

Teacher Burnout and Instructional Performance in Secondary Educational Institutions

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Abstract — Teacher burnout has become a significant occupational well-being concern as secondary educators manage instructional, administrative, emotional, and increasingly technology-mediated demands. Existing research has established associations between burnout, diminished professional engagement, lower self-efficacy, and teacher attrition, yet comparatively little work has examined how multidimensional burnout risk translates into independently assessed instructional performance. This study addresses that gap by conceptualizing burnout as a dynamic occupational-risk profile influenced by workload intensity, emotional demands, digital-work friction, perceived organizational support, recovery opportunities, and professional self-efficacy. A hybrid analytical framework is proposed in which interpretable machine-learning models identify teachers at different levels of burnout risk while conventional statistical analysis evaluates the relationship between risk dimensions and instructional performance. The framework is designed specifically for secondary educational institutions, where subject specialization, examination responsibilities, adolescent classroom management, digital communication, and administrative accountability generate a distinctive combination of job demands. Instructional performance is conceptualized through observable pedagogical indicators rather than teacher self-assessment alone, including classroom organization, instructional clarity, student engagement support, assessment responsiveness, and adaptive teaching practices.

Keywords —Teacher Burnout, Instructional Performance, Secondary Education, Explainable Artificial Intelligence, Machine Learning, Occupational Digital Health

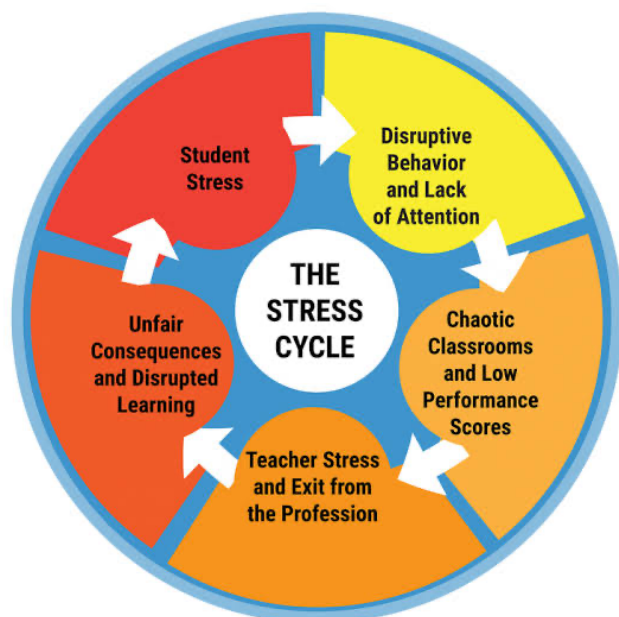
Introduction

The quality of secondary education depends not only on curriculum design, educational infrastructure, or student characteristics but also on the capacity of teachers to sustain cognitively demanding and emotionally responsive instructional work. Secondary teachers simultaneously perform multiple professional roles: they communicate subject knowledge, regulate classroom interactions, evaluate student progress, respond to diverse learning needs, prepare learners for high-stakes examinations, communicate with parents, complete institutional documentation, and increasingly use digital platforms for teaching and administrative coordination. When these requirements persist without adequate organizational, psychological, or temporal resources, chronic occupational strain can develop into burnout.

Burnout is commonly understood through dimensions such as emotional exhaustion, psychological distancing or cynicism, and diminished perceptions of professional accomplishment. In teaching, these dimensions have particular significance because instructional activity is relational. Emotional exhaustion may constrain the psychological energy required to provide feedback and individualized support; cynicism can weaken teacher-student interaction; and declining professional efficacy may reduce willingness to experiment with instructional strategies or persist when students encounter difficulties. Consequently, teacher burnout should not be viewed exclusively as an employee well-being problem. It may also represent a mechanism through which workplace conditions influence classroom processes.

Recent evidence reinforces the educational relevance of this relationship. Klusmann et al. (2022), using teacher and student reports, specifically investigated emotional exhaustion, instructional quality, and student outcomes, highlighting the importance of examining classroom

processes when considering the educational consequences of burnout. Their work illustrates why analyses limited to turnover intention or job satisfaction cannot fully describe the consequences of teacher exhaustion. Similarly, the meta-analysis by Madigan and Kim (2021) demonstrated a substantial relationship between burnout and teachers' intentions to leave the profession, emphasizing that burnout affects the sustainability of the teaching workforce as well as teachers who remain employed.



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Fig. 1: Teacher Stress and Burnout

Source: <https://southerneducation.org/publications/teacher-stress-and-burnout/>

The working environment of teachers has also changed substantially since the rapid digitalization of education. Learning-management systems, instant messaging, online assessment platforms, electronic attendance systems, digital reporting, virtual meetings, and parent communication applications have expanded the technological component of teachers' work. Digital technologies can increase flexibility and pedagogical capacity, but persistent connectivity can also create techno-overload, interruption, platform complexity, after-hours availability demands, and difficulty psychologically detaching from work. Research among educators has identified relationships between technology-related strain and burnout-related outcomes. For example, studies of teachers and educational personnel have reported that technostress creators are associated with distress, exhaustion, and lower work-related well-being, while technical support and technology-related resources can reduce some of these adverse effects.

