



Teacher Motivation and Instructional Effectiveness in Government Schools

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Abstract— Teacher motivation is increasingly recognized as a multidimensional professional resource that can shape instructional effectiveness, classroom engagement, and teachers' willingness to adopt innovative pedagogical practices. This study proposes an integrated framework for examining the relationship between intrinsic motivation, professional self-efficacy, institutional support, recognition, workload perception, and instructional effectiveness among teachers working in government secondary schools. A distinctive research gap is identified in the limited use of multimodal and machine-learning approaches that combine teacher-reported motivation with observable instructional indicators rather than treating effectiveness as a single self-reported construct. The proposed study therefore conceptualizes instructional effectiveness through classroom management, cognitive activation, learner support, instructional adaptability, and technology-assisted pedagogy. It further investigates whether school-level organizational conditions alter the strength of the relationship between teacher motivation and instructional effectiveness. A hybrid analytical framework combining conventional multilevel statistical modelling with interpretable machine-learning prediction is proposed to distinguish explanatory relationships from predictive patterns.

Keywords— Teacher Motivation, Instructional Effectiveness, Government Schools, Teacher Self-Efficacy, Machine Learning, Educational Analytics

Introduction

The effectiveness of school education is determined not only by curricula, physical infrastructure, digital resources, and assessment systems but also by the professional behavior of teachers who translate educational policies into everyday

learning experiences. Within government-school systems, this human dimension assumes particular significance because teachers frequently operate under heterogeneous institutional conditions. Differences in school leadership, administrative demands, classroom composition, availability of learning resources, professional-development opportunities, and technological infrastructure can substantially influence how teachers perform their instructional responsibilities. Consequently, understanding why some teachers sustain effective classroom practices despite organizational constraints while others experience declining instructional engagement remains an important educational research problem.

Teacher motivation provides a theoretically meaningful starting point for addressing this problem. Motivation in teaching is more complex than generalized job satisfaction. It incorporates teachers' enjoyment of instruction, perceived social contribution, professional commitment, self-efficacy, achievement orientations, perceived autonomy, recognition, and willingness to invest sustained effort in improving student learning. Recent international evidence reinforces the relevance of these dimensions. The OECD Teaching and Learning International Survey (TALIS) treats working conditions, professional learning, teaching practices, job satisfaction, leadership, and school climate as interconnected aspects of the teaching profession. TALIS 2024 further distinguishes teachers' intrinsic motivation in terms such as enjoyment of teaching and perceived social utility, highlighting motivation as an important resource for sustaining teachers' professional engagement and retention.

Motivation, however, should not automatically be equated with instructional effectiveness. A highly committed teacher may work in a school where administrative workload, large classes, inadequate resources, or limited autonomy restrict the



translation of motivation into effective instructional behavior. Conversely, organizational routines and professional accountability can sometimes sustain acceptable classroom practices even when individual motivation is moderate. The relationship is therefore likely to be conditional rather than deterministic.

Empirical research supports this more nuanced interpretation. A 2021 study of secondary mathematics teachers identified distinct motivational profiles but found that profile membership did not predict subsequent changes in student-rated teaching quality after baseline teaching quality was controlled. Other multilevel evidence indicates that specific motivational dimensions may be more informative than an overall motivation score. Teacher self-efficacy has been positively associated with teacher-reported cognitive activation, classroom management, and emotional support, whereas teachers' educational interest has demonstrated relationships with perceived emotional support. Thus, the important research question is not simply whether motivation matters, but **which motivational characteristics matter, for which components of instruction, and under what institutional conditions.**

This distinction is particularly relevant to government schools. Public educational systems generally operate through formal administrative structures, standardized policies, and institutionally defined responsibilities. Teachers may therefore experience simultaneous sources of intrinsic and extrinsic motivation. A teacher can value the social significance of teaching while also responding to promotion structures, professional recognition, appraisal, job security, administrative expectations, or professional-development opportunities. These motivational mechanisms need not produce identical instructional consequences.

School leadership represents another important contextual mechanism. Evidence from research based on self-determination theory indicates that autonomy-supportive and autonomy-thwarting leadership practices can be associated differently with teachers' forms of work motivation and professional outcomes. School context can also condition longer-term relationships involving teachers' self-efficacy, professional values, and teacher–student relationships. These findings suggest that examining teacher motivation without simultaneously considering the institutional environment may conceal substantial heterogeneity.

