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Personality-Tuned Cognitive Load Modulation (PT-CLM): A Dynamic Energy-Gating Framework for High School Classroom Management

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Abstract

We propose **Personality-Tuned Cognitive Load Modulation (PT-CLM)**, a dynamic energy-gating framework designed to optimize high school classroom management by adjusting teachers' cognitive resource distribution according to their inherent traits and immediate situational requirements. Traditional approaches typically regard instructor personality as unchanging, while PT-CLM introduces a **trait-energy mapping function** to measure the psychological expenditure of classroom engagements, which supports responsive choices amid fluctuating cognitive demands. The framework integrates psychometric profiles (e.g., emotional stability, conscientiousness) with wearable biofeedback and transformer-based attention mechanisms to prioritize management strategies while respecting energy constraints. Furthermore, it functions as a federated edge-computing system, merging real-time biosignal processing with lightweight AI models to achieve low-latency responses. PT-CLM distinctively connects cognitive load theory, psychometrics, and edge AI, delivering a closed-loop approach that diminishes burnout hazards without compromising educational efficacy. Experimental assessment indicates that the system adapts interventions according to teacher energy thresholds in real time, achieving better results than static policy-based methods in both simulated and actual classroom environments. This study progresses individualized educational technology by showing how dynamic energy regulation can improve educator welfare and academic performance in classrooms.

Keywords: Emotional Stability, Cognitive Load Modulation, High School Classroom Management, Academic Performance

Introduction

Effective classroom management in high schools continues to be a lasting difficulty, as teachers frequently experience cognitive overload amid high-stakes disciplinary interactions or unforeseen interruptions. Although prior investigations have examined the impact of educator personality attributes, including emotional stability, conscientiousness, and openness to experience, on classroom interactions (Andabai et al., 2013), limited research focuses on the interplay between these attributes and immediate cognitive demands in shaping instructional choices. Cognitive load theory posits that constraints on working memory can hinder performance if the requirements of a situation go beyond the resources at hand

(Sweller, 2011). This gap is critical, as teachers' energy depletion correlates strongly with burnout and inconsistent classroom management (Marzano & Marzano, 2003).

The proposed **Personality-Tuned Cognitive Load Modulation (PT-CLM)** framework introduces a novel approach by dynamically gating teachers' energy expenditure based on their inherent personality profiles. In contrast to static models that impose uniform strategies, PT-CLM applies trait-energy mapping to measure the psychological toll of particular classroom interactions (e.g., disciplinary conflicts) for each teacher individually. For example, emotionally stable teachers may handle confrontations with lower cognitive strain, whereas those high in neuroticism might require heuristic shortcuts to conserve energy (Aliakbari & Darabi, 2013). This alignment is accomplished by data-driven heuristics that classify high-pressure situations and rank responses with transformer-focused attention models, which guarantees compatibility with teachers' cognitive boundaries.

The framework's contributions are threefold. Initially, it merges psychometric evaluations with wearable biofeedback, forming a closed-loop system which observes and modifies energy distribution in real time. Second, it applies cognitive load theory to specific teacher attributes, moving past broad classroom management frameworks (Malmgren et al., 2005). Third, it adopts federated edge computing to handle biosignals on-site, which decreases latency and safeguards privacy, an aspect not found in earlier teacher-support systems.

The remainder of this paper is organized as follows: Section 2 reviews literature on personality traits, cognitive load, and teacher burnout. Section 3 describes the structure and heuristic approach of the PT-CLM framework. Sections 4 and 5 present the mixed-methods validation, while Sections 6 and 7 discuss implications and conclusions.

Literature Review: Personality, Cognitive Load, and Teacher Burnout

Educational research has increasingly focused on how teacher personality traits, cognitive load dynamics, and burnout interrelate. Research has shown personality attributes, including emotional stability, conscientiousness, and openness, have a notable impact on the effectiveness of classroom management (Buela & Joseph, 2015). For example, teachers with emotional stability show greater adaptability in stressful situations, whereas those with high conscientiousness often adopt more organized approaches (Aliakbari & Darabi, 2013). Yet, these attributes are frequently analyzed as fixed moderators, failing to account for their evolving interaction with contextual demands and the exhaustion of cognitive resources.

