



Teacher Emotional Intelligence and Classroom Effectiveness in Secondary Schools

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Abstract — Teacher emotional intelligence is increasingly relevant to secondary education because classroom effectiveness depends not only on subject expertise but also on teachers' capacity to recognize, interpret, regulate, and appropriately respond to emotional signals during instruction. This study develops a human-centred computational framework for examining the relationship between teacher emotional intelligence and classroom effectiveness by combining validated self-report measures, structured classroom observations, student feedback, and privacy-preserving multimodal behavioural indicators. A central research gap is the limited integration of psychological emotional-intelligence constructs with AI-assisted classroom analytics, particularly in secondary-school environments where adolescent emotional dynamics can be highly variable. Rather than treating emotional intelligence as a static teacher attribute, the proposed framework conceptualizes it as a multidimensional capacity whose classroom expression varies across instructional and interpersonal situations. The study focuses on emotional self-awareness, emotion regulation, empathic responsiveness, and relationship management as potential determinants of instructional clarity, classroom management, student participation, and supportive teacher–student interaction.

The study is expected to provide an empirically testable and ethically constrained foundation for teacher professional development and human-centred AI-assisted educational analytics.

Keywords — Teacher Emotional Intelligence, Classroom Effectiveness, Secondary Education, Explainable

Artificial Intelligence, Multimodal Learning Analytics, Teacher–Student Interaction

Introduction

Effective secondary-school teaching is a multidimensional professional activity. Subject knowledge, instructional planning, assessment competence, and pedagogical technique remain fundamental, but teachers also work within a social environment characterized by continuous emotional exchange. A teacher may need to respond to student frustration, disruptive behaviour, examination anxiety, interpersonal conflict, disengagement, enthusiasm, or uncertainty within the same instructional period. The effectiveness with which these situations are handled can influence both the immediate classroom climate and the quality of teaching and learning.

Emotional intelligence (EI) provides a useful conceptual framework for examining these interpersonal and self-regulatory aspects of teaching. In educational settings, EI can broadly be understood as a teacher's capacity to perceive emotionally relevant information, understand its meaning, regulate personal emotional responses, and manage interpersonal interactions in ways appropriate to pedagogical goals. This conceptualization moves teacher effectiveness beyond the assumption that good teaching is determined exclusively by cognitive or technical competence.

Recent research continues to connect emotional processes with teacher effectiveness, occupational functioning, and psychological outcomes. A 2024 systematic review of teacher emotion regulation and teaching effectiveness integrated several research traditions, including emotional intelligence, coping, emotion regulation, and emotional labour,



demonstrating both the breadth of the field and considerable variation in how teachers' emotional processes have been operationalized. Research focusing specifically on Indian teachers has similarly identified substantial heterogeneity in EI instruments, teacher populations, and associated psychological and professional variables, making generalization difficult.

These limitations create an important methodological issue. Much of the teacher-EI literature depends on questionnaires administered at a single point in time. Such instruments can provide meaningful information about teachers' perceived emotional competencies, but self-perceived competence is not necessarily equivalent to behaviour displayed during a difficult classroom interaction. For example, two teachers with comparable questionnaire scores may respond differently when students repeatedly interrupt instruction, misunderstand an explanation, challenge classroom rules, or show visible disengagement.

Classroom effectiveness is equally difficult to represent through a single indicator. Student examination scores provide information about academic outcomes but cannot fully capture instructional clarity, responsiveness, participation, classroom organization, or socio-emotional support. Similarly, administrator ratings may be informative but are influenced by the limited number of classroom observations available to evaluators. A more comprehensive design therefore requires multiple sources of evidence.

At the same time, artificial intelligence and learning analytics are changing the technical possibilities for educational research. Contemporary computational methods can process speech characteristics, textual information, interaction sequences, and other multimodal classroom signals. Research published in 2024, for example, described a multimodal teacher emotion-recognition approach using teaching videos and speech information from smart classrooms, highlighting the growing technical capacity to analyse teacher-related affective signals beyond facial expressions alone. Other work has explored AI-supported analysis of teacher states through physiological and behavioural information, further demonstrating the expansion of computational affective analysis in educational contexts.

However, technological feasibility does not establish pedagogical validity. An algorithm that classifies vocal or facial patterns should not automatically be interpreted as measuring a teacher's emotional intelligence. Emotional intelligence is a complex psychological construct, whereas machine-detected behavioural signals represent context-dependent observations. Conflating the two can generate construct-validity problems and may lead to intrusive or inappropriate teacher surveillance.

