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A multimethod exploration of human–AI-supported shared metacognition for inclusive educational leadership during crisis in Türkiye and Pakistan

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Abstract

This study examines how Generative AI–supported self-regulation and social media– supported co-regulation jointly contribute to Shared Metacognition and Inclusive Educational Leadership (IEL) development among pre-service teachers in crisis contexts in Türkiye and Pakistan. Using the Community of Inquiry framework and its shared metacognition extension, informing the design of AI-supported self-regulation and social-media-supported co-regulation. A quasi-experimental design was implemented with unpaired pre- and post-intervention data from 249 participants. In addition to self-reported measures, expert rubric-based evaluations were used to provide an objective assessment of leadership outcomes. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), fuzzy-set Qualitative Comparative Analysis (fsQCA), and Artificial Neural Networks (ANN) to capture linear, configurational, and non-linear associations. Results showed strong associations between social media co-regulation and IEL ($\beta = 0.477$, $p < .001$) and between AI self-regulation and IEL ($\beta = 0.354$, $p < .001$). A mediation effect of AI self-regulation between social media co-regulation and inclusive educational leadership ($\beta = 0.259$, $p < .001$) emerged in the post-intervention phase.The fsQCA indicated that the configuration of high AI self-regulation and high social media co-regulation was sufficient for high IEL. ANN analysis achieved low prediction error (MSE = 0.774; MAE = 0.690). These findings highlight a socio-technical pathway where human–AI collaboration supports inclusive, equitable leadership practices in educational crisis contexts across cultures. Given the use of unpaired cross-sectional data, findings are interpreted as associative rather than causal. This study adopts a human-centered perspective on AI-supported learning by illustrating how inclusive, human-centered leadership can foster sustainable socio-technical innovation in education during crises.

Keywords Human–AI collaboration, Inclusive educational leadership, Shared metacognition, Socio-technical innovation, Generative AI, Cross-cultural education

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1 Introduction

Natural disasters are increasingly disrupting educational systems worldwide, exposing structural inequalities and critical gaps in leadership capacity during crisis response. The 2022 floods in Pakistan displaced over 2.6 million learners [67], while the 2023 earthquakes in Türkiye affected more than 500,000 children [21]. Although emergency responses such as mobile learning and remote instruction have been implemented [53, 69], these approaches often remain fragmented and insufficient for sustaining coordinated, inclusive, and adaptive educational practices. In particular, they rarely integrate advanced technologies in ways that support collaborative sensemaking, reflective learning, and leadership development in crisis contexts. As a result, preparing educators as inclusive leaders—capable of coordinating diverse stakeholders through trauma-informed and technology-supported practices—has become an urgent priority [46].

Despite increasing digital penetration and the growing use of artificial intelligence (AI) and social media in education, existing approaches to crisis preparedness remain conceptually and practically fragmented. Significant mobile connectivity in vulnerable regions presents an opportunity to leverage technology for enhancing preparedness and response [57], yet teacher preparation programs continue to underutilize these tools for fostering collaborative competencies and inclusive leadership [71].

Emerging digital technologies, particularly Generative AI and social media platforms, are increasingly recognized as critical enablers of adaptive learning and coordination in complex environments [4, 5]. Generative AI tools provide learners with real-time feedback, support reflective thinking, and enable iterative problem-solving, thereby enhancing individual self-regulatory capabilities, particularly in terms of monitoring progress and managing strategies [51, 54]. At the same time, social media platforms facilitate distributed collaboration by enabling communication, peer feedback, and shared sensemaking across geographically dispersed groups, supporting collective monitoring of progress and coordinated management of shared tasks [60, 61]. In crisis contexts, these technologies support rapid information exchange, collaborative decision-making, and inclusive participation among diverse stakeholders [32]. Despite their growing relevance, their combined role in shaping both individual and collective regulatory processes for leadership development in disaster-response education remains insufficiently understood.

Prior research has examined self-regulated learning, collaborative learning, and leadership development largely in isolation [16], with limited integration into a unified socio-technical framework. Moreover, while emerging work on human-centered AI emphasizes inclusivity, context-awareness, and ethical alignment [18, 37], empirical studies have primarily focused on algorithmic fairness and governance rather than relational and educational processes of human–AI collaboration [43, 77]. Consequently, there remains a limited understanding of how AI-supported individual regulation and socially mediated collaborative processes jointly contribute to inclusive leadership outcomes in real-world educational crisis settings.

In addition to this conceptual gap, a methodological limitation persists in the existing literature. Much of the prior work relies on single-method approaches—typically variance-based techniques or qualitative case studies—which are insufficient to capture the complexity of socio-technical learning processes. To address these limitations, this study adopts a multimethod analytical approach integrating Partial Least Squares Structural

Equation Modeling (PLS-SEM), Fuzzy-set Qualitative Comparative Analysis (fsQCA), and Artificial Neural Network (ANN). Specifically, PLS-SEM is employed to examine linear relationships among constructs, fsQCA is used to identify configurational combinations of conditions leading to the outcome, and ANN is applied to capture non-linear patterns and assess predictive importance [6, 8, 55]. This integrated approach enables a more comprehensive understanding of how multiple regulatory mechanisms interact within complex crisis contexts [2, 58].

To address these gaps, this study conceptualizes shared metacognition as a socio-technical mechanism that connects individual and collective regulation within technology-supported learning environments. Grounded in the Community of Inquiry (CoI) framework [7, 27] and its shared metacognition extension [28], the study focuses on two interdependent regulatory processes: self-regulation and co-regulation. Self-regulation refers to the individual's capacity to plan, monitor, and adapt learning strategies [83, 84], encompassing monitoring (evaluating progress and identifying gaps) and managing (adjusting strategies and refining decisions). Co-regulation refers to the collaborative adjustment of learning through interaction and shared understanding [15], involving collective monitoring of group progress and managing coordinated actions and shared decisions. Rather than treating these processes separately, this study positions them as mutually reinforcing dimensions of a broader socio-technical system.

Within this framework, emerging technologies play a critical mediating role. Generative AI supports self-regulation by enabling adaptive feedback, reflective thinking, and iterative strategy refinement [51, 54], while social media platforms facilitate co-regulation through peer interaction, shared decision-making, and collaborative knowledge construction [60, 61]. Together, these technologies enable human–AI-supported shared metacognition, linking individual cognition with collective coordination in complex learning environments.

The outcome of these processes is conceptualized as inclusive educational leadership (IEL), defined as leadership that prioritizes equity, cultural responsiveness, shared decision-making, and psychological safety [44, 76, 80]. In crisis contexts, such leadership enables educators to coordinate diverse actors, address socio-emotional needs, and sustain trust within disrupted communities. However, despite its importance, the development of inclusive leadership as a measurable outcome of technology-supported learning processes remains underexplored, particularly in cross-cultural disaster contexts.

Building on these arguments, this study develops a socio-technical conceptual framework that integrates AI-supported self-regulation and social media–supported co-regulation within the broader process of shared metacognition. The framework posits that these interdependent regulatory processes jointly contribute to the development of inclusive educational leadership in disaster-response contexts.

This study is significant in advancing both theoretical and practical understanding of technology-supported learning in crisis contexts. First, it contributes to theory by positioning shared metacognition as a socio-technical mechanism that integrates individual and collective regulatory processes, extending its application to inclusive educational leadership in disaster-response settings. Second, it addresses an important methodological gap by employing a multimethod analytical approach—combining PLS-SEM, fsQCA, and ANN—to capture linear, configurational, and non-linear relationships, thereby offering a more comprehensive understanding of complex socio-technical phenomena.

Third, from a practical perspective, the study provides actionable insights for educators, policymakers, and technology designers by demonstrating how AI-supported self-regulation and social media–supported co-regulation can be leveraged to foster inclusive leadership in resource-constrained and crisis-affected environments. By linking technology use with leadership outcomes, the study informs the design of scalable, human-centered, and inclusive learning systems capable of enhancing resilience in disaster-prone educational settings. In this study, shared metacognition is operationalized through the interaction of AI-supported self-regulation and social media–supported co-regulation, rather than being measured as a separate construct.

2 Research question and objectives

Accordingly, this study addresses the following research question:

How are AI-supported self-regulation and social media–supported co-regulation associated with shared metacognition and inclusive educational leadership among preservice teachers in disaster-response settings?

To address this research question, the study pursues the following objectives:

1. To examine the associations between AI-supported self-regulation, social media–supported co-regulation, and shared metacognition.
2. To investigate how shared metacognition relates to inclusive educational leadership in disaster-response contexts.
3. To analyze the combined and complex patterns underlying these relationships using a multimethod analytical approach.

Based on this foundation, the following section develops hypotheses that specify the relationships among AI-supported self-regulation, social media–supported co-regulation, shared metacognition, and inclusive educational leadership.

3 Hypothesis development

Based on this theoretical framing, the following hypotheses were developed to examine the interplay between social-media-supported co-regulation, Generative AI–enabled self-regulation, and inclusive educational leadership within cross-cultural crisis contexts (See Fig. 1).