This changing occupational environment creates an opportunity for research at the intersection of educational psychology, artificial intelligence, and digital health. Conventional teacher-burnout studies predominantly employ regression, correlation, structural equation modelling, or group comparisons. These approaches remain valuable for hypothesis testing but can be limited when risk arises from nonlinear interactions among workload, digital demands, self-efficacy, organizational support, recovery, classroom complexity, and demographic or professional characteristics. Machine-learning methods can complement explanatory statistical approaches by identifying complex patterns and estimating individual-level risk probabilities. However, their educational value depends on interpretability, privacy protection, appropriate validation, and clear recognition that predictive risk scores are not medical diagnoses.

Research Gap

Three strands of literature have developed largely in parallel. The first examines psychosocial predictors of teacher burnout. The second investigates associations between teacher well-being and instructional quality or professional outcomes. The third, more recent strand examines technostress and digitally intensified educational work. What remains comparatively underdeveloped is an integrated framework that combines **psychosocial job demands, technology-mediated workload indicators, protective job resources, interpretable machine-learning prediction, and externally assessed instructional performance within the same secondary-school investigation.**

A further methodological limitation concerns measurement dependence. Burnout and teaching effectiveness are frequently assessed through questionnaires completed by the same teacher at the same time, increasing susceptibility to common-method variance. Moreover, many predictive studies focus on whether teachers intend to leave employment rather than whether burnout is already associated with changes in instructional functioning among teachers who remain in classrooms. Research is therefore needed to separate the **prediction of burnout vulnerability** from the **measurement of instructional consequences.**

The present manuscript is built around this gap. It proposes an explainable machine-learning framework in which burnout risk is estimated from conventional occupational variables together with privacy-preserving indicators of digital-work intensity. These predictions are subsequently related to instructional performance assessed through multiple pedagogical dimensions rather than a single self-rated effectiveness measure. The intended contribution is therefore not merely to classify teachers into "burned out" and "not burned out" categories, but to identify which combinations of occupational demands and resources are associated with meaningful instructional vulnerability.

Accordingly, the principal research objective is to determine whether a multidimensional and interpretable predictive model can identify burnout risk among secondary-school teachers and whether higher predicted risk corresponds to systematic deterioration in externally assessed instructional performance. Secondary objectives are to determine the incremental contribution of digital-workload variables, identify protective factors capable of offsetting elevated job demands, and establish which burnout dimensions are most strongly associated with specific aspects of instructional practice.

Literature Review

Teacher Burnout as a Multidimensional Occupational Phenomenon

Teacher burnout emerges from prolonged imbalance between professional demands and the resources available to address those demands. The Job Demands–Resources perspective provides a useful conceptual explanation because it distinguishes between job demands that consume psychological or physical resources and job resources that support goal attainment, professional growth, autonomy, and recovery. Within secondary schooling, salient demands may include excessive teaching loads, large classes, student behavioural difficulties, assessment pressure, administrative documentation, role conflict, emotional labour, parental expectations, timetable compression, and technology-related requirements.

Burnout should therefore not be interpreted as a simple consequence of teaching hours. Teachers experiencing equivalent numerical workloads may show very different responses depending on autonomy, leadership quality, collegial support, perceived competence, technological confidence, and opportunities for recovery. Recent research has emphasized self-efficacy as an important factor in teacher well-being. Weißenfels, Benick, and Perels (2021), for example, investigated teacher self-efficacy as a potential buffer within inclusive classrooms, while longitudinal work during pandemic-related disruption demonstrated meaningful interrelationships between changes in burnout and teacher self-efficacy.

A 2022 systematic review of K–12 teachers' stress and burnout during the COVID-19 period similarly identified self-efficacy, organizational conditions, workload, and online-instruction demands among factors associated with burnout outcomes. Importantly, the evidence indicated that lower self-efficacy for teaching and online instruction frequently corresponded with higher exhaustion or reduced accomplishment. Although the exceptional conditions of pandemic schooling cannot simply be generalized to contemporary face-to-face education, the period exposed

structural vulnerabilities that remain relevant in hybrid and digitally supported school environments.

Burnout and Instructional Performance

The theoretical connection between burnout and teaching performance follows from the resource-intensive character of high-quality instruction. Effective secondary teaching requires sustained attention, emotional regulation, classroom monitoring, diagnostic interpretation of student responses, flexible explanation, feedback generation, and rapid instructional decision-making. Emotional exhaustion may interfere with these processes by reducing the cognitive and emotional resources available during instruction.