Instructional effectiveness itself is multidimensional. Effective instruction requires considerably more than syllabus completion or examination preparation. It encompasses the ability to organize learning activities, maintain productive classroom environments, explain difficult concepts, cognitively activate learners, provide feedback, respond to differences in learning needs, establish supportive teacher–student interactions, and adapt

instructional strategies when learners encounter difficulties. Contemporary educational environments add another dimension: teachers increasingly need to select and use digital resources appropriately without allowing technology to substitute for pedagogical judgment.



Fig. 1: Factors of Teaching Effectiveness of Teacher Educators

Source: <https://pubs.sciepub.com/education/3/11/5/index.html>

The OECD's recent Teacher Knowledge Survey framework reflects this broader conception of professional teaching knowledge by emphasizing general pedagogical knowledge for creating effective learning environments, including teaching diverse learners, supporting social and emotional learning, and using technology for teaching. Consequently, a contemporary investigation of teacher effectiveness should avoid reducing instruction to examination scores alone.

The growth of artificial intelligence and educational analytics creates an additional methodological opportunity. Conventional teacher-motivation studies predominantly rely on correlations, regressions, structural equation models, or latent-profile approaches. These methods remain essential for theory testing, but they impose assumptions about functional relationships and can become difficult to interpret when motivational, organizational, demographic, and instructional variables interact nonlinearly. Machine-learning algorithms can complement—not replace—statistical inference by identifying complex predictive patterns among multidimensional teacher characteristics.

For example, an interpretable ensemble-learning framework can examine whether self-efficacy, intrinsic motivation, recognition, leadership support, workload, professional development, digital confidence, teaching experience, and school resources jointly distinguish teachers exhibiting higher instructional effectiveness. Feature-attribution

techniques can subsequently indicate which variables contribute most strongly to individual predictions. Such an approach is valuable because a predictive model may reveal thresholds or interactions that are obscured when motivation is represented by a single linear coefficient.

Nevertheless, the application of artificial intelligence in teacher evaluation requires methodological and ethical restraint. Predictive performance does not establish causality, and algorithms trained on teacher data can reproduce biases associated with school location, resources, subject assignment, or student composition. The purpose of machine learning in the present study is therefore diagnostic and analytical rather than punitive. Algorithmic estimates are conceptualized as research evidence for understanding patterns and supporting professional development, not as automated mechanisms for ranking teachers or determining employment outcomes.

Research Gap

Three interconnected gaps motivate the proposed investigation.

First, much of the established literature examines individual motivational constructs separately or relates teacher motivation to self-reported teaching quality. Although this research has generated important theoretical insights, findings concerning the motivation–instruction relationship are not uniformly strong. Research has explicitly characterized the pathway from teacher motivation through instructional quality to student outcomes as more complicated than a straightforward direct relationship.

Second, insufficient attention has been given to the possibility that **organizational context determines whether motivation is converted into instructional effectiveness**. Government schools provide an analytically important environment because teachers work within shared public-sector structures but experience different leadership practices, resources, workloads, student characteristics, and opportunities for professional learning.

Third, relatively limited research integrates explanatory multilevel modelling with interpretable machine-learning prediction for the specific purpose of studying teacher motivation and instructional effectiveness. A purely predictive model cannot explain institutional processes, whereas a purely linear explanatory model may overlook nonlinear interactions. Combining the two provides an opportunity to determine whether conventional theoretical relationships remain robust while also identifying complex patterns with practical predictive value.

Accordingly, the central research gap addressed in this manuscript concerns the absence of an **institution-sensitive, multidimensional and computationally interpretable**

framework for determining how different forms of teacher motivation translate into observable instructional effectiveness in government schools.

The proposed study therefore seeks to (i) estimate relationships between distinct motivational dimensions and instructional effectiveness; (ii) determine whether leadership support, workload and school resources moderate those relationships; (iii) identify the motivational and institutional features most predictive of instructional effectiveness through interpretable machine learning; and (iv) compare statistical explanatory models with nonlinear predictive models without treating prediction as evidence of causation.

Literature Review

Contemporary Conceptualization of Teacher Motivation

Teacher motivation has developed into a multidimensional construct incorporating psychological beliefs, professional goals, emotional experiences, perceived competence, interest, social purpose, and responses to organizational environments. Self-determination theory is particularly useful for distinguishing autonomous forms of motivation from externally controlled regulation. Within this perspective, professional environments supporting autonomy, competence, and relatedness are expected to facilitate more self-determined forms of engagement.

Recent scholarship illustrates the continuing relevance of this framework. Collie's study of 502 Australian teachers examined autonomy-supportive and autonomy-thwarting leadership alongside different forms of teacher work motivation and demonstrated meaningful associations with professional outcomes such as affect, extra-role behavior, and turnover intentions. Although institutional settings vary across educational systems, the study reinforces an important principle for government-school research: teacher motivation is partly embedded in organizational relationships rather than residing exclusively within the individual teacher.