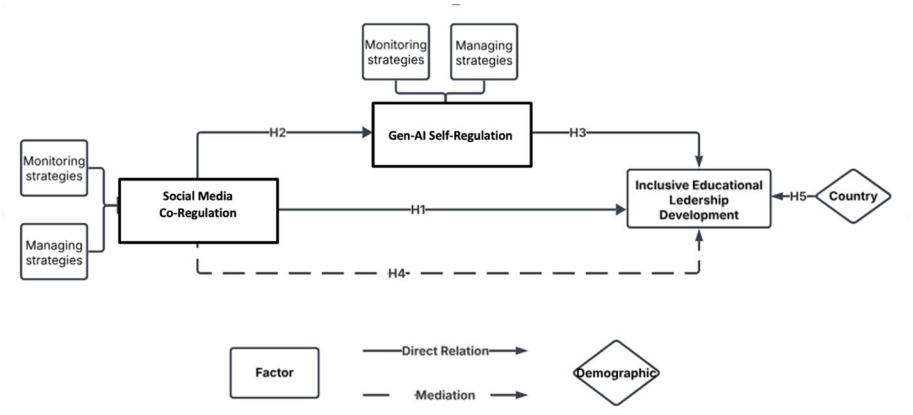


Fig. 1 Hypothetical framework

Hypothesis 1 (H1): Social media-supported co-regulation directly and positively associates with inclusive educational leadership development.
Social media platforms facilitate communication, knowledge sharing, and community engagement, all of which are critical for inclusive leadership during crises. Co-regulation through these platforms enables pre-service teachers to integrate diverse perspectives, mirroring the *bayanihan* spirit in collective crisis response [64]. This process fosters equitable participation and cultural responsiveness, affirming that inclusive leadership develops through collaborative knowledge construction [3]. The interactive nature of social media supports the co-regulated development of inclusive leadership by enabling leaders to receive real-time feedback and adapt behaviors toward inclusivity [73].

Hypothesis 2 (H2): Social media-supported co-regulation positively associates with Generative AI-supportedself-regulation.
Evidence suggests that engagement in social media-supported co-regulation of learning enhances the effectiveness of generative AI-supported self-regulation [72]. Social interactions on these platforms reflect social–cognitive mechanisms of learning [11], enabling learners to monitor, evaluate, and adjust their strategies through peer collaboration [30]. Since effective use of generative AI in education also depends on self-regulated learning skills and exists within a "network of co-regulation" between humans and machines [50], competencies developed through social co-regulation may strengthen learners' capacity to use AI tools for autonomous learning.

Hypothesis 3 (H3): Generative AI-supported self-regulation positively associates with inclusive educational leadership development.
Generative AI tools can enhance individual self-regulation by offering personalized feedback, diverse strategy generation, and iterative refinement [10]. Such adaptive learning capacities are central to inclusive leadership, which requires equitable problem-solving and perspective taking [26]. By supporting reflective strategy management, AI interaction aids in cultivating inclusivity-oriented leadership skills inclusively [74]. In crisis contexts, AI also supports leaders' emotional regulation and decision-making by providing real-time feedback and guidance [33], helping sustain psychological resilience and inclusivity [59]. However, the use of AI in leadership and crisis communication must be managed carefully to avoid perceptions of inauthenticity or ethical concerns [68].

Hypothesis 4 (H4): The association between social media-supported co-regulation and inclusive educational leadership is partially mediated by Generative AI-supported self-regulation.
Social media co-regulation supports the co-construction of leadership through continuous interactive exchanges that promote inclusivity, transparency, and responsiveness [29, 82]. Simultaneously, generative AI facilitates leaders' self-regulation by providing adaptive feedback and reflective learning opportunities [42], thereby strengthening self-efficacy and adaptability in addressing diverse team needs [13]. Prior research also highlights the interdependence of co-regulation and self-regulation in collaborative learning processes [81], suggesting that these dynamics can collectively enhance inclusive and participatory leadership behaviors. Accordingly, while social media co-regulation directly contributes to inclusive leadership, AI-enabled self-regulation enhances

and partially mediates this association by enabling continuous monitoring, adaptation, and alignment toward inclusivity.

Null Hypothesis 05 (H05) There is no significant association between country and inclusive educational leadership.

Emerging technologies such as social media and generative AI have played vital roles globally in sustaining education during crises and preparing future leaders with resilience and cultural awareness. Platforms like Facebook enable international knowledge exchange and exposure to diverse perspectives [22], while global AI initiatives emphasize collaboration to improve equity and accessibility [47, 49]. Although local contexts influence crisis response [48], the affordances of AI and social media support universal mechanisms of hybrid learning. Therefore, inclusive leadership development through AI- and social-media-supported co-regulation is expected to associate with technological engagement rather than country context.

4 Research methods

4.1 Justification of analytical approach and comparison to state-of-the-art

This study employs a multi-method analytical approach—Partial Least Squares Structural Equation Modeling (PLS-SEM) [31], fuzzy-set Qualitative Comparative Analysis (fsQCA) [9, 62, 78], and Artificial Neural Networks (ANN) [34]—to capture linear, configurational, and non-linear associations among constructs. While PLS-SEM explains structural relationships among constructs, ANN enhances predictive sensitivity by capturing hidden non-linear interactions among regulatory processes, which are common in socio-technical learning environments. Although state-of-the-art machine learning and Natural Language Processing models, including large language models (LLMs), have advanced predictive and generative analytics, they are not directly applicable here because the dataset consists of structured, survey-based variables representing latent constructs rather than textual or unstructured data. The study's objective is explanatory and relational—focused on understanding how technology-supported regulation associates with inclusive leadership—rather than predictive.

To establish a relevant baseline, a multiple linear regression (MLR) model was first estimated on the same dataset. While MLR was aimed to confirm basic associations, without capturing complex interdependencies. The integration of PLS-SEM, fsQCA, and ANN therefore enabled a more comprehensive interpretation: PLS-SEM identified direct and indirect paths, fsQCA revealed configurational sufficiency and necessity. ANN was employed to capture potential non-linear and interaction effects that cannot be fully represented in variance-based SEM models. While PLS-SEM identifies linear relationships and mediation, ANN complements this by detecting complex patterns and improving predictive robustness, thereby enhancing the explanatory depth of the multi-method design.Unlike predictive frameworks that prioritize accuracy, this study emphasizes interpretability. Accordingly, SHAP (SHapley Additive exPlanations) [52] analysis was applied within the ANN model to determine the relative importance of each construct, providing model-agnostic insights into their associative strength. This approach aligns with the study's explanatory goals. Expert validation further strengthened interpretive reliability. The overall analytical framework is shown in Fig. 2.

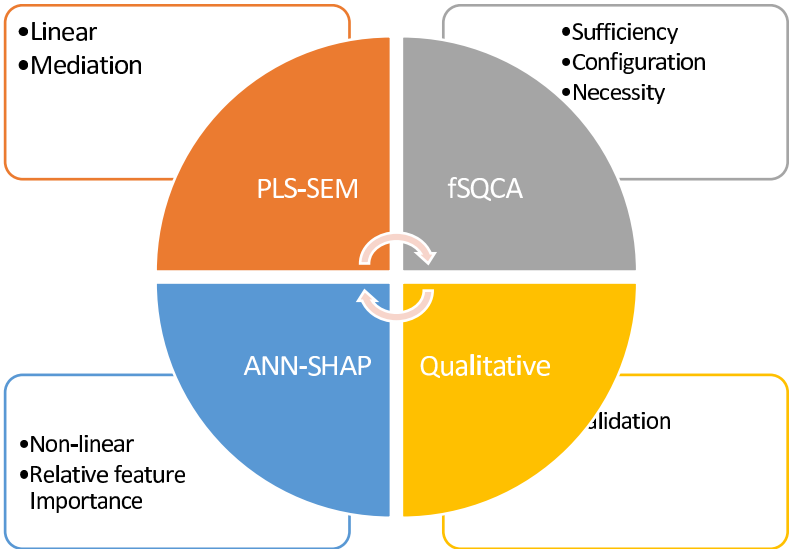


Fig. 2 Multi-method analysis

4.1.1 Study design and intervention

This study employed a quasi-experimental pre-test/post-test control group design with stratified random sampling. Because responses could not be matched at the individual level across time points, the design represents repeated cross-sectional comparisons rather than true longitudinal tracking. A quasi-experimental design was selected because randomized controlled trials are often infeasible in educational contexts, where participation is voluntary and ethical considerations limit full randomization [25, 70]. Given the quasi-experimental design and unpaired samples, potential contamination and maturation effects cannot be fully ruled out, particularly as participants may have been exposed to similar external learning experiences over time. To strengthen internal validity, the design incorporated both experimental and control groups, parallel pre- and post-test surveys, and formal testing of measurement invariance across groups.