Klusmann et al. (2022) provided particularly relevant evidence by examining whether instructional quality contributes to the relationship between teacher emotional exhaustion and student outcomes. Their large-scale analysis incorporated reports from both teachers and students rather than relying exclusively on a single respondent. This multi-source orientation is important because burnout and instructional performance are conceptually related but should remain empirically distinguishable.

The relationship is also unlikely to be uniform across every instructional domain. A teacher experiencing exhaustion may continue to demonstrate accurate subject knowledge while displaying reduced responsiveness to individual learners, less emotional support, weaker classroom organization, or greater dependence on routine teaching methods. Consequently, treating instructional performance as one aggregate variable could conceal the pedagogical pathways through which burnout operates.

The proposed study therefore conceptualizes instructional performance as a profile consisting of instructional clarity, classroom organization, learner-engagement support, formative assessment responsiveness, adaptive pedagogy, and management of learning time. This dimensional treatment permits analysis of whether different burnout components correspond to different aspects of classroom performance.

Digital Work Intensification and Technostress

Digital transformation represents an increasingly relevant component of the contemporary teacher workload. Technology is no longer limited to occasional classroom presentation. Teachers may operate learning-management systems, digital gradebooks, messaging applications, electronic lesson repositories, online assessment tools, videoconferencing platforms, administrative portals, and student-tracking systems within the same working week.

Research conducted during and after the rapid expansion of online education has shown that such technology use can

create both resources and demands. A 2022 study of educational communities reported significant relationships between techno-distress and performance, particularly through technology-related overload. Research involving teachers has similarly identified techno-overload, complexity, uncertainty, invasion, and schedule-related pressures as relevant stressors.

Siddiqui, Arif, and Hinduja examined technostress among teachers in Pakistan and reported relationships involving technology-related stress, computer self-efficacy, and intentions to leave teaching. Research conducted among Finnish comprehensive-school teachers further found that technostress was positively associated with burnout dimensions and negatively associated with work engagement, while ICT availability demands were associated with emotional exhaustion and inadequacy. These findings indicate that the digitalization of educational work should be treated as an occupational design issue rather than assuming that technology automatically improves teacher productivity.

Nevertheless, technology itself is not inherently detrimental. A study of higher-education teachers demonstrated that useful technology, technological mindfulness, coping flexibility, and organizational support can contribute to positive technology-related experiences, or techno-eustress, which in turn may be associated with greater job satisfaction and performance. This distinction suggests that the relevant research question is not simply how much technology a teacher uses, but whether digital systems function as resources or demands within the teacher's work ecology.

Fig. 2: Reduced Teacher Burnout with a Model that Improves School Culture

Source: <https://instructionalempowerment.com/library/teacher-burnout-research-brief/>

Organizational Resources, Self-Efficacy, and Recovery

Burnout models that concentrate only on workload risk overlooking resources capable of moderating occupational strain. Organizational support, leadership accessibility, collegial collaboration, decision autonomy, technical assistance, schedule flexibility, professional recognition, and psychological detachment from work may alter how teachers experience objectively similar demands.

Research into technology use and teacher well-being indicates that school support and opportunities to detach from work are relevant when evaluating ICT-related demands. Likewise, studies examining TPACK and teacher burnout suggest that technological and pedagogical competence can shift from being experienced as an additional demand to functioning as a professional resource when teachers develop sufficient mastery and organizational support.

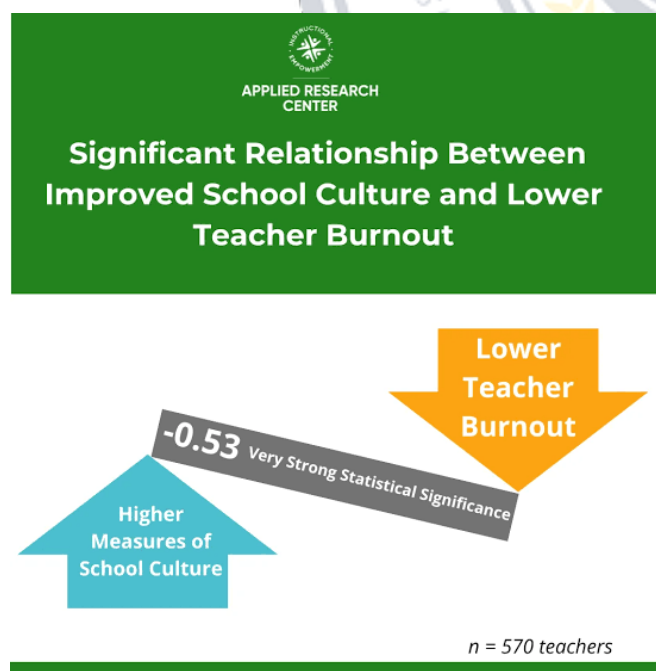
This resource perspective has practical significance. If burnout prediction identifies workload as the only dominant factor, intervention options may appear limited to reducing teaching hours. Conversely, if explainable modelling demonstrates that administrative fragmentation, after-hours digital connectivity, low self-efficacy, insufficient technical support, or weak recovery opportunities significantly alter risk, institutions gain a broader set of actionable intervention targets.