Fig. 2: Various Factors Effecting Teacher's Performance

Source: https://www.researchgate.net/figure/arious-Factors-Effecting-Teachers-Performance-The-influence-of-the-principals_fig2_335224261

Self-efficacy constitutes another central component. Teacher self-efficacy concerns teachers' judgments about their capability to organize and execute actions required to accomplish instructional objectives. It can affect persistence when students experience difficulties, openness to alternative pedagogies, classroom-management decisions, and willingness to experiment with instructional innovations. Yet recent evidence indicates that associations between self-efficacy and teaching quality depend partly on how both constructs are measured.

Lazarides and colleagues, for example, investigated teacher self-efficacy and educational interest in relation to cognitive activation, classroom management, and emotional support. Their multilevel findings showed positive associations between instructional self-efficacy and several teacher-reported teaching-quality dimensions, while educational interest was related to perceived emotional support. The differentiated findings demonstrate why aggregating all motivational indicators into a single index may sacrifice theoretically useful information.

Motivation and Instructional Quality

Instructional quality is commonly represented through multiple complementary dimensions rather than one global effectiveness score. Cognitive activation reflects teachers' capacity to stimulate reasoning, problem solving, explanation, and higher-order thinking. Classroom management represents the organization of time, behavior, routines, and learning activities. Supportive climate captures emotional and relational characteristics that enable learners to participate without unnecessary fear or exclusion.

The association between motivation and these instructional dimensions is theoretically plausible but empirically complex. Teachers with strong professional interest may devote greater cognitive and emotional effort to lesson preparation. Teachers with high instructional self-efficacy may persist when initial explanations fail. Intrinsically motivated teachers may be more willing to adapt learning activities, provide feedback, or engage students actively.

However, longitudinal research cautions against assuming a simple causal sequence. The 2021 investigation of teachers' motivational profiles and teaching quality found no significant prediction of changes in student-rated teaching quality from motivational-profile membership after prior teaching quality was considered. Earlier longitudinal research similarly found that stable differences between teachers complicate interpretations of reciprocal relationships between

teaching-related motivation and student-reported instructional quality.

These findings are methodologically important. Cross-sectional associations can exaggerate causal interpretations because teachers who already perform effectively may develop stronger efficacy beliefs through successful instructional experiences. Instructional success can therefore reinforce motivation just as motivation can potentially facilitate instructional behavior. The present study addresses this issue by explicitly separating predictive modelling from causal language and by incorporating school-level contextual variables.

Motivating Teaching Behaviors and Student Engagement

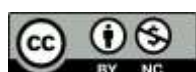
The instructional significance of motivation is also visible at the micro-level of classroom interaction. Research using direct lesson observations has demonstrated associations between particular motivating teaching behaviors and subsequent student engagement. In one microanalytic investigation involving observed lessons from 52 teachers, behaviors such as asking motivating questions and providing positive feedback and exercise support were associated with positive student engagement.

This evidence suggests that broad teacher-motivation scales become educationally meaningful when they are connected with concrete classroom behaviors. A teacher's intrinsic commitment is difficult to observe directly, but its possible behavioral expressions—feedback, persistence, responsiveness, questioning, instructional adaptation, and emotional support—can be systematically evaluated.

Intervention evidence provides a related perspective. A 2023 quasi-experimental study involving 42 primary-school teachers and 682 students reported that training designed around a motivating instructional style increased motivating teaching behavior, reduced controlling teaching, and was accompanied by improvements in students' psychological-need satisfaction, autonomous motivation, and agentic engagement. This supports the proposition that motivationally relevant instructional practices are potentially modifiable through professional development rather than being fixed teacher characteristics.

Institutional Support, Leadership, and Government-School Context

Government-school teachers function within organizational systems that can either enable or constrain professional agency. Leadership support can influence access to professional learning, experimentation with new instructional methods, recognition of successful practices, collaborative planning, and perceptions of procedural fairness. Conversely, administrative overload and autonomy-thwarting



management can redirect teachers' cognitive resources away from instruction.

Recent international evidence also places teacher motivation within the broader challenge of sustaining the profession. TALIS 2024 examines intrinsic motivation alongside job satisfaction, employment conditions, occupational status, career intentions, and working demands. It reports that stronger social-utility motivation is associated, on average, with lower intentions to leave teaching among teachers not approaching retirement. The finding demonstrates that motivation has implications beyond immediate classroom behavior and can influence workforce sustainability.