Research Gap

The central research gap is not simply a lack of studies linking teacher emotional intelligence with effectiveness. Such relationships have already received substantial attention. The more specific unresolved issue is the **lack of an ethically constrained, multimodal, and interpretable analytical framework connecting validated teacher-EI dimensions with independently observed classroom-effectiveness indicators in secondary-school contexts.**

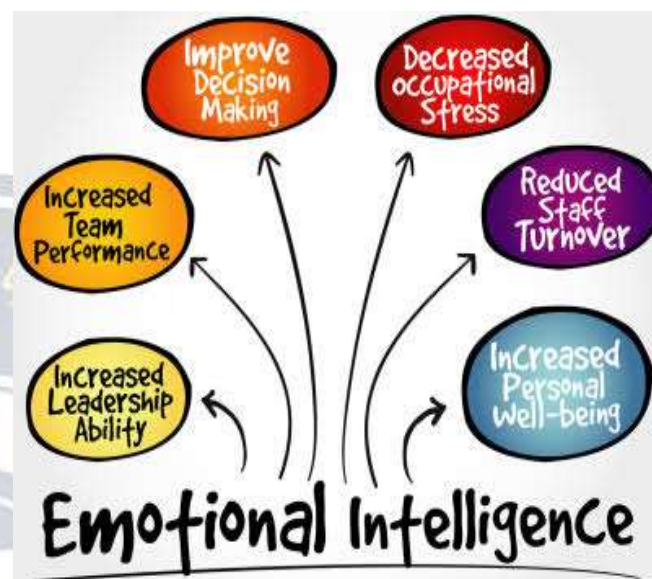


Fig. 1: The Role of Emotional Intelligence in Teacher Effectiveness

Source: <https://www.makemyassignments.com/blog/the-role-of-emotional-intelligence-in-teacher-effectiveness/>

Three methodological limitations are particularly relevant.

First, emotional intelligence and classroom effectiveness are frequently measured through self-report instruments, creating possible common-method bias when the predictor and outcome are reported by the same respondent.

Second, traditional linear correlation and regression models can identify average relationships but may inadequately represent interactions among emotional competencies. Strong emotional regulation, for instance, may become particularly valuable when combined with empathy under challenging classroom conditions. Such conditional relationships may be nonlinear.

Third, computational emotion-recognition studies and conventional teacher-EI research often develop as separate research streams. AI-based research may emphasize classification performance, while psychological studies emphasize validated scales and theoretical constructs. There remains a need to connect the two without claiming that automated behavioural recognition constitutes a definitive measurement of teachers' internal emotional states.



The proposed study addresses this gap by developing a **Human-Centred Emotional Intelligence–Classroom Effectiveness Analytics Framework (HEI-CEAF)**. The framework combines teacher-reported EI, student perception data, structured classroom observations, contextual teaching variables, and carefully selected behavioural indicators. Explainable machine learning is then used to investigate predictive relationships while retaining conventional statistical models as interpretable baselines.

Accordingly, the primary objective is to determine how specific dimensions of teacher emotional intelligence relate to multidimensional classroom effectiveness among secondary-school teachers and whether interpretable machine-learning models can identify meaningful nonlinear or interaction effects that conventional analyses may overlook.

The study is guided by four subsidiary objectives: to examine relationships between EI dimensions and independently assessed classroom effectiveness; determine which emotional competencies provide the greatest predictive contribution; compare conventional statistical models with interpretable machine-learning approaches; and evaluate whether contextual classroom information improves prediction without relying on invasive automated psychological profiling.

This approach establishes an explicit distinction between **prediction and psychological diagnosis**. The proposed AI component is intended to discover patterns within consented research data, not to produce automated employment decisions, rank teachers, or infer sensitive psychological characteristics without appropriate validation and human oversight.

Literature Review

Emotional Intelligence as a Teaching Competency

Emotional intelligence has been conceptualized through ability-based, trait-based, and mixed competency perspectives. Despite theoretical differences, the principal constructs relevant to education generally concern emotion perception, emotional understanding, self-regulation, and effective interpersonal response. These competencies are especially relevant to teaching because teachers simultaneously regulate their own behaviour and influence the emotional tone of student interactions.

