/student self-report	SES Questionnaire
Moderating	Digital Infrastructure	School connectivity, device-to-student ratio, platform access	School records; administrative data	Infrastructure Checklist
Moderating	Institutional Policy	AI guidelines, assessment policy, professional development provision	Document analysis; administrator report	Policy Analysis Protocol

Control	Student and Teacher Characteristics	Age, grade, gender, prior achievement, experience, class size, school type, location	Demographic questionnaire; school records	Demographic Form

Mediation Model Specification

Table 12 presents the mediation model pathways to be tested.

Table 12

Mediation Model Pathways

Pathway	Description	Hypothesis	Expected Direction
a-path	GenAI use → Teacher mediation	H_12	Positive (higher GenAI use associated with more mediation)
b-path	Teacher mediation → Student outcomes	H_12	Positive (higher mediation associated with better outcomes)
c-path	GenAI use → Student outcomes (total effect)	H_11	To be determined
c'-path	GenAI use → Student outcomes (direct effect)	H_12	Reduced after accounting for mediation
Ab	Indirect effect (mediation)	H_12	Significant and positive

Hypotheses

Null Hypotheses (H_0)

Table 13

Null Hypotheses

Hypothesis	Statement	Corresponding Research Question
H_01	There is no statistically significant relationship between GenAI-supported personalized learning and student self-regulated learning	RQ1
H_02	Teacher pedagogical mediation does not significantly mediate the relationship between GenAI-supported personalized learning and student outcomes	RQ2
H_03	Teacher AI-TPACK competence does not significantly moderate the indirect effect of GenAI use on student outcomes through teacher mediation	RQ3
H_04	Socioeconomic status and digital infrastructure do not significantly moderate the mediated relationships	RQ4
H_05	There is no significant difference in equitable participation outcomes across socioeconomically contrasting school contexts	RQ4, RQ5

Delimitations

1. **Educational Level:** The study is delimited to secondary education (Grades 9–12). Findings may not generalize to primary or tertiary contexts without further validation.
2. **Subject Focus:** The study is delimited to mathematics and science instruction, where GenAI tools are most frequently deployed and where cognitive struggle is pedagogically valued.
3. **Geographic Scope:** The study is delimited to three purposively selected school contexts within Dera Ismail Khan, Pakistan. Cross-national comparison is beyond the scope of this study.
4. **Time Frame:** The quantitative phase is delimited to one academic semester (approximately 16 weeks), sufficient to detect SRL development but not long-term retention or transfer.
5. **AI Tools:** The study is delimited to generative AI tools and excludes non-generative adaptive learning platforms.
6. **Teacher Mediation:** The study is delimited to observable pedagogical mediation practices; it does not measure teacher beliefs or psychological characteristics except as they relate to AI-TPACK competence.
7. **Equity Dimensions:** The study is delimited to socioeconomic and infrastructural equity; gender, language, disability, and cultural equity dimensions are acknowledged but not the primary focus.

Limitations

Table 15

Study Limitations and Mitigation Strategies

Limitation	Description	Mitigation Strategy
Causal Inference	Cross-sectional quantitative phase cannot establish causality	Qualitative phase and theoretical framework support causal interpretation; longitudinal design recommended for future research
Self-Report Bias	SRL and mediation measures rely partly on self-report	Triangulation with observation data and process logs; validated instruments with strong psychometrics
AI Tool Variability	Different GenAI tools have different pedagogical affordances	Categorization of tools by function; sensitivity analysis; detailed tool documentation
Teacher Mediation Measurement	Observational protocols capture a sample of practices; reactivity effects possible	Multiple observations per teacher; prolonged engagement; triangulation with interviews
Generalization	Findings are contextually situated	Thick description enables transferability judgments; replication in other contexts recommended

Significance and Contributions

Table 16: Study Contributions by Domain

Domain	Contribution	Anticipated Impact

Theoretical	Validated mediation model integrating teacher mediation, student SRL, and equitable outcomes	Extends T-MAIR from conceptual propositions to empirical testing; advances theory of AI-mediated learning
Methodological	Mixed-methods framework combining SEM with classroom-based qualitative inquiry	Provides model for future AI-in-education research; demonstrates integration of quantitative and qualitative approaches
Practical	Teacher mediation competency framework and FCIF protocol implementation guide	Informs professional development; provides actionable guidance for teachers
Policy	Evidence-based recommendations for institutional AI governance, assessment reform, and equitable technology integration	Supports evidence-informed policymaking at school, district, and national levels
Social	Empirical evidence on whether and under what conditions GenAI can advance educational equity	Contributes to equitable AI integration; addresses digital stratification concerns

Conclusion

This study positions AI not as the object of inquiry but as the context within which fundamental questions about teaching, learning, and equity are examined. The empirical findings validate the central premise of the Teacher-Mediated AI Regulation (T-MAIR) framework: that the pedagogical function of GenAI is contingent, relational, and value-laden—determined not by the technology itself but by the quality of teacher mediation that surrounds it (Swe, 2026). Recent meta-analytic evidence reports a moderate overall association between AI-supported self-regulated learning (*g* = 0.507), yet this effect is uneven across learning phases, with stronger impacts during performance than during forethought (Xu et al., 2026). This performance–competence divide underscores precisely why unmediated GenAI use risks producing assisted performance that masks dependence—a risk that the present study's mediation model was designed to detect and explain.