The intervention spanned four weeks and was implemented through a blended digital environment comprising the *"E-Inclusion 4.0"* Facebook group, WhatsApp, and synchronous video-conferencing tools (Zoom, Microsoft Teams). It combined two complementary elements:

1. AI-supported self-regulation—Participants used Generative AI tools to design, refine, and monitor disaster-response strategies, supporting metacognitive processes such as goal-setting, self-monitoring, and reflective adjustment.
2. Social media-supported co-regulation—Participants collaborated via online discussions, WhatsApp groups, and synchronous meetings to exchange feedback, critique strategies, and co-construct contextually responsive solutions.

The intervention followed four phases: Week 1 (orientation and onboarding), Weeks 2–3 (strategy development, with Pakistani participants focusing on Türkiye and Turkish participants on Pakistan), and Week 4 (finalization and expert evaluation). Independent experts assessed outputs using a rubric measuring inclusivity, adaptability, equity, cultural responsiveness, and collaboration.

The control group did not participate in the structured activities but completed the same pre- and post-test surveys. This "business-as-usual" condition provided a valid baseline for comparison [20].

4.1.2 Population, sample, sample selection, and data collection

This subsection describes the dataset used for analysis, detailing its composition, collection procedure, and sampling structure across experimental conditions. This study employed a quasi-experimental design with data collected at two time points (pre-intervention and post-intervention). The study population comprised 500 pre-service teachers in the "e-Inclusion 4.0" Facebook group. Using stratified random sampling, 150 participants were selected from this population and invited to participate in the study. This selection was stratified to ensure proportional representation from both countries and assigned to either the experimental group ($n = 90$) or the control group ($n = 60$). These same 150 participants were invited to complete voluntary surveys at both time points. Due to the voluntary nature of participation and the methodological decision to remove incomplete surveys to ensure data quality, the number of valid responses collected varied between the two waves.

The final dataset consisted of 249 valid, unpaired responses across the four conditions: pre-experimental ($n = 67$), post-experimental ($n = 86$), pre-control ($n = 49$), and post-control ($n = 47$). Because the pre- and post-test responses could not be paired to individual participants, all subsequent analyses (including PLS-SEM MGA) were conducted by treating the four conditions as independent, cross-sectional groups. To ensure cross-group comparability, Measurement Invariance of Composite Models (MICOM) was conducted in SmartPLS 4 [35]. Configural invariance was satisfied, as the same indicators and model specifications were applied across groups. These results demonstrate that the constructs were specified and formed equivalently across groups, allowing for meaningful comparison of structural relationships (path coefficients) between experimental and control conditions and across countries.

An a priori power analysis was conducted using G*Power 3.1 [24]. Assuming a medium effect size ($f^2 = 0.25$), $\alpha = 0.05$, and power = 0.80, the minimum required sample size was 68. The finalized dataset of 249 responses more than doubled this threshold, confirming adequacy for robust inferential and multi-group analysis.

Table 1 summarizes the demographic distribution of the raw dataset ($N = 249$). The largest subgroup was the post-experimental group (34.54%), followed by

Table 1 Demographic distribution of study participants

Category	Subgroup	Frequency (*n*)	Percentage (%)
Group	Pre-experimental	67	26.91
	Post-experimental	86	34.54
	Pre-control	49	19.68
	Post-control	47	18.88
Country	Pakistan	151	60.64
	Türkiye	98	39.36
Gender	Female	197	79.12
	Male	52	20.88
Nativity	Rural	207	83.13
	Urban	42	16.87
Program	Undergraduate	131	52.59
	Postgraduate	118	47.41

pre-experimental (26.91%), pre-control (19.68%), and post-control (18.88%). A majority of participants were from Pakistan (60.64%), with Türkiye contributing 39.36%. The dataset was female-dominated (79.12%), reflecting the typical female skewed demographic structure in teacher education cohorts in different countries as reflected in studies [14, 19]. Most participants reported rural nativity (83.13%), while 16.87% identified as urban. Program enrollment was balanced, with 52.59% undergraduates and 47.41% postgraduates. These characteristics reflect diversity in background while maintaining representativeness of teacher education populations in Pakistan and Türkiye. The sample is context-specific and gender-imbalanced, which may limit the generalizability of findings beyond similar educational and cultural settings.

4.2 Instrument development

The self-reported measures used in this study were designed to capture participants' perceptions of their engagement in technology-supported regulatory and collaborative processes and their development of inclusive leadership skills.

Self-regulated learning (SRL) The SRL construct was measured using 12 items adapted from "Thinking Collaboratively" [28]. This measure captured participants' perceptions of their individual cognitive processes, focusing on the sub-factors of GenAI-supported managing strategies (e.g., "I know my level of motivation") and GenAI- supported monitoring strategies (e.g., "I am aware of my effort"). The construct demonstrated high reliability (Cronbach's alpha = 0.874). These items capture the individual cognitive processes that AI was intended to augment. The questionnaire was designed to assess the individual's ability to autonomously direct their learning and problem-solving, which was a core focus of the AI-enabled portion of the intervention.

Social media co-regulation This construct was measured using 10 items, also adapted from "Thinking Collaboratively" [28]. The items focused on the collaborative processes that occurred within the Facebook group, including sub-factors such as social media-supported managing strategies (e.g., "I pay attention to the ideas of others") and social media- supported monitoring strategies (e.g., "I consider the feedback of others"). This instrument aimed to capture the collective efforts of the group to refine and adapt their shared strategies. The construct showed good reliability (Cronbach's alpha = 0.863). These items capture the collective communication, coordination, and collaborative sensemaking facilitated by the social media platform.

Inclusive educational leadership The measure for this construct was adapted from the Inclusive Leaders Self-Assessment (Inclusive Leaders Group, [40]). This nine-item questionnaire assessed participants' self-perceived competencies relevant to leading inclusively in a crisis, such as seeking feedback from diverse sources and adapting one's style to achieve better results. Sample items included "How often do you seek and act on feedback from a variety of people?", "Do you know your strengths, weaknesses, limits, and opportunities?", "When working with diverse team members, do you adapt your style to achieve better results?", and "Have you taken time to learn about your own personal biases?" Participants rated their agreement on a 5-point Likert scale. The questionnaire demonstrated good reliability (Cronbach's alpha = 0.865). These items capture the self-

perceived development of leadership skills crucial for effective teamwork and coordination in diverse crisis settings.

Rubric assessment To provide a more objective measure of the intervention's outcome, expert evaluations were conducted using a competency-based rubric. This rubric assessed the final strategies developed by the student teams based on five key criteria:

1. Inclusive educational stakeholder engagement: Assessed the extent to which proposed strategies involved diverse stakeholders, reflecting the capacity for effective coordination.
2. Equity-centered solutions: Evaluated whether strategies prioritized equitable resource distribution for marginalized groups.
3. Culturally responsive strategies: Assessed the integration of local practices and sensitivities into the solutions.
4. Crisis adaptability: Evaluated the flexibility of the strategies to dynamic conditions.
5. Collaboration: Assessed the understanding of and use of collaborative action and tools.

Strategies were scored by five experts to maintain the reliability and validity of assessment on a 5-point scale (1 = Inadequate, 5 = Exemplary). Only strategies achieving a score of Proficient (4) or higher were considered to have met a threshold of effectiveness in demonstrating inclusive educational leadership competencies. Students whose strategies met this threshold were recognized, and their performance scores were used as an objective indicator of the intervention's efficacy in developing collaborative and leadership capacities. This rubric assessment serves as an objective behavioral outcome measure, complementing self-reported data and strengthening construct validity through methodological triangulation.

5 Data analysis

We employed a multi-faceted analytical framework comprising three distinct approaches: Partial Least Squares Structural Equation Modeling (PLS-SEM), Fuzzy-Set Qualitative Comparative Analysis (fsQCA), and Artificial Neural Networks (ANN). This multi-method approach allows us to examine different facets of the data and gain a more holistic understanding of how technology influences collaborative processes and outcomes. This triangulation strengthens the validity of our findings by capturing linear, configurational, and non-linear associations.

5.1 Symmetrical analysis (partial least squares structural equation modeling – PLS-SEM)

PLS-SEM was selected for the symmetrical analysis due to its suitability for exploring and confirming hypothesized linear relationships and mediation effects, particularly in complex models with latent variables [39, 56]. It is robust for exploratory research and for assessing latent variables [31]. The multi-group analysis feature of PLS-SEM is critical for our quasi-experimental design, allowing us to statistically isolate the effect of the technology-supported intervention by comparing structural relationships before and after implementation. Accordingly, all structural relationships, including mediation effects, are interpreted as statistical associations rather than causal pathways.

The analysis proceeded in three primary steps. Outer Model Assessment (Measurement Model) confirms the reliability and validity of the constructs by examining the

relationship between the observed indicators and their latent variables. Inner Model Assessment (Structural Model) evaluates the hypothesized linear relationships (path coefficients) between the latent constructs, including mediation effects and explained variance (R^2). Multi-Group Analysis (MGA) uses Measurement Invariance of Composite Models (MICOM) to ensure comparability across groups, followed by MGA to test for statistical differences in path coefficients (e.g., pre- vs. post-intervention, Pakistan vs. Türkiye).