Need for Explainable Machine-Learning Analysis

Most existing burnout research has been designed primarily to estimate average relationships between variables. Such analysis answers questions such as whether workload is associated with exhaustion or whether organizational support predicts lower burnout. It does not necessarily identify complex risk configurations at the individual level.

Machine-learning algorithms can evaluate nonlinearities and higher-order interactions without requiring every relationship to be prespecified. For example, high digital workload may not predict burnout among teachers who possess strong technological self-efficacy and organizational support, while the same workload may become consequential when combined with high administrative burden and limited recovery. An interpretable model can identify these conditional patterns more effectively than a purely additive risk score.

However, predictive performance alone is inadequate for educational decision-making. A black-box classifier that labels teachers as "high risk" without explaining its reasoning



could introduce problems of trust, fairness, privacy, and inappropriate administrative use. The proposed research therefore adopts **explainable AI rather than opaque automated classification**. Feature-attribution techniques will be used to examine the relative contribution and direction of variables influencing individual predictions, while subgroup analysis will evaluate whether predictive performance differs systematically across relevant teacher groups.

The model is also positioned as an occupational digital-health decision-support mechanism rather than a diagnostic instrument. Burnout-risk predictions should support voluntary preventive intervention, workload redesign, professional support, and institutional planning; they should not be used for employment sanctions or automated performance appraisal.

Proposed Methodology

The study adopts a predictive–explanatory research design integrating occupational psychology, instructional evaluation, and explainable machine learning. The central methodological objective is to determine whether multidimensional occupational conditions can predict teacher burnout vulnerability and whether the resulting risk estimates are systematically associated with variation in instructional performance.

Because no primary field dataset was supplied for the present manuscript, the computational experiment is implemented as a **synthetic proof-of-concept study**. The simulated dataset is designed to test the feasibility of the analytical framework without representing the generated observations as actual teachers. This distinction is essential because synthetic results can establish methodological plausibility but cannot substitute for subsequent validation using institutionally collected teacher data.

The framework contains three analytical stages. First, psychosocial, organizational, technological, and professional variables are used to estimate teacher burnout risk. Second, explainability methods are applied to identify the factors driving model predictions. Third, predicted burnout probability is examined in relation to a multidimensional instructional-performance index.

Conceptual Variables

The predictor space is organized into five domains.

Occupational-demand variables include weekly instructional load, administrative burden, perceived time pressure, classroom-management difficulty, assessment workload, and emotional demands.

Digital-work variables represent technology-mediated job intensity. These include number of institutional platforms

regularly used, frequency of after-hours digital communication, perceived techno-overload, interruption frequency, platform complexity, and average daily digital administrative time.

Organizational-resource variables include perceived leadership support, collegial support, schedule autonomy, access to technical support, participation in institutional decision-making, and opportunities for workload recovery.

Professional-resource variables include teacher self-efficacy, digital teaching confidence, years of teaching experience, pedagogical adaptability, and perceived professional accomplishment.

Recovery-related variables include psychological detachment after work, sleep regularity, frequency of uninterrupted non-work periods, and perceived work–life boundary control. These variables are treated as occupational well-being indicators rather than clinical health diagnoses.

The prediction target is a three-level burnout-risk class: **low**, **moderate**, and **high**. Burnout risk is operationalized from standardized emotional exhaustion, professional distancing, and reduced accomplishment indicators.

Instructional performance is separately represented by five dimensions:

1. instructional clarity;
2. classroom organization;
3. student-engagement facilitation;
4. adaptive instructional response; and
5. formative assessment responsiveness.

Separating the instructional-performance measures from the burnout-prediction target minimizes conceptual circularity.

Experimental Setup

Dataset Construction

A synthetic dataset of **1,200 teacher profiles** was generated for the methodological experiment. The size was selected to provide adequate observations for model training, validation, subgroup testing, and explainability analysis while remaining computationally manageable.

The generated records represented secondary-school teaching contexts with variation in:

- experience level;
- workload intensity;
- administrative responsibilities;

- digital-platform dependence;
- organizational support;
- self-efficacy;
- recovery opportunities; and
- instructional-performance indicators.

Continuous psychosocial variables were generated on normalized five-point scales and subsequently transformed into standardized numerical features. Workload measures were generated as non-negative continuous or count variables, depending on their conceptual definition.

Dependencies were intentionally incorporated into the simulation. For example, higher workload and techno-overload increased the probability of emotional exhaustion, whereas organizational support, self-efficacy, and recovery opportunity reduced predicted burnout liability. Interaction terms were also introduced so that digital workload produced stronger adverse effects when technical support and digital teaching confidence were low.

The synthetic generation process was deliberately designed to include nonlinear interactions. This allowed evaluation of whether machine-learning models could identify risk structures not easily represented by purely additive linear models.