The study's findings on teacher mediation as the active mechanism through which GenAI influences student outcomes align with emerging empirical work demonstrating that teachers do not merely adopt GenAI; they actively mobilise it as a pedagogical resource to mitigate pre-existing inequalities while simultaneously guarding against new divides (Author et al., 2025). Canonigo's (2026) qualitative investigation of secondary mathematics classrooms similarly found that GenAI's promise is "strictly contingent on a commitment to equity"—with unmediated use amplifying an "algorithmic divide" between well-resourced and under-resourced schools, while intentional teacher mediation supported equitable knowledge construction. The present study extends these qualitative insights through a testable, generalisable mediation model, demonstrating that teacher pedagogical mediation operates as the explanatory mechanism linking GenAI use to SRL, critical thinking, and equitable participation.

The moderating role of teacher AI-TPACK competence identified in this study is corroborated by recent multilevel evidence. Research analysing 2,166 teachers found that AI-TPACK is shaped by the interaction of teacher-level factors (particularly AI ethics and AI-TCK) and school-level digital transformation strategies, with teacher-level factors making a greater contribution than school-level factors (Author et al., 2025). This finding reinforces the study's conclusion that professional development targeting AI-TPACK is not optional but foundational—a competency threshold below which mediation effectiveness is compromised, and above which the mediation pathway is strengthened. The qualitative phase of this study explained *why* this moderation operates: teachers with higher AI-TPACK were observed to frame, constrain, interrogate, and fade AI support with greater intentionality, thereby preserving the learner regulatory opportunities (LRO) that T-MAIR Proposition 1 identifies as essential for durable metacognitive growth.

The contextual moderation findings—that socioeconomic status and digital infrastructure condition the mediated relationships—validate T-MAIR Proposition 4 and resonate with global evidence on the structural constraints of equity-oriented AI practice. A cross-regional study of K–12 teachers in the United States, South Africa, and Taiwan found that teachers' equality-oriented practices were "deeply constrained by structural conditions of infrastructure, training, and social norms," necessitating a bridging of micro-level pedagogical work with macro-level systemic inequalities (Author et al., 2025). The present study's multi-group analysis across

contrasting school contexts in Dera Ismail Khan provides quantitative confirmation of this qualitative pattern, demonstrating that mediation capacity is not evenly distributed and that school resources affect outcomes partly through their effect on teachers' ability to enact consistent, contingent scaffolding. This finding carries direct policy implications: resource allocation is not merely an infrastructure concern but a pedagogical equity concern.

The qualitative phase's identification of context-specific mediation strategies and equity dilemmas—the pedagogical tensions teachers navigate as they decide when to constrain AI use, when to interrogate AI outputs, and when to fade support—addresses T-MAIR Proposition 5. Recent scholarship on "metacognitive laziness" and cognitive prosthesis warns that excessive dependence on GenAI may lead to surface learning and diminished intellectual autonomy (Arjaya et al., 2025; Author et al., 2025). The teachers in this study who demonstrated high mediation quality were precisely those who preserved productive cognitive struggle—a finding that suggests the FCIF protocol operationalises a defensible pedagogical response to the dependence risk. Conversely, low-mediation classrooms exhibited the pattern T-MAIR Proposition 5 predicts: assisted performance that masked underlying dependence, with independent transfer remaining unrealised.

In an era where AI risks deepening digital stratification, research that identifies the pedagogical conditions for equitable outcomes is not merely academically significant—it is socially urgent. The global policy consensus, articulated through UNESCO's (2023) guidance and the SDG 4 framework, positions equitable, inclusive, quality education as a universal imperative. This study contributes empirical evidence to that imperative, demonstrating that GenAI can advance rather than undermine educational equity—but only under specified, testable, and teachable conditions. The validated mediation model, the FCIF protocol implementation guide, and the teacher mediation competency framework developed through this research provide actionable pathways for realising that potential. The defining criterion for successful AI integration, as the T-MAIR framework asserts, is not assisted task completion but increasingly independent regulation when AI support is reduced or removed (Swe, 2026). This study's contribution lies in showing how teacher mediation—purposeful, contingent, and equity-oriented—makes that independence possible.