1. *Measurement model (outer model)*: This links the observed indicators (items) to their latent constructs.

$$\mathbf{x} = \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta} \quad \text{and} \quad \mathbf{y} = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\epsilon}$$

Where:

- $\mathbf{x}$, $\mathbf{y}$: Vectors of observed indicators for exogenous and endogenous constructs, respectively.
- $\boldsymbol{\xi}$,$\boldsymbol{\eta}$: Vectors of latent exogenous and endogenous constructs, respectively.
- $\boldsymbol{\Lambda x}$, $\boldsymbol{\Lambda y}$: Matrices of factor loadings, representing the relationship (correlation) between the latent constructs and their indicators.
- $\boldsymbol{\delta}$,$\boldsymbol{\epsilon}$: Vectors of measurement errors.

Structural model (inner model) This specifies the linear relationships (paths) between the latent constructs.

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\,\boldsymbol{\xi} + \boldsymbol{\zeta}$$

Where:

- $\boldsymbol{\eta}$,$\boldsymbol{\xi}$: Vectors of endogenous and exogenous latent constructs.
- $\mathbf{B}$: Matrix of path coefficients between the endogenous constructs.
- $\boldsymbol{\Gamma}$: Matrix of path coefficients between the exogenous and endogenous constructs.
- $\boldsymbol{\zeta}$: Vector of errors (disturbances) in the structural equations.

5.2 Outer model assessment results (reliability and validity)

5.2.1 First-order reliability and validity

Construct reliability and convergent validity were assessed against recommended thresholds: Cronbach's α ≥ 0.70, Dillon–Goldstein's ρa ≥ 0.70, Composite Reliability (ρc) ≥ 0.70, and Average Variance Extracted (AVE) ≥ 0.50 [31]. All first-order constructs met these standards, demonstrating satisfactory internal consistency and indicator convergence. Specifically, Cronbach's α ranged from 0.736 to 0.936, ρa from 0.738 to 0.936, ρc from 0.850 to 0.945, and AVE between 0.505 and 0.716. Furthermore, all standardized item loadings exceeded 0.640, surpassing the minimum acceptable threshold of 0.40, supporting strong indicator reliability (See Fig. 3; Table 2).

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio of Correlations (HTMT). All HTMT values between the main latent variables (e.g., Inclusive Leadership vs. Social Media Co-Regulation) were below the recommended threshold of 0.90 [36], confirming satisfactory discriminant validity at the first-order level.

However, the HTMT values between the sub-factors (e.g., GenAI Managing Strategies and GenAI Monitoring Strategies) and their respective higher-order constructs (GenAI

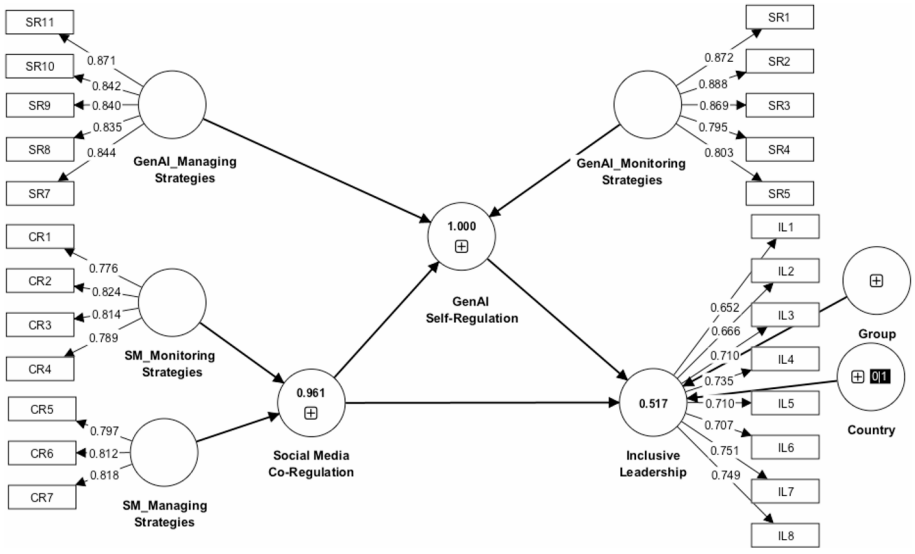


Fig. 3 Item loadings

Table 2 Reliability and validity of constructs

Factors	α	rho_a	rho_c	AVE
Inclusive Educational Leadership	0.86	0.863	0.891	0.505
GenAI Self-Regulation	0.936	0.936	0.945	0.634
GenAI Managing Strategies	0.901	0.901	0.927	0.716
GenAI Monitoring Strategies	0.900	0.901	0.926	0.716
Social Media Co-Regulation	0.838	0.839	0.878	0.509
SM Managing Strategies	0.736	0.738	0.85	0.654
SM Monitoring Strategies	0.814	0.815	0.878	0.642

Table 3 Heterotrait-monotrait (HTMT)

	1	2	3	4	5	6	7
GenAI self-regulation							
GenAI managing strategies	1.025						
GenAI monitoring strategies	1.025	0.856					
InclusiveLeadership	0.65	0.623	0.624				
SM managing strategies	0.647	0.63	0.611	0.855			
SM monitoring strategies	0.608	0.559	0.608	0.724	0.828		
Social media co-regulation	0.763	0.744	0.72	0.82	1.05	1.131	

Self-Regulation) were high (e.g., 1.025). This high association is consistent with theoretical expectations for hierarchical component models, where sub-factors are dimensions of a broader concept. The constructs were therefore modeled as second-order components (Higher-Order Constructs – HOCs), where the sub-factors served as reflective indicators of the HOCs, confirming the theoretical structure of Generative AI Self-Regulation and Social Media Co-Regulation (See Table 3).

5.3 Inner model assessment (structural model)

Multicollinearity within the structural model was assessed using the Variance Inflation Factor (VIF). All VIF values for the latent constructs were well below the conservative

Table 4 Outer variance inflation factor

	VIF
GenAI-managing strategies	2.45
GenAI-monitoring strategies	2.45
IL1	1.548
IL2	1.593
IL3	1.746
IL4	1.875
IL5	1.684
IL6	1.606
IL7	1.96
IL8	1.757
SM-managing strategies	1.705
SM-monitoring strategies	1.705

Table 5 Model fit indices

	Saturated model	Estimated model
SRMR	0.069	0.069
d_ULS	0.377	0.377
d_G	0.205	0.205
Chi-square	326.91	326.91
NFI	0.775	0.775

Table 6 Effect size (f^2) analysis

	GenAI _Self Regulation	Inclusive_Leadership
GenAI self regulation		0.096
Social media co-regulation	0.532	0.466

threshold of 5 [66], indicating that multicollinearity was not an issue in the structural model (See Table 4).

Model fit was evaluated using the Standardized Root Mean Residual (SRMR) and Normed Fit Index (NFI). The SRMR for both saturated and estimated models was 0.069 and 0.069 respectively, meeting the cutoff below the value of 0.08 [38], indicating a good fit. The NFI for both models was 0.775 and 0.775 [12]. Although the NFI value (0.775) indicates moderate fit, this is acceptable in exploratory PLS-SEM studies involving complex models and smaller subgroup samples, where emphasis is placed on predictive relevance and variance explanation rather than strict covariance-based fit indices. Furthermore, the satisfactory SRMR values and substantial R^2 values indicate that the model demonstrates adequate explanatory power despite moderate global fit indices. These fit indices suggest that the estimated model provides a reasonable representation of the data (See Table 5).

The effect size (f^2) was calculated to determine the practical significance of the relationships [17], using benchmarks where 0.02, 0.15, and 0.35 are considered small, moderate, and large effects, respectively. The path from Social Media Co-regulation to Generative AI Self-Regulation had an f^2 of 0.532, representing a large effect. The path from Social Media Co-regulation to Inclusive Leadership Development had an f^2 of 0.466, representing a large effect. The path from Generative AI Self-Regulation to Inclusive Leadership Development had an f^2 of 0.096, representing a small to moderate effect (See Table 6).

Table 7 R-square

	R-square	*R*-square adjusted
GenAI self regulation	0.347	0.345
Inclusive leadership	0.554	0.551

Table 8 MICOM Step 2a

Group	Constructs	Correlation permutation mean	5.00%	Permutation *p* value
Control & Experimental	GenAI-Self Regulation	1	0.998	0.895
	Inclusive Leadership	0.994	0.986	0.115
	SM Co-Regulation	0.997	0.988	0.144
Pakistan & Türkiye	GenAI-Self Regulation	1	0.999	0.24
	Inclusive Leadership	0.998	0.996	0.066
	SM_Co-Regulation	0.999	0.998	0.69

The R^2 for Inclusive Leadership Development was 0.554 (adjusted R^2 = 0.551), indicating that Generative AI Self-Regulation and Social Media Co-regulation collectively explain approximately 55% of the variance in inclusive leadership. The R^2 for Generative AI Self-Regulation was 0.347. According to [31] these R^2 values are considered substantial ($R^2 > 0.25$) and indicate that the model has significant explanatory power for the collaborative regulatory processes and leadership outcomes (See Table 7).