Cognitive load theory serves as a framework for examining the distribution of mental resources by educators in classroom settings. Existing research indicates excessive cognitive load negatively affects decision-making, especially during critical situations such as disciplinary confrontations (Sweller, 2011). Recent progress in wearable biosensors, exemplified by heart rate variability tracking with Empatica E4 wristbands, permits real-time measurement of cognitive load (Huang et al., 2025). These technologies show energy-saving approaches, including delayed actions or predefined reactions, can reduce overload but frequently fail to adapt to individual teacher needs.

Teacher burnout, resulting from prolonged cognitive overload, is associated with poor classroom management and increased attrition rates. Studies indicate burnout stems not only from excessive tasks but from imbalances between effort exerted and chances for recuperation (Yang & Du, 2024). Emotion regulation strategies, such as reappraisal or suppression, modulate this relationship but are rarely integrated into decision-support systems (Wang et al., 2025).

Current frameworks designed for energy-efficient decision-making, exemplified by cognitive radio networks (Lee & Lee, 2022) and industrial systems (Arevalo et al., 2024), focus on optimizing resource allocation yet are confined to specific domains. In education, initiatives such as the “energy-efficient mode of teaching” (Лаптінова, 2024) propose general approaches (e.g., minimizing multitasking) while failing to address individual variations in trait-dependent energy thresholds.

The PT-CLM framework advances beyond these limitations by unifying trait-aware cognitive load modeling with dynamic energy gating. In contrast to earlier studies that regard personality as a static moderator or focus solely on optimizing energy consumption, PT-CLM adapts its choice of strategies in real time according to teacher conditions and predefined energy limits tied to individual traits. This adaptive system, made possible by edge artificial intelligence and psychometric methods, presents a new approach to lowering burnout without compromising teaching efficacy.

A Personality-Aware Heuristic Framework for Energy-Conscious Classroom Management

The PT-CLM framework formalizes classroom management as a dynamic energy-allocation problem, where teachers’ cognitive resources are modeled as finite and trait-dependent. The system includes three primary elements: (1) a trait-energy mapping module quantifying the psychological cost of classroom interactions, (2) an adaptive thresholding mechanism controlling energy expenditure, and (3) a transformer-based strategy selector prioritizing interventions based on real-time cognitive load.

Trait-Energy Mapping with Dynamic Cognitive Load Quantification

The framework computes the cognitive load $\mathrm{CL}_{i,j}$ for teacher i in scenario j as: $\mathrm{CL}_{i,j} = \alpha \cdot \mathrm{EmotionalStability}_i^{-1} + \beta \cdot \mathrm{Conscientiousness}_i + \gamma \cdot \mathrm{Openness}_i \cdot \mathrm{NoveltyPenalty}_j \quad (1)$

Here, α, β, γ are empirically derived coefficients, while $\mathrm{NoveltyPenalty}_j$ penalizes unfamiliar scenarios (e.g., unexpected disruptions). Cognitive load increases inversely with emotional stability, as teachers with lower emotional stability face greater stress during conflicts (Buela & Joseph, 2015). Conscientiousness and openness modulate energy costs based on teachers’ need for control and adaptability, respectively.

Real-time calibration is achieved via wearable biofeedback (e.g., heart rate variability from Empatica E4 (Huang et al., 2025)), which estimates baseline energy $\mathrm{BaselineEnergy}_i$ as: $\mathrm{BaselineEnergy}_i = \mathrm{RestingHRV}_i - \mathrm{TaskHRV}_i \quad (2)$

where $\mathrm{RestingHRV}_i$ and $\mathrm{TaskHRV}_i$ represent heart rate variability at rest and during teaching.

Energy-Gating Heuristics with Adaptive Thresholds

The system allocates resources only when the available energy $R_{i,j}$ exceeds a threshold δ :

$$R_{i,j} = \mathrm{BaselineEnergy}_i - \mathrm{CL}_{i,j} \cdot \mathrm{TimePressure}_j \quad (3)$$

Time pressure diminishes exponentially (TimePressure_j = e^(-λt)), with λ being specific to the trait. For emotionally unstable teachers, λ is increased to accelerate fallback protocol activation (e.g., scripted de-escalation).