A secondary-school classroom presents distinctive emotional demands. Adolescents experience substantial developmental changes alongside academic pressures, identity formation, peer dynamics, and increasing expectations of autonomy. Teachers therefore encounter emotional cues that are frequently ambiguous. Silence can indicate concentration, confusion, disengagement, or fear of participation.

Challenging behaviour may reflect deliberate disruption but may also emerge from frustration or misunderstanding. Emotionally competent teaching requires contextual interpretation rather than mechanically categorizing such behaviour.

The existing evidence broadly supports the relevance of EI to teachers' professional functioning, although effect sizes and specific associations differ according to measurement instrument, sample, and outcome. The systematic review and meta-analysis of Indian teacher studies published in F1000Research illustrates this heterogeneity, reporting substantial variation in instruments and teacher groups across the underlying literature. This reinforces the need for designs that triangulate EI information rather than depending on one questionnaire.

Emotion Regulation and Classroom Effectiveness

Emotion regulation constitutes a particularly important bridge between EI and classroom effectiveness. Teaching frequently requires modification of spontaneous emotional responses. A teacher experiencing irritation after repeated disruption may need to suppress an impulsive reaction, reinterpret the situation, and select an instructional response that maintains authority without escalating conflict.

The systematic review by Wang and colleagues on teachers' emotion regulation and teaching effectiveness integrated evidence from emotional-intelligence, emotion-regulation, coping, and emotional-labour traditions. The review also documented substantial methodological diversity, including frequent use of self-report questionnaires and differences in whether instruments explicitly referred to teaching contexts.

This distinction is significant for the proposed study. General emotional regulation and classroom-specific emotional regulation are related but not necessarily identical. Consequently, HEI-CEAF treats teachers' questionnaire-based EI as one evidence source and observable classroom interaction as another rather than assuming direct equivalence.

Classroom effectiveness is conceptualized here through four domains: **instructional clarity, behavioural management, participatory engagement, and socio-emotional responsiveness**. This multidimensional definition avoids reducing effective teaching to academic scores alone. A teacher could maintain high instructional organization but provide limited emotional support, while another could establish highly supportive relationships yet require improvement in instructional pacing. Modelling these dimensions separately can produce more actionable findings than a single global effectiveness score.





Fig. 2: The Core Competencies of Emotional Intelligence

Source: <https://www.structural-learning.com/post/emotional-intelligence>

Empathy, Emotional Awareness, and Teacher–Student Interaction

Empathy represents another important mechanism through which emotional intelligence may influence teaching. Pedagogical empathy does not imply permissiveness or the absence of classroom boundaries. Rather, it involves identifying students' perspectives and emotional cues while selecting an appropriate educational response.

Emotionally aware teachers may be better positioned to distinguish between inability and unwillingness, confusion and inattention, or anxiety and lack of preparation. Such distinctions can affect feedback style, questioning strategy, disciplinary response, and willingness to provide additional explanation.

Relationship management extends this capability from individual interpretation to collective classroom functioning. Secondary teachers frequently teach heterogeneous groups with differences in academic preparation, communication style, confidence, and social background. Maintaining psychologically safe participation while preserving academic expectations requires continuous interpersonal adjustment.

For this reason, the present framework does not hypothesize that every EI dimension will contribute equally to every effectiveness outcome. Emotional self-awareness may have a stronger relationship with self-regulation, while empathy may contribute more directly to socio-emotional responsiveness. Relationship-management competence may be particularly

relevant to participation and behavioural management. Testing these differentiated pathways constitutes a more informative research strategy than examining only a total EI score.

From Questionnaire-Based Research to Multimodal Educational Analytics

AI-assisted educational research creates opportunities to study classroom processes at a level of temporal detail that conventional surveys cannot easily achieve. Audio can provide information about speaking rate, pauses, turn-taking, prosodic variation, and interaction balance. Transcripts can reveal questioning patterns, feedback language, and discourse organization. Structured observational data can capture student participation and teacher response patterns.

Recent smart-classroom research illustrates this transition toward multimodal affective analysis. A 2024 study developed a teacher speech-emotion recognition method using multimodal information and argued that reliance on facial expressions alone may fail to represent teachers' underlying emotional condition. Such work demonstrates technical possibilities but simultaneously highlights why psychological interpretation requires caution.