5.4 Multiple group analysis (MGA)

Multiple group analysis (MGA) was conducted to compare the path coefficients and the indirect effect between the pre-intervention and post-intervention groups, as well as across countries Pakistan and Türkiye directly assessing the outcome of the technology-supported intervention. Measurement invariance was established using the MICOM procedure [35]. Step 2 of MICOM confirmed measurement invariance, with non-significant permutation p-values for the correlations between constructs across groups (see Table 8).

The multi-group analysis (MGA) bootstrapping results revealed notable variations across the experimental and control groups. The association between Generative AI-enabled self-regulation and inclusive leadership was statistically significant in both the post-control (β = 0.339, SD = 0.091, $p < .001$) and post-experimental (β = 0.354, SD = 0.097, $p < .001$) groups, whereas the relationship was not significant in the pre-control (β = 0.206, SD = 0.173) and pre-experimental (β = 0.155, SD = 0.134) groups. The link between social media co-regulation and Generative AI-enabled self-regulation appeared strongest in the post-experimental group (β = 0.731, SD = 0.050, $p < .001$), with meaningful positive relationships also observed in the pre-control (β = 0.571, SD = 0.080, $p < .001$) and pre-experimental (β = 0.603, SD = 0.072, $p < .001$) groups. In contrast, the post-control path showed a weaker, non-significant association (β = 0.344, SD = 0.201).

Similarly, social media co-regulation showed positive associations with inclusive leadership across all groups, with significant relationships in the post-control (β = 0.632, SD = 0.110, $p < .001$), post-experimental (β = 0.477, SD = 0.095, $p < .001$), pre-control (β = 0.548, SD = 0.133, $p < .001$), and pre-experimental (β = 0.602, SD = 0.113, $p < .001$) conditions. Finally, the indirect association through Generative AI-enabled self-regulation reached statistical significance only in the post-experimental group (β = 0.259, SD =

Table 9 MGA bootstrapping results

Path	Post_Control	Post_Exp	Pre_Control	Pre_Exp
GenAI Self-Regulation → Inclusive Edu. Leadership	0.339*** (SD = 0.091)	0.354*** (SD = 0.097)	0.206 (SD = 0.173)	0.155 (SD = 0.134)
SM Co-Regulation → GenAI Self-Regulation	0.344 (SD = 0.201)	0.731*** (SD = 0.050)	0.571*** (SD = 0.080)	0.603*** (SD = 0.072)
SM Co-Regulation → Inclusive Edu. Leadership	0.632*** (SD = 0.110)	0.477*** (SD = 0.095)	0.548*** (SD = 0.133)	0.602*** (SD = 0.113)
SM Co-Regulation → GenAI Self-Regulation → Inclusive Edu. Leadership	0.119 (SD = 0.081)	0.259*** (SD = 0.075)	0.118 (SD = 0.103)	0.093 (SD = 0.082)

*$p < .05$, **$p < .01$, ***$p < .001$

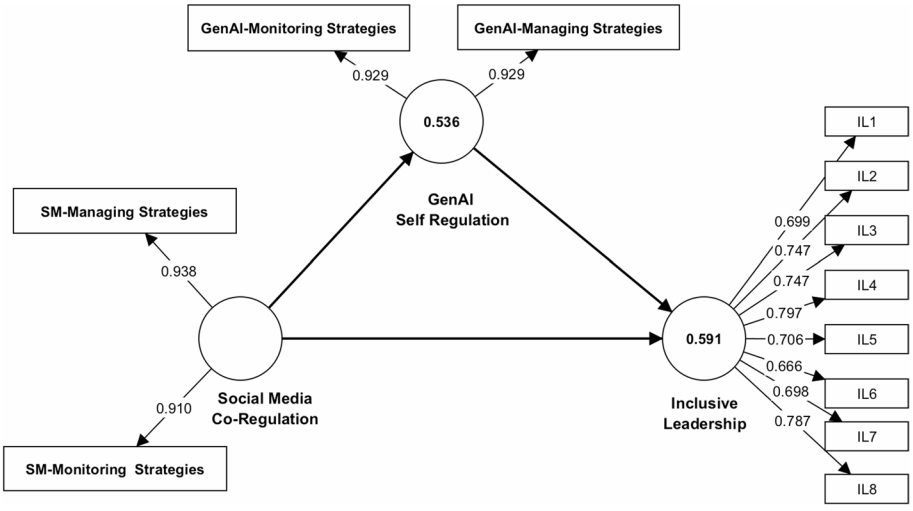


Fig. 4 Direct relations for post intervention group

0.075, $p < .001$), while the post-control (β = 0.119, SD = 0.081), pre-control (β = 0.118, SD = 0.103), and pre-experimental (β = 0.093, SD = 0.082) groups did not exhibit statistically meaningful indirect effects (see Table 9).

Higher mean values indicate stronger associations as given in post intervention direct paths in Fig. 4.

The multi-group analysis (MGA) results indicated no statistically significant differences in the associational patterns between Pakistan and Türkiye. Although the association between Generative AI– supported self-regulation and inclusive leadership was somewhat stronger in Pakistan than in Türkiye (Δ = 0.162, $p = .174$, two-tailed), this difference did not reach statistical significance. Similarly, the relationship between social media co-regulation and inclusive leadership appeared slightly stronger in Türkiye (Δ = −0.190, $p = .066$, two-tailed), though this variation also fell below conventional significance thresholds. The indirect association through Generative AI– supported self-regulation was non-significant (Δ = 0.092, $p = .222$, two-tailed). Overall, the pattern of relationships was broadly consistent across both countries (See Table 10).

5.5 Asymmetrical analysis (fsQCA)

While symmetrical statistical methods such as Structural Equation Modeling (SEM) and multiple regression estimate net effects and linear relationships, they often overlook the causal complexity underlying leadership processes [63]. Leadership outcomes may arise

Table 10 Multi-group analysis (MGA) results: country differences (Pakistan vs. Türkiye)

Path	Difference (Pakistan – Türkiye)	*p* (1-tailed)	*p* (2-tailed)
GenAI Self-Regulation → Inclusive Leadership	0.162	0.087	0.174
Social Media Co-Regulation → GenAI Self-Regulation	-0.009	0.54	0.92
Social Media Co-Regulation → Inclusive Leadership	-0.19	0.967	0.066
Social Media Co-Regulation → GenAI _Self Regulation → Inclusive Leadership	0.092	0.111	0.222

from multiple combinations of conditions (equifinality), and the causes of an outcome may differ from the causes of its absence (causal asymmetry). To capture these dynamics, this study employed Fuzzy-set Qualitative Comparative Analysis (fsQCA) [62]. As a set-theoretic approach, fsQCA identifies configurational pathways (causal recipes) that are sufficient for producing an outcome. This approach is particularly appropriate for socio-technical phenomena where outcomes emerge from interacting conditions rather than isolated variables. In this study, fsQCA complements the symmetrical and predictive analyses by identifying how combinations of co-regulation and self-regulation relate to leadership outcomes.

The core formulas for assessing necessary and sufficient conditions are:

1. *Sufficiency*: A combination of conditions (X) is *sufficient* for an outcome (Y) if X is a subset of Y. The consistency score for sufficiency (Cons) is defined by the following ratio (where μ represents set membership scores):

$$\mathbf{Cons}\,(\mathbf{X} \leq \mathbf{Y}) = \frac{\min \sum \left(\mu_{\mathbf{X}_i}, \mu_{\mathbf{Y}_i}\right)}{\sum \mu_{\mathbf{X}_i}}$$

Where μXi and μYi are the set membership scores (0 to 1) for the i-th case in condition X and outcome Y, respectively. A high Cons (e.g., ≥ 0.8) supports sufficiency.

2. *Necessity*: A condition (X) is *necessary* for an outcome (Y) if Y is a subset of X. The consistency score is defined as:

$$\mathbf{Cons}(\mathbf{Y} \leq \mathbf{X}) = \frac{\sum \min(\mu_{\mathbf{Y}_i}, \mu_{\mathbf{X}_i})}{\sum \mu_{\mathbf{Y}_i}}$$

Following Ragin [62], raw scores for Co-Regulation, Self-Regulation, and Leadership were calibrated into fuzzy-set membership scores ranging from 0 (full non-membership) to 1 (full membership). A percentile-based calibration approach was used to ensure meaningful set membership. The 95th percentile represented full membership (1.0), the 50th percentile the crossover point (0.5), and the 5th percentile full non-membership (0.0).

A necessity analysis was then conducted to assess whether any condition consistently appears whenever the outcome occurs. In fsQCA, a condition is considered necessary when consistency ≥ 0.90 (See Table 11).