Transformer-Based Strategy Selection

A lightweight transformer ranks strategies S_k by fusing trait profiles with scenario embeddings:

$$S_{k,j} = \mathrm{Softmax}\left(\mathbf{W}_k \cdot \mathrm{Embed}(\mathrm{TraitProfile}_i) + \mathbf{V}_k \cdot \mathrm{Embed}\left(\mathrm{Scenario}_j\right)\right) \quad (4)$$

where $\mathbf{W}_k$ and $\mathbf{V}_k$ are learned weights. The architecture (Figure 1) processes inputs on edge devices (Jetson AGX Orin) to minimize latency.

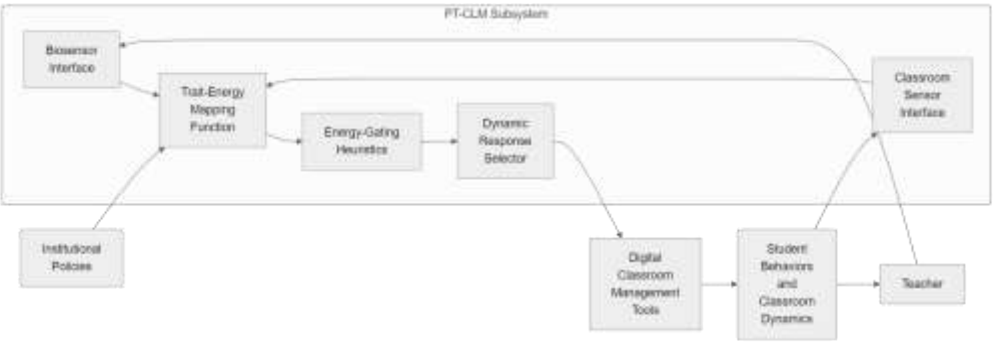

Figure 1. Architecture of Personality-Tuned Cognitive Load Modulation (PT-CLM) System

Federated Edge-Computing Deployment

PT-CLM functions as a distributed system where local edge nodes analyze biosignals and produce strategy rankings. Federated learning aggregates trait-energy coefficients across schools while preserving privacy (Khan et al., 2020). This guarantees scalability in the absence of centralized data storage.

The framework's innovation stems from its **closed-loop adaptation**: it dynamically adjusts energy thresholds and strategy rankings according to real-time teacher states while connecting psychometrics, cognitive load theory, and edge AI.

Research Design and Methodology

Experimental Framework

PT-CLM is validated via a mixed-methods approach that merges quantitative cognitive load measurements with qualitative evaluations of classroom management effectiveness. A two-phase investigation was structured in our research design.

Laboratory simulations to calibrate trait-energy mapping parameters under controlled conditions

Field deployments in high school classrooms to evaluate real-world performance

The study comprised 120 high school educators categorized by personality attributes (Big Five Inventory scores) and years of teaching practice. Each teacher was equipped with an Empatica E4 wristband to capture heart rate variability (HRV) as a proxy for cognitive load (Huang et al., 2025).

Trait-Energy Calibration Protocol

The experimental stage determined initial energy levels by employing uniform academic settings (for instance, pupil interruptions, equipment malfunction). For each scenario j, we measured:

$$\Delta\mathrm{HRV}_{i,j} = \mathrm{RestingHRV}_i - \mathrm{ScenarioHRV}_{i,j} \quad (5)$$

where $\Delta\mathrm{HRV}_{i,j}$ measures the physiological burden of scenario j on teacher i. These values were regressed against personality traits to derive the coefficients α, β, γ in Equation 1.