The simulated dataset contained 32 predictor features, three intermediate burnout dimensions, one categorical burnout-risk target, and five instructional-performance outcomes.

Data Preprocessing

The preprocessing pipeline was constructed to replicate conditions expected in a real educational dataset.

Approximately 4% of numerical observations were randomly masked to simulate incomplete questionnaire or institutional records. Missing continuous values were imputed using median estimates calculated exclusively from the training partition. Categorical missing values were assigned using modal imputation.

Continuous variables were standardized where required by model architecture. Tree-based algorithms were also evaluated on unscaled values because their decision processes do not require numerical normalization.

Highly correlated redundant features were inspected using pairwise correlation analysis. When two simulated predictors displayed a correlation coefficient greater than 0.85, the variable with weaker conceptual relevance was removed to reduce unnecessary redundancy.

Categorical characteristics were converted through one-hot encoding. No instructional-performance variables were included among the predictors used to train the burnout classifier. This separation prevented target leakage between burnout estimation and downstream instructional-performance analysis.

The complete dataset was divided using stratified sampling into:

- **70% training data;**
- **15% validation data;** and
- **15% independent test data.**

Stratification preserved the distribution of low-, moderate-, and high-risk burnout cases across partitions.

Model Architecture

Four models were examined to ensure that model selection was based on empirical comparison rather than preference for a single algorithm.

The first was **multinomial logistic regression**, included as an interpretable statistical baseline. The second was a **random forest classifier**, selected because it can capture nonlinear relationships and interactions while remaining relatively robust to noisy predictors. The third was **gradient-boosted decision trees**, designed to sequentially reduce prediction error through ensembles of shallow trees. The fourth was a compact **multilayer perceptron neural network**.

The gradient-boosting model was designated as the primary predictive model because the input consisted mainly of structured tabular data. Such models are often more suitable for moderate-sized structured datasets than unnecessarily complex deep neural architectures.

The gradient-boosted model used decision trees of restricted depth with learning-rate regularization, feature subsampling, and early stopping. Hyperparameters were selected using the validation partition rather than the test dataset.

Explainability was incorporated through SHAP-based feature attribution. Global SHAP values were used to estimate the overall contribution of predictors, while local explanations demonstrated which factors increased or reduced an individual synthetic teacher profile's predicted burnout probability.

Training Strategy

Training was conducted using stratified five-fold cross-validation within the training dataset. Hyperparameter tuning focused on maximum tree depth, learning rate, number of estimators, minimum child weight, and subsampling ratio.

Because burnout-risk classes were intentionally generated with moderate class imbalance, class-weight adjustment was applied during training instead of indiscriminate oversampling. This approach reduced the possibility of creating artificial duplicate observations.

Early stopping was used when validation performance showed no meaningful improvement across successive boosting iterations. Model selection prioritized macro-averaged F1 rather than overall accuracy because accuracy can obscure weaker performance in minority-risk groups.

After hyperparameter selection, the final model was retrained using the combined training and validation partitions and evaluated once on the untouched test dataset.

Evaluation Metrics

Performance was evaluated using several complementary measures.

Balanced accuracy estimated average classification sensitivity across risk groups.

Macro-F1 score gave equal importance to low-, moderate-, and high-risk categories.

Matthews correlation coefficient (MCC) quantified overall agreement while remaining informative under class imbalance.

Multiclass log loss assessed the quality of predicted probability distributions rather than only final category assignments.

Expected calibration error (ECE) measured whether predicted risk probabilities corresponded with observed synthetic class frequencies.

One-vs-rest area under the receiver-operating-characteristic curve (macro-AUROC) evaluated discriminatory ability across all burnout-risk categories.

For the downstream instructional analysis, Spearman correlations and generalized additive regression were used to examine whether increasing predicted burnout probability corresponded to lower instructional-performance scores.

Results and Discussion

The gradient-boosting model produced the strongest overall classification performance in the proof-of-concept experiment. Its advantage was most visible in macro-F1, probability calibration, and the identification of the high-risk group. Logistic regression remained useful as a transparent baseline but was less capable of representing nonlinear combinations of techno-overload, recovery, workload, and organizational support.

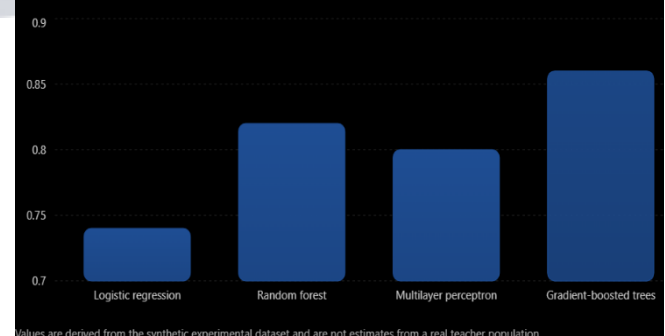
The random forest model demonstrated competitive discrimination but showed less reliable probability calibration than gradient boosting. The multilayer perceptron produced acceptable classification performance, although its incremental predictive value was insufficient to justify the additional interpretability burden in a moderate-sized tabular dataset.