To identify combinations of conditions sufficient for the presence or absence of leadership, truth tables were constructed for both outcomes. A frequency threshold of five cases and a consistency cutoff of 0.80 were applied. Intermediate solutions were derived based on theoretical expectations that both regulatory mechanisms contribute positively to leadership (See Table 12).

Table 11 Analysis of necessary conditions

Condition	Leadership consistency	Coverage	~Leadership Consistency	Coverage
Co-Regulation	0.769	0.811	0.616	0.504
~Co-Regulation	0.483	0.595	0.847	0.811
Self-Regulation	0.720	0.861	0.575	0.534
~Self-Regulation	0.450	0.491	0.873	0.740

Table 12 Configurations for the presence and absence of leadership

Configuration	Presence: Pathway 1	Absence: Pathway 2	Absence: Pathway 3
Co-Regulation	●	⊗	●
Self-Regulation	●	⊗	⊗
Consistency	0.826	0.929	0.933
Raw Coverage	0.738	0.671	0.361
Unique Coverage	0.738	0.671	0.361
PRI	0.272	0.488	0.163

Solution Consistency (Presence): **0.826**; Solution Coverage (Presence): **0.738**

● Indicates presence of a condition, ⊗ indicates absence

The results demonstrate causal asymmetry in leadership processes. The joint presence of Co-Regulation and Self-Regulation represents the primary pathway associated with leadership outcomes (Consistency = 0.826), suggesting that leadership emerges when collaborative and individual regulatory capacities operate together. However, the relatively low PRI value (0.272) indicates that this configuration is not uniquely associated with leadership and may also appear in cases without the outcome. These conditions can therefore be interpreted as INUS conditions—insufficient but non-redundant components within a broader causal configuration.

In contrast, the absence of leadership appears more deterministic. The simultaneous absence of both regulatory mechanisms (~ Co-Regulation * ~Self-Regulation) forms a highly consistent pathway explaining leadership absence (Consistency = 0.929). Additionally, Pathway 3 shows that even when co-regulation is present, the absence of self-regulation is sufficient to undermine leadership outcomes (Consistency = 0.933), highlighting individual regulation as a potential weak-link condition.

5.6 Artificial neural network (ANN)

Artificial neural networks (ANNs) were employed to explore complex, non-linear associations that may not be captured through traditional linear models [34]. This analytical lens complements the PLS-SEM and fsQCA results, offering a comparative perspective on the predictive relationships among the study constructs. Benchmarking the ANN against a baseline linear regression provided descriptive evidence that the non-linear approach yielded comparatively better performance, thereby supporting its use as an additional analytical layer within the study's triangulation design.

The experimental dataset was preprocessed to ensure comparability across features. Input variables—Generative AI Self-Regulation and Social Media Co-Regulation—were standardized using the StandardScaler procedure. The dataset was divided into training (80%) and testing (20%) subsets to facilitate model evaluation. A simple linear regression model was first fitted to establish a baseline. Subsequently, an ANN model was defined with a single hidden layer comprising 32 units and a Rectified Linear Unit (ReLU) activation function. To reduce overfitting, L2 regularization (0.0007) and a dropout rate (0.3)

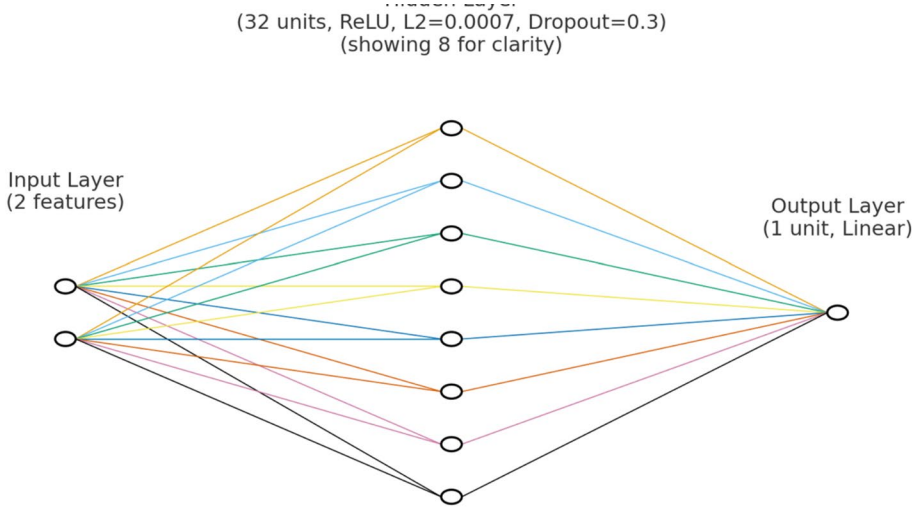


Fig. 5 ANN architecture

Table 13 Comparison of model performance

Model	Evaluation	MSE	MAE
Linear Regression	Test Set	0.833	0.702
ANN (32 units, L2 + Dropout, ES)	Test Set	0.774	0.690
ANN (32 units, L2 + Dropout, ES)	5-Fold CV	0.597 (± 0.128)	0.5980 (± 0.058)

were applied. The model was compiled using the Adam optimizer with Mean Squared Error (MSE) as the loss function.

Training was conducted with an internal validation split, employing early stopping (patience = 15) to monitor performance stability. To further evaluate the model's generalization capacity, a 5-fold cross-validation procedure was implemented. Model performance on the independent test set was then assessed descriptively using standard evaluation metrics (e.g., MSE, MAE, R^2) (See Fig. 5).

The performance comparison indicated that the regularized ANN model achieved lower error values on the test set (MSE = 0.774, MAE = 0.690) relative to the baseline linear regression model (MSE = 0.833, MAE = 0.702). The results from the 5-fold cross-validation (MSE = 0.597) also demonstrated the ANN's enhanced ability to represent non-linear associations within the data structure. These findings suggest that the ANN provided a more nuanced description of the underlying relationships among the constructs, thereby supporting the analytical robustness of the integrated shared metacognition framework. Table 13 summarizes the performance comparison between the linear regression and regularized ANN models.

The ANN model produced lower mean squared error (MSE) and mean absolute error (MAE) values than the linear regression model in both cross-validation and test evaluations, indicating comparatively better association of performance.

5.6.1 SHAP analysis

SHAP (SHapley Additive exPlanations) values were used to interpret the black-box ANN model, quantifying the marginal contribution of each predictor to the model output based on cooperative game theory [52]. This provides transparent, model-agnostic insights into feature importance. SHAP values quantify the marginal contribution of

each predictor to the model output based on cooperative game theory [52]. The explanation model for the prediction f(x) is defined as a sum of feature contributions:

$$g(z') = \phi_0 + \sum_{j=1}^{M} \phi_j z'_j$$

Where:

- g(z') is the explanation model (a linear approximation).
- z' is the simplified input (a vector representing a coalition of features).
- M is the number of features.
- $\phi 0$ is the expected output of the model (the base value when no features are known).
- ϕ j is the SHAP value for the j-th feature, representing its contribution to the prediction.

The SHAP value ϕj is calculated by averaging the marginal contribution of feature j across all possible permutations of features (S):

$$\phi_j = \sum_{S \subseteq \{F\{j\}\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} \left[f_{S \cup \{j\}}\left(x_{S \cup \{j\}}\right) - f_S\left(x_S\right) \right]$$

Where:

- F is the set of all features.
- S is any subset of F that does not include feature j.
- $f_{S\cup\{j\}}$ $(X_{S\cup\{j\}})$ is the prediction when the features in S and feature j are present.

The SHAP analysis indicated that core regulatory processes contributed positively to the predicted levels of Inclusive Educational Leadership. Social Media Co-Regulation exhibited a consistently positive influence, reflecting that greater collective dialogue and shared understanding were associated with higher predicted leadership outcomes. Generative AI Self-Regulation also showed a positive association, where higher feature values corresponded to stronger leadership predictions within the model. The SHAP summary plot further illustrated that both Generative AI Self-Regulation and Social Media Co-Regulation emerged as key features influencing the ANN's predictions for Inclusive Educational Leadership, showing convergence with the patterns observed in the symmetrical and asymmetrical analyses (see Fig. 6).

Thus, ANN does not replace SEM but extends it by validating whether non-linear patterns support the observed associative relationships.