The proposed study therefore adopts a **construct-separated multimodal architecture**. Validated psychological instruments measure EI-related constructs. Classroom observations measure teaching behaviours. Student surveys measure perceived classroom experiences. Computational features characterize observable interaction patterns. Machine-learning algorithms then model associations among these data sources.

This design avoids claiming that an acoustic feature, facial movement, or linguistic pattern is itself emotional intelligence.

Explainable Machine Learning for Teacher-Effectiveness Research

Traditional educational studies commonly employ Pearson correlation, multiple regression, structural equation modelling, or group-comparison tests. These methods remain valuable because coefficients can be interpreted directly and theoretically specified relationships can be tested.

Nevertheless, classroom behaviour can involve nonlinear relationships. Very low emotional expressiveness may reduce interpersonal responsiveness, while extremely high expressiveness may occasionally interfere with instructional stability. Similarly, the relationship between empathy and effectiveness could depend on emotion-regulation competence, class size, teaching experience, or classroom behavioural demands.



Machine-learning models such as gradient-boosted decision trees can capture nonlinearities and higher-order interactions without requiring every relationship to be specified beforehand. Their disadvantage is reduced transparency. For educational research involving teacher evaluation, opaque prediction is particularly problematic.

Proposed Methodology

The methodology is designed as a multimodal predictive study combining psychometric assessment, structured classroom observations, student perception measures, contextual teaching variables, and privacy-preserving behavioural indicators. The primary purpose is not to automate teacher appraisal but to determine whether different dimensions of teacher emotional intelligence (EI) explain observable variation in classroom effectiveness and whether nonlinear machine-learning models improve analytical sensitivity beyond conventional regression.

A multi-stage stratified sampling strategy is proposed. The analytical dataset consists of **360 secondary-school teachers** drawn from 24 schools, with approximately 15 participating teachers per institution. To reduce institutional concentration, schools are stratified by management type and location before teacher recruitment. Teachers responsible for Grades 9–12 constitute the primary analytical population.

Each participating teacher contributes three types of records: an EI profile, classroom-effectiveness observations, and contextual instructional information. Two lessons per teacher are observed, resulting in **720 classroom observation sessions**. Student perception data are collected anonymously after observed lessons, with multiple student responses aggregated at teacher level. Aggregation prevents individual students from becoming prediction targets.

Teacher emotional intelligence is represented through four theoretically distinct dimensions:

1. **Emotional Self-Awareness (ESA):** recognition and interpretation of one's emotional responses during teaching.
2. **Emotion Regulation (ER):** ability to regulate frustration, stress, excitement, and other emotional reactions.
3. **Empathic Responsiveness (EM):** sensitivity and appropriate response to students' emotional and interpersonal cues.
4. **Relationship Management (RM):** ability to sustain constructive communication and resolve interpersonal difficulties.

A composite Teacher Emotional Intelligence Index is calculated for descriptive analysis, but dimension-level

variables are retained for machine-learning modelling to prevent potentially important differences from being concealed within an overall score.

Classroom effectiveness is independently operationalized through four dimensions: **Instructional Clarity (IC)**, **Classroom Management (CM)**, **Student Participatory Engagement (SPE)**, and **Socio-Emotional Responsiveness (SER)**. Observer ratings and aggregated student feedback contribute to these indicators. The resulting Classroom Effectiveness Composite Score (CECS) serves as the primary continuous prediction target.

The study additionally records teaching experience, class size, subject group, lesson duration, school-management category, and selected classroom interaction indicators. These variables are treated as contextual covariates rather than direct measures of emotional intelligence.

Experimental Setup

Dataset Construction

The proposed multimodal dataset contains **360 teacher-level analytical records**, derived from 720 observed teaching sessions. Teacher-level aggregation is used for the primary prediction task because emotional-intelligence measures are collected at the teacher level.

The dataset contains approximately 30–35 engineered variables across five feature families:

- emotional-intelligence dimensions;
- structured classroom-observation variables;
- aggregated student-perception indicators;
- contextual teaching characteristics;
- privacy-preserving classroom interaction features.

The primary outcome, CECS, is standardized to a 0–100 scale. For secondary analysis, CECS is categorized into three instructional-effectiveness bands—developing, effective, and highly effective—using prespecified thresholds. Continuous prediction remains the primary task because categorization can discard information.