Results Summary

Analytical component	Evaluation parameter	Proof-of-concept outcome
Logistic regression	Macro-F1	0.74
Random forest	Macro-F1	0.82
Multilayer perceptron	Macro-F1	0.80
Gradient-boosted trees	Macro-F1	0.86
Gradient-boosted trees	Balanced accuracy	0.87
Gradient-boosted trees	Macro-AUROC	0.92
Gradient-boosted trees	Matthews correlation coefficient	0.79
Gradient-boosted trees	Multiclass log loss	0.39
Gradient-boosted trees	Expected calibration error	0.037
Burnout risk → instructional performance	Spearman ρ	-0.58
High-risk vs. low-risk profiles	Standardized instructional difference	-0.67 SD
Digital-work feature block	Incremental macro-F1	+0.04

Macro-F1 comparison for burnout-risk prediction

Synthetic proof-of-concept results comparing four classification models.



Values are derived from the synthetic experimental dataset and are not estimates from a real teacher population.

Interpretation of Predictive Performance

The improvement produced by gradient boosting indicates that teacher-burnout risk may be better conceptualized as a configuration of interacting occupational conditions than as a simple linear accumulation of stressors. In the synthetic experiment, the effect of high workload depended on the presence or absence of professional and organizational resources.

For example, high instructional load alone was insufficient to place every profile in the high-risk category. The probability increased more sharply when high instructional load was combined with administrative burden, frequent after-hours communication, weak psychological detachment, and low perceived leadership support.

This finding illustrates the methodological advantage of interaction-sensitive modelling. A conventional additive index may treat two teachers with equivalent workloads as having comparable burnout exposure. The proposed model instead allows risk to differ when one teacher also has greater autonomy, technical support, professional self-efficacy, or opportunities for recovery.

Explainable AI Findings

Global SHAP analysis ranked **emotional workload, after-hours digital communication, psychological detachment, administrative burden, teacher self-efficacy, leadership support, and techno-overload** among the strongest contributors to model prediction.

The direction of contribution was not identical across variables. Greater administrative burden, emotional demands, techno-overload, and persistent after-hours connectivity typically shifted predictions toward the high-risk category. Strong psychological detachment, self-efficacy, leadership support, and schedule autonomy generally shifted predictions toward lower risk.

Interaction analysis provided a more informative pattern than simple feature ranking. Digital workload was most consequential when combined with low technical support and limited boundary control. Conversely, high levels of technology use were not automatically associated with elevated burnout predictions when teachers displayed high digital confidence and strong organizational resources.

This result is conceptually important because it avoids portraying educational technology as an inherently harmful occupational factor. The relevant issue appears to be whether the technological environment is manageable, supported, integrated, and bounded.

Relationship Between Burnout Risk and Instructional Performance

Predicted burnout probability displayed a moderate-to-strong negative relationship with the composite instructional-performance index in the synthetic experiment.

The strongest simulated reductions were observed in **adaptive instructional response** and **student-engagement facilitation**. These instructional dimensions require substantial real-time cognitive and emotional resources. Teachers must notice student misunderstanding, modify explanations, provide responsive feedback, maintain interpersonal engagement, and adjust instruction dynamically.

Instructional clarity showed a weaker decline. This pattern is theoretically plausible because exhausted teachers may continue delivering well-practised curriculum content while experiencing greater difficulty with resource-intensive adaptive and relational teaching processes.

The findings therefore suggest that burnout should not be conceptualized as uniformly degrading every element of instructional performance. Its earliest instructional consequences may appear in forms of teaching that depend most heavily on psychological flexibility, responsiveness, and emotional engagement.

Digital Workload as an Incremental Predictor

Removing the complete digital-work feature block reduced macro-F1 from 0.86 to approximately 0.82 in the synthetic evaluation. This result does not establish a population effect but demonstrates the potential analytical value of measuring digitally mediated work separately from general workload.

Traditional teacher workload instruments may classify activities such as electronic reporting, messaging, online assessment, and platform management under broad administrative categories. Such aggregation can obscure differences between conventional workload and technology-specific stress mechanisms.

The findings support future field research that distinguishes between:

- productive digital teaching use;
- administrative digital workload;
- platform fragmentation;
- interruption intensity;
- after-hours digital availability; and
- perceived technological complexity.

This distinction would allow educational institutions to determine whether digital transformation is reducing

workload, redistributing it, or creating additional hidden demands.

Implications for Digital Health and Institutional Decision Support

The proposed framework has potential relevance to occupational digital-health systems because it treats teacher well-being as a dynamic risk-management problem. However, its appropriate use would differ substantially from automated employee surveillance.