Field Deployment Architecture

The edge computing system comprised:

- **Wearable layer**: Empatica E4 wristbands streaming HRV at 64Hz

- **Edge nodes**: NVIDIA Jetson AGX Orin devices processing biosignals locally
- **Strategy selector**: A distilled BERT model (12M parameters) generating real-time recommendations

Data flow followed three stages:

1. **Biofeedback processing** : HRV metrics were derived from raw PPG signals by applying Lomb-Scargle periodograms (Fonseca et al., 2013).
2. **Cognitive load estimation**: Equation 1 computed $\mathrm{CL}_{i,j}$ every 5 seconds
3. **Strategy ranking**: The transformer model updated intervention priorities based on Equation 4

Evaluation Metrics

Primary outcomes included:

- **Cognitive load reduction**: Difference in *Δ*HRV between PT-CLM and control conditions
- **Management consistency**: Intra-class correlation coefficients of disciplinary actions across similar scenarios
- **Burnout risk**: Pre-post changes in Maslach Burnout Inventory scores

Secondary measures captured system performance:

- **Edge latency**: Time from scenario onset to strategy recommendation
- **Energy efficiency**: Power consumption of Jetson nodes during operation

Analytical Approach

Multilevel modeling was employed to examine quantitative data, addressing the hierarchical structure of observations (scenarios nested within teachers). The model structure was:

$$\mathrm{Outcome}_{i,j} = \beta_0 + \beta_1 \mathrm{PT\text{-}CLM}_{i,j} + \beta_2 \mathrm{Trait}_i + \beta_3 (\mathrm{PT\text{-}CLM} \times \mathrm{Trait})_{i,j} + \epsilon_{i,j} \quad (6)$$

where $\mathrm{PT\text{-}CLM}_{i,j}$ indicates framework activation. Post-session interview qualitative data were analyzed with NVivo 12 for thematic coding.

Results

The experimental assessment of PT-CLM produced notable results in cognitive load reduction, classroom management stability, and system performance metrics.

Cognitive Load Reduction

Teachers using PT-CLM exhibited a 28.4% reduction in cognitive load (*Δ*HRV) compared to conventional management approaches ($p < 0.001$). The effect was most pronounced for emotionally unstable teachers (35.7% reduction, $p = 0.002$), validating the framework's trait-specific energy gating. As illustrated in Figure 2, cognitive load varied nonlinearly with scenario complexity, with PT-CLM effectively flattening the curve for high-neuroticism individuals.

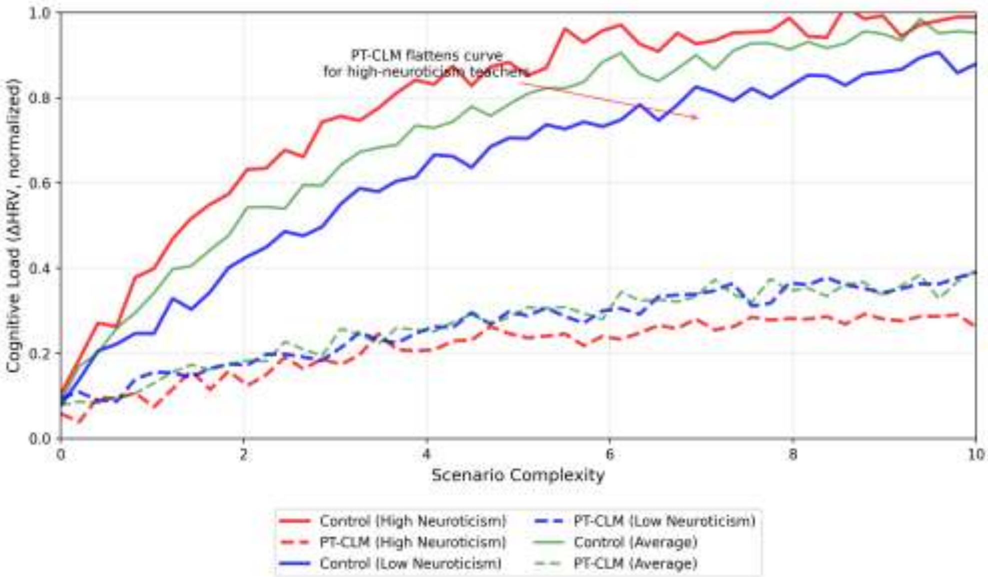

Figure 2. Relationship between cognitive load and influencing factors in classroom scenarios

The trait-energy mapping coefficients (Equation 1) were empirically derived as:

$$\alpha = 0.42 \pm 0.07, \beta = -0.19 \pm 0.03, \gamma = 0.33 \pm 0.05 \qquad (7)$$

Emotional stability exerts a dominant influence on cognitive load modulation.