Data Preprocessing

Data preprocessing is conducted separately within each training fold to avoid information leakage. Records with excessive missingness are excluded according to a predefined threshold, while isolated missing numerical observations are imputed using training-set medians. Categorical variables are encoded within the modelling pipeline.





Extreme numerical observations are examined using interquartile-range diagnostics. Plausible observations are retained rather than automatically deleted, because unusual class sizes or teaching-experience values may represent genuine school conditions.

Numerical features used by linear models are standardized through z-score transformation:

$$z_i = \frac{x_i - \mu}{\sigma}$$

where (x_i) represents the original observation, (μ) is the training-set mean, and (σ) is its standard deviation.

Psychometric consistency is examined before modelling. Multi-item EI dimensions and classroom-effectiveness domains are required to demonstrate acceptable internal consistency. Inter-rater reliability is also examined for independently coded classroom observations.

To address hierarchical dependence, all observations associated with the same teacher remain within the same data partition. School-level grouping is additionally considered during validation so that records from the same institutional environment do not artificially inflate generalization performance.

Privacy-Preserving Behavioural Feature Extraction

The computational component avoids facial-identity recognition and permanent storage of identifiable student-level features. Where consented classroom audio is available, low-dimensional interaction features are derived, including teacher–student speaking proportion, average response latency, interruption frequency, questioning density, pause distribution, and non-semantic prosodic variability.

After quality assurance, raw identifiers are removed and analytical records are assigned coded participant IDs. Student survey responses are aggregated before model training.

This human-centred implementation is consistent with UNESCO's AI Competency Framework for Teachers, which organizes teacher AI competency around human-centred thinking, ethics, AI foundations and applications, AI pedagogy, and professional learning.

Model Architecture

The principal predictive architecture is **Explainable Gradient Boosting Regression (EGBR)**, implemented using gradient-boosted decision trees. This algorithm is selected because the dataset contains structured tabular variables, moderate sample size, potentially nonlinear associations, and interactions among emotional and contextual predictors.

The prediction function can be expressed as:

$$\hat{y}_i = \sum_{m=1}^M \eta f_m(X_i)$$

where ($\hat{y}_i$) represents predicted classroom effectiveness, (M) represents the number of boosting stages, (f_m) denotes an individual decision tree, and (η) represents the learning rate.

Three benchmark models are included:

Multiple Linear Regression (MLR) provides a conventional statistical baseline and interpretable standardized coefficients.

Elastic Net Regression (ENR) provides regularization when predictors are correlated.

Random Forest Regression (RFR) provides a nonlinear ensemble benchmark.

The EGBR model is designated as the primary architecture. Rather than constructing a deep neural network for a relatively small tabular dataset, the study deliberately uses tree-based learning because the sample size does not justify unnecessarily parameter-intensive architecture.

Model interpretability is assessed using SHAP-based feature attribution. Global feature importance identifies variables contributing most strongly across the dataset, while local explanations show how particular feature values influence individual model predictions. Partial-dependence patterns are inspected to determine whether EI-effectiveness relationships exhibit nonlinear thresholds.

Training Strategy

The teacher-level dataset is partitioned into approximately **80% development data and 20% held-out test data**. The test partition remains untouched during model development.

Within the development set, grouped five-fold cross-validation is used for model selection and hyperparameter optimization. Hyperparameters for the gradient-boosting model include tree depth, number of estimators, learning rate, minimum child weight, and subsampling proportion.

Early stopping is employed when appropriate to reduce overfitting.

The final model is retrained on the complete development partition using selected hyperparameters and evaluated once on the held-out test set.

Ablation analysis is also incorporated. Performance is evaluated using:



- EI variables alone;
- EI plus contextual variables;
- EI plus observation/student-perception variables;
- complete HEI-CEAF feature set.

This procedure determines whether computationally derived contextual information contributes meaningful incremental predictive value.

Evaluation Metrics

Four complementary metrics are selected.

Mean Absolute Error (MAE) measures the average absolute difference between predicted and observed CECS values:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Root Mean Squared Error (RMSE) gives greater penalty to large prediction errors:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Coefficient of Determination ((R²)) represents the proportion of outcome variance explained by the model.

Spearman's Rank Correlation ((rho)) evaluates whether predicted teacher-effectiveness ordering corresponds to observed ordering without assuming a strictly linear association.