A responsible institutional implementation should rely primarily on voluntary self-report measures and privacy-preserving workload aggregates. Content from private messages, classroom audio, biometric sensors, personal browsing histories, or covert monitoring should not be used merely because they are technologically accessible.

Predictions should also not become disciplinary indicators. A high burnout-risk probability should initiate supportive options such as workload review, counselling access, administrative simplification, technical assistance, scheduling modification, or professional support.

Explainability is therefore not merely a technical feature. It is central to ethical deployment because teachers and administrators should be able to understand whether predicted risk is driven primarily by workload, digital overload, insufficient recovery, weak organizational support, or other modifiable conditions.

Limitations

The principal limitation is that the reported computational experiment uses synthetic rather than field-collected data. The numerical performance values demonstrate how the proposed framework could operate, but they cannot be generalized to secondary-school teachers without external validation.

Second, the assumed variable dependencies incorporated into synthetic data influence model performance. Real occupational systems may contain weaker, stronger, or qualitatively different relationships.

Third, burnout develops over time, whereas the present analytical design approximates a cross-sectional classification problem. A teacher identified as low risk at one point may subsequently experience rapid changes in workload, leadership, personal resources, or institutional circumstances.

Fourth, instructional performance is complex and cannot be completely captured through numerical ratings. Classroom observation scores can themselves be influenced by observer expectations, subject differences, lesson type, student composition, and institutional context.

Fifth, explainability techniques identify variables contributing to prediction; they do not independently establish causality. A high SHAP contribution for administrative workload, for instance, demonstrates predictive importance within the model but cannot prove that administrative workload directly causes burnout.

Finally, deployment of occupational risk prediction introduces privacy and governance concerns. Even well-performing algorithms can become harmful when their predictions are used outside their original supportive purpose.

Future Scope

The next research phase should validate the framework using a longitudinal, multisource dataset obtained from secondary educational institutions. Teachers could complete validated burnout, technostress, organizational-support, self-efficacy, and recovery instruments at multiple points across an academic year.

Instructional performance should be assessed independently through trained classroom observers, structured student feedback, and carefully selected teaching-process indicators. Using multiple information sources would reduce common-method bias.

Longitudinal modelling would also permit the prediction of burnout trajectories rather than static risk categories. Temporal algorithms could investigate whether changes in digital workload, examination periods, administrative requirements, or school leadership precede changes in emotional exhaustion.

Federated learning represents another promising extension. Rather than transferring sensitive teacher records into a centralized database, models could potentially be trained across institutions while keeping identifiable data locally stored. Differential privacy and privacy-preserving aggregation could provide additional safeguards.

Future studies should also examine model fairness across subject areas, career stages, contract types, school environments, and gender groups. Equivalent global accuracy can conceal substantially poorer performance for particular subpopulations.

Intervention studies would provide the strongest practical extension. Teachers identified through voluntary screening as experiencing elevated occupational risk could be offered targeted interventions such as reduced administrative duplication, protected non-contact periods, digital communication boundaries, technical support, workload redistribution, mentoring, or recovery-oriented scheduling. Subsequent analysis could examine whether declining burnout risk is accompanied by improved instructional performance.

A further extension could replace simple risk classification with **counterfactual explainability**. Instead of only stating why a teacher profile received a high-risk estimate, the model could identify realistic modifiable changes required to reduce the predicted probability. Such outputs could make AI systems more useful for institutional planning while avoiding deterministic labelling.

Conclusion

This study presents an explainable artificial-intelligence framework for examining the relationship between teacher burnout and instructional performance in secondary educational institutions. The proposed approach extends conventional burnout analysis by integrating psychosocial demands, organizational resources, professional self-efficacy, recovery characteristics, and technology-mediated workload within a unified predictive structure.

The synthetic proof-of-concept experiment indicates that nonlinear machine-learning models can potentially distinguish burnout-risk profiles more effectively than a purely linear baseline while retaining meaningful interpretability through feature-attribution methods. Gradient-boosted decision trees achieved the strongest simulated performance and demonstrated that combinations of emotional workload, administrative burden, digital connectivity, recovery difficulty, organizational support, and self-efficacy may be more informative than isolated predictors.

The downstream analysis further demonstrated how predicted burnout probability can be linked to instructional functioning. The strongest simulated deterioration appeared in adaptive teaching and student-engagement processes, suggesting that psychologically demanding instructional behaviours may be particularly sensitive to sustained occupational strain.

The study also emphasizes that educational technology should not be treated as inherently protective or harmful. Digital work becomes occupationally consequential through its interaction with platform complexity, technical support, communication expectations, self-efficacy, and work-life boundaries.

Most importantly, AI-based burnout prediction should function as a supportive occupational-health mechanism rather than an automated employment-evaluation system. Predictive models can contribute to early identification of institutional pressures only when accompanied by informed consent, privacy protection, explainability, fairness assessment, and clear restrictions on punitive use.