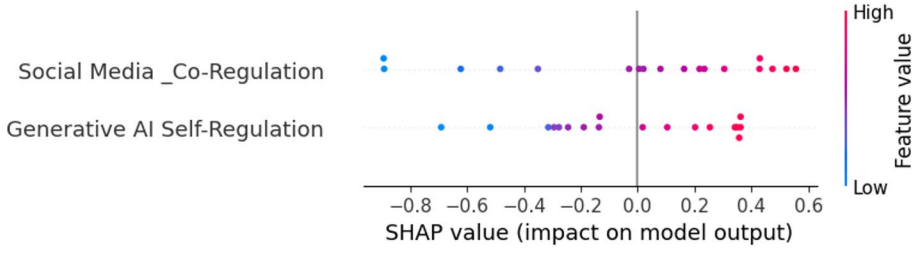


Fig. 6 SHAP values

5.7 Experts' validation

The expert validation process added a qualitative layer of methodological rigor by aligning the intervention outcomes with the study's hypothesized framework of shared metacognition. A panel of educational experts—each with experience mentoring pre-service teachers during cross-cultural training—evaluated the student outputs using a rubric designed to assess inclusive stakeholder engagement, equity-centered solutions, cultural responsiveness, crisis adaptability, and collaboration. Their assessments were informed by both their direct interactions with students during the intervention and their rubric-based evaluations of student-generated strategies.

These expert evaluations complemented the statistical findings by providing descriptive evidence that the observed quantitative patterns translated into demonstrable behaviors and strategies. The experts' observations offered grounded insights into how inclusive leadership was enacted through reflective and adaptive regulation of learning —both individually (AI self-regulation) and collaboratively (social media co-regulation). The integration of these insights confirmed the consistency between quantitative and qualitative findings, highlighting the complementary nature of mixed-method triangulation in validating the shared metacognition framework. Collectively, these qualitative insights confirmed that inclusive leadership competencies—such as equity, empathy, and collaboration—were not abstract constructs but observable learning outcomes, enacted through shared metacognition mediated by technology (See Table 14).

6 Discussion

These findings collectively support the conceptualization of shared metacognition as an emergent socio-technical process, operationalized through the interaction of AI-supported self-regulation and social media–supported co-regulation rather than as an independently measured construct. This study contributes to understanding how AI-supported self-regulation and social-media-supported co-regulation jointly relate to inclusive educational leadership through shared metacognitive processes. This study

Table 14 Experts validation

Pre-defined themes (based on hypotheses)	Codes (rubric categories)	Open codes (emergent concepts)	Supporting quotations (expert observations)
H1: Collaboration, Stakeholder engagement, Inclusivity	Cross-cultural collaboration, Equity-driven teamwork	Cross-cultural interaction, Diverse perspectives	"Social media harmonised students' learning for equity as Turkish and Pakistani students were interacting from different cultural backgrounds."
H2: Co-regulation, Peer monitoring, Dialogue	Peer communication, Shared responsibility	Peer reminders, Shared posts, Task scheduling	"Students coordinated tasks through group posts and reminders, ensuring everyone participated equally in decision-making."
H3: Self-regulation, Managing strategies, Monitoring strategies	Goal setting, Reflection, Ethical awareness	Equity orientation, Strategy refinement, Autonomy	"Students wrote strategies that were more equity-oriented, considering marginalized groups such as people with special needs, women, and minorities."
H4: Synergy, Mediation, Integration	Integration of AI and social media, Cognitive balance	Balanced strategies, Cultural understanding	"Social media regulation of learning enhanced generative AI regulation, combining to produce inclusive and balanced crisis strategies."
H5: Universality, Cross-cultural consistency	Technology-mediated communication, Accessibility	Translation tools, Reduced linguistic barriers	"Turkish students posted their comments in Turkish, and Facebook helped translate them into English, enabling inclusive interaction without discrimination."

contributes to theory by (1) extending the Community of Inquiry and shared metacognition models to cross-cultural crisis education; (2) linking individual and collective regulation mechanisms with leadership outcomes; and (3) empirically illustrating how collaboration, and inclusivitycan manifest in human–AI learning interactions.

Building on these contributions, the study interprets its findings as robust symmetrical and asymmetrical associative patterns, not as causal pathways. The multi-method evidence (PLS-SEM, fsQCA, and ANN) substantiates the hypothesized relationships, revealing how Generative AI and social media jointly correspond to the development of inclusive educational leadership capabilities across contexts. The inclusion of expert-based rubric evaluation reduces reliance on self-reported perceptions and provides partial objective validation of leadership outcomes. By framing inclusivity as a measurable socio-technical outcome, this study responds to calls for more human-centered and practitioner-oriented approaches [18] to AI-supported learning [18, 65].

6.1 Theoretical implications

The Multi-Group Analysis (MGA) comparing the pre-, post-, control-, and experimental groups provided an understanding of how the intervention was associated with variations in the relationships among constructs within the shared metacognition framework. Rather than implying directionality, these findings highlight patterned associations that advance the conceptualization of shared metacognition as a cross-cultural, AI-supported framework for leadership development.

Consistent with H1, social-media-supported co-regulation showed a positive and stable association with inclusive leadership across all groups. This indicates that collaborative digital environments foster equitable participation, trust, and mutual monitoring—key conditions of inclusive coordination [23, 45]. The slightly lower coefficient in the Post-Experimental group compared with the Post-Control group suggests that once structured AI-supported self-regulation was introduced, some influence previously expressed through social collaboration was redistributed within the AI-mediated pathway, aligning with previous observations that digital collaboration evolves as tools become more intelligent [73].

Supporting H2, the strong association between social-media-supported co-regulation and Generative AI self-regulation—most evident in the Post-Experimental condition—reflects how dialogic and peer-monitoring practices enhance learners' capacity for autonomous regulation in AI-mediated contexts [30]. This reinforces prior work emphasizing that peer interaction nurtures self-regulatory awareness [50] and adaptive control mechanisms [11]. The absence of a significant association in the Post-Control group, however, indicates that without structured guidance, the transfer from collective to individual regulation remains limited, suggesting that the two must be deliberately scaffolded to interact effectively.

In line with H3, the relationship between Generative AI self-regulation and inclusive leadership became significant only after the intervention, illustrating how AI-supported reflective feedback can strengthen equitable and adaptive decision-making [26]. This association suggests that Generative AI functions as a cognitive partner, augmenting awareness and strategic reasoning—skills integral to inclusive leadership [75]. Such augmentation supports leaders' capacity for fairness and empathy, echoing earlier findings on the transformative role of AI in leadership training [42].

Consistent with H4, the indirect association of social-media-supported co-regulation with inclusive leadership through Generative AI self-regulation emerged significantly only in the Post-Experimental group, capturing the complete shared-metacognition pathway envisioned in the study. This finding highlights how collaborative monitoring on social media and adaptive management through AI form an integrated socio-technical cycle, demonstrating human–AI collaboration as enacted practice [13]. The alignment between human and AI regulation in this mediated pathway reflects structural complementarity rather than causal sequencing, providing empirical grounding to the notion of Shared Metacognition [29, 82].This unique finding isolates the intervention's influence on the complete, functional shared metacognition cycle [81]. The emergence of this mediated pathway indicates a strengthened structural alignment between human and AI regulation rather than temporal causality.

Finally, consistent with H5, the comparison between Pakistan and Türkiye showed no significant difference in the model's structural paths. This suggests that the dynamics of shared metacognition operate similarly across both cultural contexts, possibly due to the global affordances of AI and social media as learning mediators [47, 49]. While replication with larger samples is warranted, this cross-context stability challenges assumptions of cultural determinism in digital leadership development and supports the framework's potential scalability [74].

Overall, these findings extend theoretical understanding by integrating individual and collective regulation within a human-centered socio-technical learning framework. Inclusive leadership thus emerges as a demonstrable socio-technical outcome of human–AI supported shared metacognition.

6.2 Triangulation of results and methodological addition

To ensure interpretive rigor, this study employed a multi-method triangulation strategy integrating PLS-SEM, fsQCA, and ANN, supported by expert qualitative validation (see Fig. 7). This design offered complementary analytical lenses to examine how human–AI shared metacognition relates to inclusive educational leadership across contexts.

PLS-SEM captured the average associative strengths among constructs [31], confirming that the indirect association between social-media-supported co-regulation and inclusive leadership through Generative AI self-regulation became significant only after the intervention. This indicates that structured AI-supported reflection reinforces collaborative learning dynamics and aligns with calls to integrate explanatory and interpretive approaches in socio-technical research.

fsQCA revealed asymmetrical and configurational relationships [62], showing that high Generative AI self-regulation combined with strong social-media co-regulation was sufficient for high inclusive leadership outcomes. This underscores that both individual and collective regulatory capacities must coexist for inclusivity to emerge meaningfully [1].

ANN extended these insights by modeling non-linear patterns [34]. Using SHAP (SHapley Additive exPlanations) [52], the model identified both regulatory constructs as substantial contributors to leadership outcomes, confirming the robustness and interpretability of the socially shared-regulation of learning framework across methods [41].