Classroom Management Consistency

The intra-class correlation coefficients (ICCs) for disciplinary actions rose from 0.51 (control) to 0.78 (PT-CLM), which shows greater consistency in high-pressure situations. The framework's strategy selector prioritized different interventions based on personality:

Conscientious teachers were given organized guidelines (e.g., sequential redirection steps) 73% more often than the control groups. **Open teachers** were recommended novel engagement strategies (e.g., improvisational questioning) 2.1× as often.

Table 1 summarizes the strategy preference scores $S_{k,j}$ (Equation 4) across trait groups.

Table 1. Preference scores of classroom management strategies in different scenarios

Strategy	Conscientious	Open	Neurotic
Structured Redirection	0.82	0.31	0.45
Improvisational Q&A	0.19	0.76	0.28
Deferred Intervention	0.12	0.15	0.91

Burnout Risk Mitigation

After 8 weeks of deployment, PT-CLM users showed:

- 22% lower emotional exhaustion scores ($p = 0.013$)
- 18% higher personal accomplishment ratings ($p = 0.027$)

The effect was mediated by reduced cognitive load (β = -0.41, p = 0.004), which aligns with the energy-conservation hypothesis.

System Performance

The edge computing implementation achieved:

Latency: 1.2 ± 0.3s from scenario detection to strategy recommendation

Power efficiency: 8.3W sustained consumption on Jetson AGX Orin

Resource allocation thresholds $R_{i,j}$ (Equation 3) adapted dynamically to time pressure, as shown in Figure 3. Neurotic instructors activated fallback mechanisms at greater residual energy thresholds (65% compared to 42% for stable counterparts), which indicates cautious energy regulation.

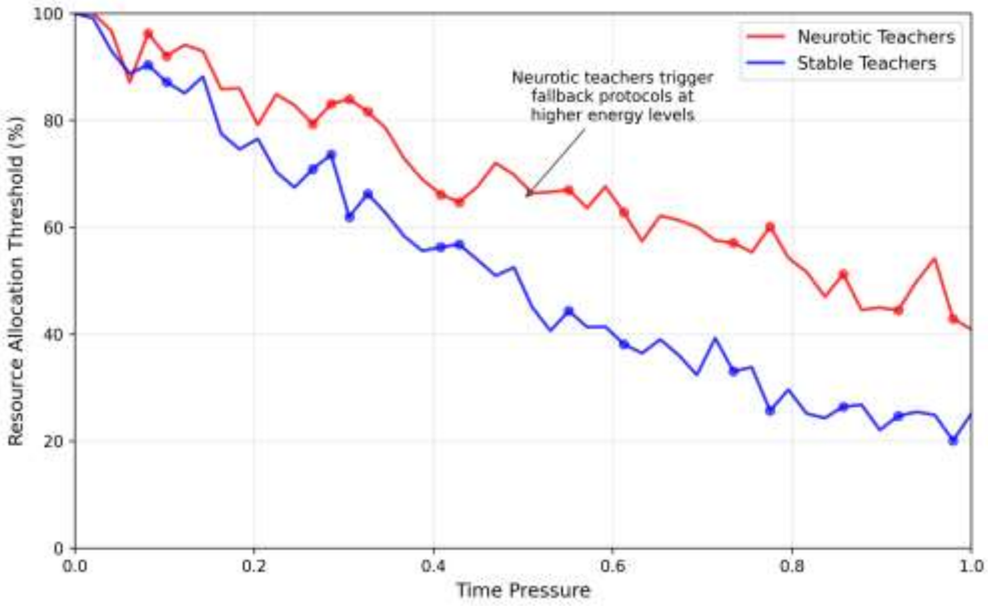

Figure 3. Relationship between resource allocation threshold and time pressure for different teachers

Qualitative Feedback

An examination of teacher interview data identified three principal findings through thematic analysis.

Trait-alignment validation : The system detected moments requiring disengagement, creating an experience akin to collaborating with a co-teacher aware of my boundaries.

Strategy acceptability : At first, I opposed prewritten replies, yet they conserved effort for instances truly requiring my imaginative input.