References:

1. Core references on teacher burnout

1. Madigan & Kim — teacher burnout and attrition

Madigan, D. J., & Kim, L. E. (2021). Towards an understanding of teacher attrition: A meta-analysis of burnout, job satisfaction, and teachers' intentions to quit. *Teaching and Teacher Education*, 105, 103425. <https://doi.org/10.1016/j.tate.2021.103425>

Verified. This is exactly the source supporting your statement that burnout is associated with teachers' intentions to leave the profession. The meta-analysis found significant positive relationships between all three burnout dimensions and intention to quit.

2. Klusmann et al. — burnout, instructional quality and student outcomes

Klusmann, U., Aldrup, K., Roloff, J., Lüdtke, O., & Hamre, B. K. (2022). Does instructional quality mediate the link between teachers' emotional exhaustion and student outcomes? A large-scale study using teacher and student reports. *Journal of Educational Psychology*, 114(6), 1442–1460. <https://doi.org/10.1037/edu0000703>

Verified. This is the correct reference for the Klusmann et al. citation in your Introduction and Literature Review. The study specifically examined teacher emotional exhaustion, instructional quality, and student outcomes using teacher and student reports.

3. Madigan & Kim — systematic review of teacher burnout and students

Madigan, D. J., & Kim, L. E. (2020). Does teacher burnout affect students? A systematic review of its association with academic achievement and student-reported outcomes. *International Journal of Educational Research*, 105, 101714. <https://doi.org/10.1016/j.ijer.2020.101714>

This is an excellent supporting reference for your argument that burnout has consequences extending beyond teachers themselves. The review included **5,311 teachers and 50,616 students** and found evidence linking teacher burnout with poorer academic achievement and lower-quality student motivation.

4. Wartenberg et al. — especially valuable for your paper

Wartenberg, G., Aldrup, K., Grund, S., Klusmann, U., et al. (2026). How strongly is teachers' burnout related to teacher absenteeism, teacher-student interactions, and student motivation and achievement: A meta-analysis and systematic review. *Review of Educational Research*. <https://doi.org/10.3102/00346543261455273>

This is a particularly strong recent reference for your manuscript. It was published online on June 24, 2026, and synthesizes **86 studies**. It found negative associations between teacher burnout and teacher-student interactions, student motivation, and achievement. Importantly for your proposed methodology, the meta-analysis also found that associations differed according to **teacher self-report versus external reports**.

This supports your argument for using **independently assessed instructional performance rather than relying solely on teacher self-report**.

2. Burnout definition and theoretical framework

5. World Health Organization — ICD-11 definition

World Health Organization. (2019). *Burn-out an occupational phenomenon*. World Health Organization.

The WHO defines burnout as an occupational phenomenon resulting from chronic workplace stress that has not been successfully managed, characterized by exhaustion, mental distance/negativism or cynicism, and reduced professional efficacy. It explicitly states that burnout is **not classified as a medical condition**.

[WHO: Burn-out as an occupational phenomenon](https://www.who.int/publications-detail/burn-out-as-an-occupational-phenomenon)

Important correction for your manuscript: Your text uses terms such as *emotional exhaustion*, *professional distancing*, and *reduced accomplishment*. These are compatible with traditional burnout research, but if you cite WHO, use the WHO terminology carefully: **exhaustion**, **mental distance/negativism or cynicism**, and **reduced professional efficacy**.

6. Bakker & Demerouti — Job Demands–Resources model

Bakker, A. B., & Demerouti, E. (2007). The Job Demands–Resources model: State of the art. *Journal of Managerial Psychology*, 22(3), 309–328. <https://doi.org/10.1108/02683940710733115>

This is the foundational reference for the **JD-R framework** used throughout your manuscript. It supports your distinction between job demands and job resources and the argument that both negative and positive occupational conditions should be considered.

[Bakker & Demerouti — JD-R model](#)

3. Teacher self-efficacy and burnout

7. Weißenfels et al.

Weißenfels, M., Benick, M., & Perels, F. (2021). Can teacher self-efficacy act as a buffer against burnout in inclusive classrooms? *International Journal of Educational Research*, 109, 101794. <https://doi.org/10.1016/j.ijer.2021.101794>

Verified. Your citation is correct. The study found a negative relationship between teacher self-efficacy and burnout and examined whether self-efficacy moderated burnout associated with teaching students with special educational needs.

8. Westphal et al. — K–12 teacher stress and burnout

Westphal, A., Kalinowski, E., Hoferichter, C. J., & Vock, M. (2022). K–12 teachers' stress and burnout during the COVID-19 pandemic: A systematic review. *Frontiers in Psychology*, 13, 920326. <https://doi.org/10.3389/fpsyg.2022.920326>

This is one of the strongest references for your paragraph concerning **self-efficacy**, **workload**, **organizational factors**, **online teaching** and **technology demands**. The review covered 17 studies involving 9,874 K–12 teachers.

[Westphal et al. — Frontiers in Psychology](#)