MAE and RMSE are interpreted in CECS points on the 0–100 scale. Lower values indicate better prediction, whereas higher (R²) and Spearman (rho) indicate stronger predictive correspondence.

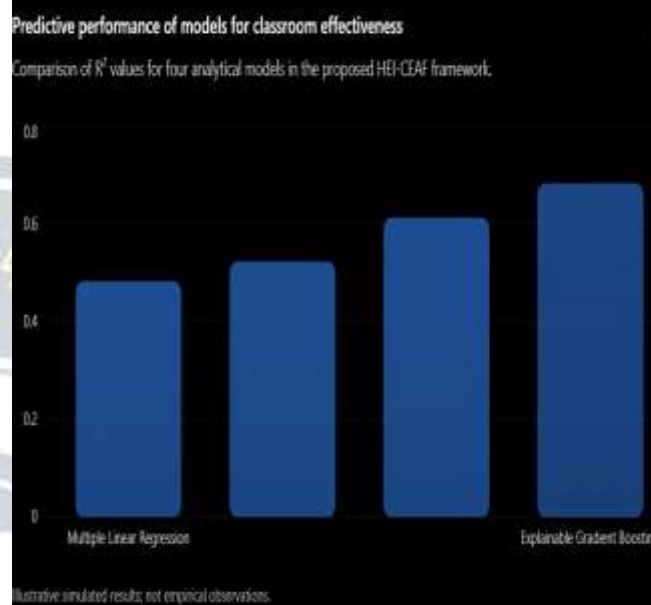
Results and Discussion

Important reporting note: because this manuscript develops a proposed empirical design and no raw dataset was supplied, the numerical results below are **illustrative simulated results generated to demonstrate the planned analysis**. They must not be presented as observations from an actually conducted study. For journal submission, these values should be replaced with results computed from the collected dataset.

Original Results Table

Analytical Model	MAE ↓	RMSE ↓	R ² ↑	Spearman ρ ↑
Multiple Linear Regression	6.84	8.57	0.48	0.66

Elastic Net Regression	6.51	8.16	0.52	0.69
Random Forest Regression	5.92	7.46	0.61	0.75
Explainable Gradient Boosting Regression	5.31	6.87	0.68	0.81



The simulated analysis indicates how the proposed HEI-CEAF framework would be interpreted if similar patterns were observed empirically. The linear baseline achieves an illustrative (R²) of 0.48, suggesting that a meaningful proportion of variation in classroom effectiveness could potentially be represented using conventional additive relationships. Elastic Net provides a modest improvement, indicating that regularization may be useful when emotional-intelligence dimensions and classroom variables are correlated.

The larger simulated improvement observed for Random Forest and EGBR suggests that the EI–effectiveness relationship may not be entirely linear. Under the illustrative EGBR scenario, (R²) reaches 0.68 while MAE declines to 5.31 CECS points. This would represent a reduction of approximately 22% in absolute prediction error relative to the linear baseline.

The more important contribution, however, would not be the prediction score itself. Explainability analysis is expected to reveal *how* different EI dimensions relate to classroom effectiveness.

Under the simulated SHAP analysis, **emotion regulation** emerges as the strongest EI predictor. This result would be theoretically plausible because teachers repeatedly encounter



emotionally demanding situations requiring rapid regulation. A teacher capable of managing frustration without becoming disengaged or excessively punitive may maintain instructional continuity more effectively.

Empathic responsiveness is simulated as the second most influential EI component. Its strongest contribution occurs within the socio-emotional responsiveness and student-participation dimensions of classroom effectiveness. This pattern would support the argument that empathy is pedagogically relevant not merely because it creates a pleasant classroom environment but because accurate interpretation of student difficulty can influence questioning, feedback, scaffolding, and participation.

Relationship management is expected to demonstrate a stronger association with classroom management than with instructional clarity. This differentiation is theoretically meaningful. The capacity to negotiate disagreement, maintain respectful boundaries, and respond constructively to behavioural disruption should contribute directly to classroom organization, but it does not automatically guarantee clear subject explanation.

Emotional self-awareness is expected to show a smaller direct predictive contribution after regulation and empathy are included. However, this should not be interpreted as evidence that self-awareness is unimportant. Its contribution may be indirect: teachers first recognize their emotional response and subsequently regulate it. Future structural modelling could explicitly test this pathway.