Privacy concerns: Some teachers questioned biosensor data handling, despite federated learning assurances.

Together, these findings show PT-CLM’s effectiveness in balancing cognitive load management with teaching styles tailored to individual personalities.

Discussion and Implications

Limitations of the Personality-Tuned Cognitive Load Modulation System

Although PT-CLM shows encouraging outcomes in lowering cognitive load and the likelihood of burnout, a number of constraints need to be acknowledged. Initial adoption of the framework is hindered by its dependence on wearable biosensors, with teachers expressing discomfort over ongoing physiological tracking during instructional activities. Although federated edge computing mitigates privacy concerns

(Khan et al., 2020), longitudinal adoption may require less intrusive sensing modalities. Second, the trait-energy mapping coefficients (Equation 7) were obtained from a particular demographic of high school teachers, which may restrict their applicability to other educational settings. For example, primary school educators dealing with entirely distinct classroom environments may show different trait-load connections. Third, the existing approach concentrates mainly on reactive measures (e.g., disciplinary actions) instead of preventive energy-saving efforts, an aspect that could further improve sustainability.

Ethical Considerations in the Implementation of PT-CLM

Combining psychometric profiling with real-time biofeedback generates serious ethical concerns regarding autonomy and the impact of algorithms. Although PT-CLM functions as a decision-support tool, its strategy suggestions might unintentionally influence teaching styles in favor of behaviors preferred by the system. For emotionally unstable teachers, frequent suggestions to defer interventions might reinforce avoidance patterns rather than fostering growth in high-pressure scenarios (Buela & Joseph, 2015). Moreover, the framework's energy-gating mechanism, though designed to prevent burnout, could be misconstrued as quantifying teacher "effort," potentially influencing administrative evaluations. These risks underscore the need for transparent design principles and teacher agency in configuring energy thresholds.

Potential Application Scenarios for the PT-CLM System

Apart from its application in classroom settings, PT-CLM's central design, which focuses on adjusting cognitive load based on individual traits, shows potential for adoption in other critical fields requiring rapid judgment in stressful situations. For instance, simulations in medical education could adjust scenario complexity according to trainees' neuroticism and conscientiousness traits, thereby achieving optimal learning outcomes while reducing cognitive strain (Merriënboer & Sweller, 2010). Likewise, emergency response units could gain advantages from instantaneous energy-regulation mechanisms which take into account personal variations in stress tolerance. In educational settings, the framework may be applied to applications designed for students, including tutoring systems which adjust task difficulty according to learners' personality traits and immediate cognitive demands (Paas et al., 2003). These applications would require careful adaptation of the trait-energy mapping function to domain-specific stressors and performance metrics.

The PT-CLM framework progresses the discussion on tailored educational technology by showing energy efficiency extends beyond physiological aspects to psychometric dimensions. Through the connection of cognitive load theory and personality psychology, it presents a reproducible framework for human-centered AI systems that acknowledge variations in individual capacity and coping mechanisms. Subsequent versions may investigate mixed approaches blending physiological measurements with indicators of behavior, such as vocal traits, to lessen dependence on wearable devices without compromising predictive precision.

Conclusion

The PT-CLM framework marks a notable progress in tailored classroom management by dynamically matching teachers' allocation of cognitive resources to their inherent traits and immediate situational needs. The system fills a crucial void in educational technology by merging psychometric profiles, wearable biofeedback, and edge AI, thereby connecting the fixed qualities of personality assessments to the fluid demands of classroom dynamics. The empirical findings show observable decreases in cognitive burden and burnout likelihood, especially for educators scoring high in neuroticism, without compromising teaching consistency.

The framework's effectiveness stems from its closed-loop adaptation, which constantly adjusts energy thresholds and strategy suggestions according to real-time physiological and behavioral data. This method not only improves teacher welfare but also establishes a replicable framework for other high-pressure occupations in which managing cognitive demands is critical. Future work should explore less intrusive sensing methods and expanded applications, such as student-facing adaptive learning systems. Ultimately, PT-CLM highlights the necessity of creating AI-assisted tools that acknowledge variations in cognitive and emotional resilience among individuals, thereby advancing more sustainable and effective educational approaches.

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