Together, these complementary analyses converge on a single interpretation: shared metacognition operates as a dynamic socio-technical mechanism where human and AI

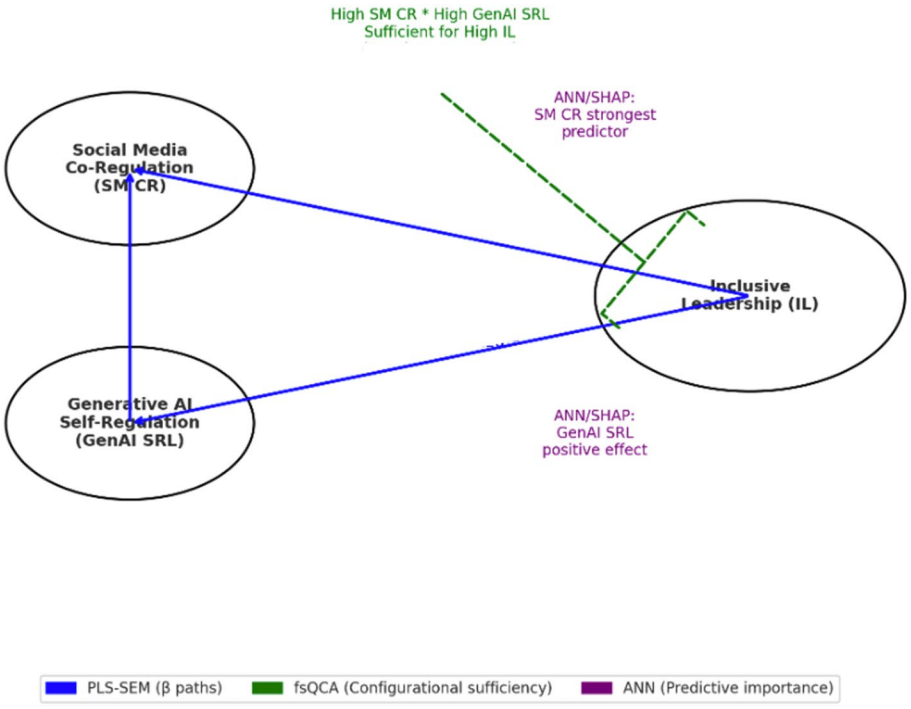


Fig. 7 Triangulated findings

regulation interact to sustain inclusivity and collaborative leadership. This methodological synthesis provides a robust methodological approach for examining socio-technical learning processes, demonstrating inclusivity as a measurable relational construct and offering a replicable analytical model for studying socio-technical complexity in education.

6.3 Practical implications

The implications of this study specifically highlight how regulatory processes—self-regulation and co-regulation—can be intentionally designed and supported through AI and social media to foster inclusive educational leadership. Practically, this research highlights how inclusive, human-centered leadership can guide the effective and human-centered integration of AI in education and beyond. The proposed model illustrates pathways for designing AI-supported systems that contribute to inclusive and sustainable innovation ecosystems. In particular, the findings hold policy relevance for educational leaders, instructional designers, technology developers, and teacher educators who aim to build equitable, adaptive, and scalable frameworks for inclusive educational leadership within a human-centered AI-supported learning framework.

6.3.1 For educational institutions and policymakers—embedding cross-cultural scalability

The evidence suggests that leadership preparation programs should embed regulatory skill-building directly into curricula, moving from collaborative co-regulation via social media to reflective self-regulation through Generative AI tools. This iterative process cultivates shared metacognition as a transferable competency across diverse cultural and crisis contexts. The comparable patterns observed between Türkiye and Pakistan highlight the framework's adaptability, supporting its use as a scalable pedagogical model

aligned with human-centered and ethical AI design considerations [43, 79]. Training initiatives can thus prioritize *learning-to-lead through regulation*—where inclusive leadership becomes the emergent outcome of deliberate socio-technical design rather than incidental exposure.

6.3.2 For technology designers—integrating socio-technical systems

Developers of educational technologies should conceptualize collaboration and self-regulation as complementary dimensions of a unified learning experience. Platforms that interlink AI-enabled adaptive feedback with social interaction tools can enhance user reflection and promote equitable participation. Integrating transparency and personalization features grounded in transparency, fairness, and human-centered AI design considerations [77] can transform such platforms into ecosystems that actively foster empathy, trust, and cultural sensitivity, rather than simply delivering content [65].

6.3.3 For educators and pre-service teachers—developing regulative leadership competence

For educators, inclusivity and leadership should be understood as *learnable*, *regulative practices* rather than static traits. Teachers can strengthen leadership capacity through iterative cycles of social monitoring (e.g., peer dialogue, mutual feedback) and AI-supported self-management (e.g., reflective goal setting, adaptive planning). This dual-regulation process enhances their ability to coordinate diverse stakeholders during crises while sustaining empathy and fairness [46]. Embedding such practices in teacher education can nurture reflective, technologically fluent leaders equipped to manage complexity with inclusivity and cultural responsiveness.

Collectively, these implications illustrate that inclusive leadership is a designable socio-technical outcome—one that emerges from the deliberate alignment of pedagogy, AI tools, and collaborative learning structures. By integrating Shared Metacognition into educational ecosystems, institutions can foster a new generation of educators who embody human-centered and inclusive AI-supported learning environments not just as a policy ideal but as a lived professional competence.

7 Conclusion

This study proposes and empirically examines a human-centered AI-supported learning framework. Using mixed methods, it demonstrated that Generative AI– supported self-regulation and social media–mediated co-regulation jointly function as interdependent dimensions of cross-cultural shared metacognition. Together, they are associated with Inclusive Educational Leadership Development among pre-service teachers in Türkiye and Pakistan. The findings revealed that while social media platforms associate with collaborative awareness and equitable participation, Generative AI associates with reflective and adaptive self-regulation. The interplay between these two forms of regulation—conceptualized as Shared Metacognition—was found to be strongly associated with leadership competencies rooted in empathy, equity, and collective decision-making. This integrated process became statistically and practically meaningful only in the post-intervention group's data, highlighting the potential of structured, technology-supported approaches associated with inclusivity during educational crises.

Moreover, the lack of detected significant country differences suggests this socio-technical framework has potential cross-cultural applicability, indicating its potential

usefulness across diverse educational systems. In theoretical terms, by embedding shared metacognition into AI-augmented education, it provides a human-centered pathway associated with leadership capable of navigating complex, multicultural, and crisis-prone environments. The central contribution of this study lies in demonstrating that inclusive educational leadership can be understood as a socio-technical outcome emerging from the interaction between individual and collective regulatory processes, rather than as an isolated leadership trait.

Symbol	Definition	Context
β	Path Coefficient (Standardized Regression Weight)	PLS-SEM
R^2	Coefficient of Determination (Variance Explained)	PLS-SEM
AVE	Average Variance Extracted	PLS-SEM
μX	Set Membership Score (0 to 1) for Condition X	fsQCA
Cons	Consistency Score (of a configuration)	fsQCA
ϕj	SHAP Value for Feature j	ANN Sensitivity Analysis
η, ξ	Vectors of Endogenous and Exogenous Latent Constructs	PLS-SEM (Structural Model)
Λ	Matrix of Factor Loadings	PLS-SEM (Measurement Model)

7.1 Limitations and future research

This study has several limitations. First, the design relied on unpaired, cross-sectional data collected at two time points. Therefore, all findings, including the mediation pathway, represent associations, not causation or longitudinal development. Accordingly, the mediation findings should be interpreted as associational patterns rather than evidence of causal mechanisms. This design limitation is highlighted by an anomaly: the path from GenAI Self-Regulation to Inclusive Leadership was significant in both the post-experimental and post-control groups. This pattern may reflect contamination, maturation effects, or uncontrolled external influences, which are inherent limitations of quasi-experimental designs using unpaired samples. While the expert rubric provided crucial objective triangulation, it was not the main dependent variable. Third, the generalizability of findings is limited due to sample imbalance (e.g., gender distribution), context specificity (Türkiye and Pakistan), and the focus on pre-service teachers, which may not fully represent broader educational or professional populations.

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Author contributions
FM: Conceptualization; Methodology; Project administration; Resources; Supervision; Validation; Visualization; Roles/Writing - original draft; and Writing - review & editing.MZA: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Roles/Writing - original draft; and Writing - review & editing.MB: Conceptualization; Methodology; Supervision; Validation; Visualization; Roles/Writing - original draft; and Writing - review & editing.

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Data availability
The data and materials used in this study are available from corresponding author upon request.

Declarations

Ethics approval and consent to participate
This study involved experimentation on human subjects and was conducted in accordance with established ethical guidelines, including the Declaration of Helsinki. Approval for the research was obtained from the Ethics Committee of the Open University of Catalonia, Barcelona as a host university to implement the intervention. Additionally, the study complies with all applicable regulations and adheres to the ethical standards set by the Open University of Catalonia. The Human Participant Declaration form, as required, has been completed and submitted alongside the manuscript. Informed consent was obtained in two steps. First, participants received an information sheet outlining

the study's purpose, procedures, rights, and data protection measures. They were informed that participation was voluntary, and they could withdraw at any time without penalty. Participants then agreed consent form, confirming their understanding and agreement to participate. The data was anonymized before analysis, and access was restricted to authorized researchers. Verbal informed consent was also obtained.

Consent for publication
The authors confirm that they have read and approved the final version of the manuscript and agree to its publication in this journal.

Competing interests
The authors declare no competing interests.

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