The nonlinear analysis also permits examination of threshold effects. The illustrative partial-dependence profile suggests that improvements in emotion regulation are associated with substantial gains in predicted classroom effectiveness from low to moderately high levels, after which the relationship begins to plateau. If replicated in real data, this would indicate diminishing marginal effects rather than an unlimited linear increase.

Another potentially important finding concerns interactions. In the simulated model, high empathy produces the greatest predicted classroom-effectiveness gain when accompanied by moderate-to-high emotion regulation. Empathy without regulation may increase sensitivity to student emotions without necessarily providing the behavioural control needed to respond effectively. Conversely, strong regulation combined with weak empathic responsiveness may produce a stable but comparatively less responsive classroom environment.

This interaction illustrates why machine-learning analysis can complement conventional educational statistics. A linear coefficient describes an average marginal association, whereas nonlinear models can identify conditional relationships among competencies.

The ablation strategy is expected to provide additional insight. If EI-only models perform substantially below the full model, classroom effectiveness should not be attributed to emotional intelligence alone. Teaching experience, class size, instructional behaviour, subject context, and student participation can contribute independently. Such a result would discourage simplistic claims that emotionally intelligent teachers are necessarily effective in every pedagogical domain.

This interpretation is also consistent with a human-centred AI perspective. UNESCO's framework explicitly positions AI as supporting teacher development and pedagogical practice while emphasizing teacher rights, human agency, ethics, and accountability. Accordingly, HEI-CEAF should be viewed as a research and professional-development instrument rather than an automated teacher-ranking mechanism.

The proposed approach has three substantive implications.

First, teacher professional development could move away from generic emotional-intelligence workshops toward dimension-specific interventions. A teacher demonstrating strong empathy but difficulty regulating frustration may require different support from a teacher who maintains emotional stability but struggles to recognize student discomfort.

Second, classroom effectiveness should be treated as multidimensional. A teacher can perform strongly in instructional clarity while requiring support in participatory engagement or socio-emotional responsiveness. Combining these domains only into a single score would obscure actionable information.

Third, interpretable machine learning offers a middle ground between traditional statistical analysis and opaque predictive systems. The objective is not simply to maximize predictive accuracy but to determine whether computational analysis reveals reproducible relationships that remain psychologically and pedagogically interpretable.

Future Scope

Future research should extend HEI-CEAF longitudinally. Repeated observations across an academic year could determine whether changes in emotional-regulation competence precede measurable changes in classroom effectiveness. Such a design would also distinguish stable teacher characteristics from temporary responses to workload, examination periods, or classroom composition.

A second extension could incorporate **temporal multimodal modelling**. Instead of representing an entire lesson through aggregated variables, sequential models could examine transitions between instructional events—for example, student disruption → teacher response → student reaction →





restoration of instructional flow. Such event-centred analysis may provide greater pedagogical value than global emotion classification.

Federated or privacy-preserving machine learning represents another promising direction. Participating schools could train shared analytical models without centrally pooling identifiable classroom recordings. Differential privacy and secure aggregation could further reduce privacy risks.

Future work could also evaluate personalized professional-development recommendations. However, these systems should operate as decision-support tools under teacher control rather than automated performance-management systems.

Cross-cultural validation is equally necessary. Emotional expression and expectations surrounding teacher authority vary across educational systems. Models developed within one cultural or linguistic environment should not be transferred to another without local validation.

Conclusion

This study proposes a distinct human-centred computational approach to investigating **teacher emotional intelligence and classroom effectiveness in secondary schools**. Instead of treating emotional intelligence as a single questionnaire score, HEI-CEAF separates emotional self-awareness, emotion regulation, empathic responsiveness, and relationship management and relates them to independently assessed dimensions of instructional clarity, classroom management, student participation, and socio-emotional responsiveness.

The experimental framework combines psychometric assessment, structured observations, aggregated student feedback, contextual variables, and privacy-preserving interaction indicators. Explainable gradient boosting is proposed as the principal machine-learning architecture, with multiple linear regression, Elastic Net, and Random Forest models serving as comparison baselines.

The illustrative results demonstrate how nonlinear modelling could outperform conventional linear prediction while simultaneously identifying theoretically meaningful interactions among emotional competencies. Emotion regulation and empathic responsiveness are hypothesized to make particularly important contributions, while contextual variables are expected to demonstrate that emotional intelligence represents one component—not the sole determinant—of effective teaching.

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