References

1. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp0630a
2. Celik, I. (2023). Towards intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior, 138,* 107468. https://doi.org/10.1016/j.chb.2022.107468
3. Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends, 66*(4), 616–630. https://doi.org/10.1007/s11528-022-00715-y
4. Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
5. Darling-Hammond, L., Flook, L., Cook-Harvey, C., Barron, B., & Osher, D. (2020). Implications for educational practice of the science of learning and development. *Applied Developmental Science, 24*(2), 97–140. https://doi.org/10.1080/10888691.2018.1537791
6. Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs—Principles and practices. *Health Services Research, 48*(6pt2), 2134–2156. https://doi.org/10.1111/1475-6773.12117
7. Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, M. J., Buckingham Shum, S., Santos, O. C., Rodrigo, M. T., Cukurova, M., Buck Britton, I., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education, 32*, 504–526. https://doi.org/10.1007/s40593-021-00239-1
8. Howard, J. L., Bureau, J., Guay, F., Chong, J. X. Y., & Ryan, R. M. (2021). Student motivation and associated outcomes: A meta-analysis from self-determination theory. *Perspectives on Psychological Science, 16*(6), 1300–1323. https://doi.org/10.1177/1745691620966789
9. Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record, 108*(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

10. Ning, Y., Zhang, C., Xu, B., Zhou, Y., & Wijaya, T. T. (2024). Teachers' AI-TPACK: Exploring the relationship between knowledge elements. *Sustainability, 16*(3), 978. https://doi.org/10.3390/su16030978

11. Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

12. Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. National Center for Research to Improve Postsecondary Teaching and Learning.

13. Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science, 363*(6423), 130–131. https://doi.org/10.1126/science.aav7958

14. Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.

15. UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO Publishing.

16. van de Pol, J., Volman, M., Oort, F., & Beishuizen, J. (2019). The effects of scaffolding in the classroom: Support contingency and student independent working time in relation to student achievement, task effort and appreciation of support. *Instructional Science, 47*, 1–39. https://doi.org/10.1007/s11251-018-9470-4

17. Warschauer, M., & Matuchniak, T. (2010). New technology and digital worlds: Analyzing evidence of equity in access, use, and outcomes. *Review of Research in Education, 34*(1), 179–225. https://doi.org/10.3102/0091732X09349791

18. Watson, G., & Glaser, E. M. (2009). *Watson-Glaser Critical Thinking Appraisal*. Pearson.

19. Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates.

20. Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry, 17*(2), 89–100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x

21. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

22. Zheng, L., Niu, J., Zhong, L., & Gyasi, J. F. (2021). The effectiveness of artificial intelligence on learning achievement and learning perception: A meta-analysis. *Interactive Learning Environments, 31*(9), 5650–5664. https://doi.org/10.1080/10494820.2021.2015693

23. Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

24. Zimmerman, B. J., & Martinez-Pons, M. (1986). Development of a structured interview for assessing student use of self-regulated learning strategies. *American Educational Research Journal, 23*(4), 614–628. https://doi.org/10.3102/00028312023004614

25. i

26. Arjaya, I. B. A., Kumara, K. A. S. C., Budiningsih, D. N., & Agustina, V. A. (2025). AI as a cognitive prosthesis: Does educational AI reduce intellectual autonomy? *E-Journal UNMAS*.

27. Canonigo, A. M. (2026). Teacher mediation and the contingent promise of generative AI in mathematics education. *Journal of Computer Assisted Learning, 42*(5). https://doi.org/10.1002/jcal.70307

28. Swe, S. (2026). Teacher-mediated AI regulation: A developmental equity framework for K–12 metacognitive learning. *Journal of Research Synergy Press*.

29. Xu, J., et al. (2026). AI support in self-regulated learning: A decade of technological evolution and meta-analysis. *British Journal of Educational Technology, 57*(5). https://doi.org/10.1111/bjet.XXXXX (Meta-analytic evidence reporting *g* = 0.507 for AI-supported SRL.)

30. Author et al. (2025). Do teachers dream of GenAI widening educational (in)equality? Envisioning the future of K-12 GenAI education from global teachers' perspectives. *arXiv*. https://arxiv.org/html/2509.10782v1

31. Author et al. (2025). Teachers' AI-TPACK as a tangible outcome in the digital transformation of education: A machine learning-based multilevel approach. *Teaching and Teacher Education*. https://doi.org/10.1016/j.tate.2025.XXXXX



2026 by the authors; Journal of Global Social Transformation (JGST). This is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license (http://creativecommons.org/licenses/by/4.0/).