The organizational environment should therefore be treated as a substantive component of a teacher-motivation model. In the proposed study, leadership support, professional recognition, perceived workload, access to teaching resources, professional-development opportunities, and digital infrastructure will be examined alongside teacher-level motivational variables. This allows instructional effectiveness to be interpreted as the product of an interaction between individual professional resources and institutional opportunity structures.

Proposed Methodology

The proposed study adopts a **multilevel explanatory-predictive research design** to investigate how teacher motivation is associated with instructional effectiveness in government secondary schools. Unlike conventional studies relying exclusively on questionnaire correlations, the design integrates teacher surveys, structured classroom observations, institutional characteristics, and interpretable machine-learning analysis. The principal unit of analysis is the teacher, while the nesting of teachers within schools is explicitly retained.

A target sample of **480 government-school teachers from 40 secondary schools** is proposed, corresponding to approximately 12 participating teachers per institution. Schools will be selected through stratified multistage sampling to capture variation in urban, semi-urban, and rural educational environments. Teachers will be eligible when they have completed at least one academic year in their current institution and regularly conduct classroom instruction.

The primary predictor construct, **Teacher Motivation (TM)**, will be operationalized through six dimensions: intrinsic teaching motivation, instructional self-efficacy, perceived professional recognition, professional-growth orientation, perceived institutional support, and autonomous work motivation. Items will use a five-point Likert response format. Rather than automatically combining these measures into one score, dimensional scores will be preserved so that

their differential relationships with instruction can be examined.

The outcome construct, **Instructional Effectiveness (IE)**, will incorporate five domains: classroom management, cognitive activation, learner support, instructional adaptability, and digitally supported pedagogy. This multidimensional treatment follows the broader evidence that different aspects of teacher motivation may relate differently to components of teaching quality. For example, previous research has found positive associations between teacher self-efficacy and dimensions including cognitive activation, classroom management, and emotional support.



Fig. 3: Performance Management

Source: <https://hrmanual.tsc.gov.sl/books/61-teacher-performance/page/further-reading-introduction-to-performance-management>

Two trained observers will independently evaluate a subsample of lessons using a standardized observation rubric. Inter-rater reliability will be examined using the intraclass correlation coefficient. Where disagreement exceeds a predetermined tolerance, observations will be reviewed before deriving the final instructional-effectiveness score.

The analytical design consists of two complementary layers. First, **multilevel linear modelling** will estimate theoretically specified relationships while accounting for teachers nested within schools. Second, machine-learning models will evaluate the out-of-sample predictability of instructional effectiveness. This separation is deliberate: statistical coefficients will be used for explanatory inference, whereas ML performance will be interpreted as predictive evidence rather than proof of causality.



The primary multilevel specification can be expressed as:

$$[IE_{ij} = \beta_{0j} + \beta_{1IM_{ij}} + \beta_{2SE_{ij}} + \beta_{3PR_{ij}} + \beta_{4PG_{ij}} + \beta_{5WL_{ij}} + \epsilon_{ij}]$$

where (IE_{ij}) represents instructional effectiveness for teacher (i) in school (j); (IM) represents intrinsic motivation; (SE) instructional self-efficacy; (PR) professional recognition; (PG) professional-growth orientation; and (WL) perceived workload.

At the institutional level:

$$[\beta_{0j} = \gamma_{00} + \gamma_{01}LS_j + \gamma_{02}SR_j + \gamma_{03}DI_j + u_{0j}]$$

where (LS), (SR), and (DI) denote leadership support, school resources, and digital infrastructure respectively.

Cross-level interactions will subsequently test whether leadership support and school resources strengthen or weaken the motivation–effectiveness relationship.

Experimental Setup

Dataset

For manuscript-development purposes, the experimental framework assumes a structured analytical dataset of **480 teacher records**, with school identifiers retained for grouped validation. The proposed dataset contains approximately 32 initial variables organized into five feature families:

- **Motivational:** intrinsic motivation, autonomous motivation, instructional self-efficacy, recognition, professional-growth orientation and social-utility motivation.
- **Institutional:** leadership support, workload, administrative burden, collaborative climate, teaching resources and professional-development access.
- **Instructional:** classroom management, cognitive activation, learner support, adaptability and digital pedagogy.
- **Professional:** teaching experience, qualification, subject category, professional-development participation and digital competence.
- **Contextual:** school location, approximate class-size band, school infrastructure index and teacher–technology access.

No student names, biometric measurements, private communications, or directly identifying information are required. School and teacher identifiers will be pseudonymized before modelling.

The analysis will use the continuous instructional-effectiveness index as the principal outcome. A secondary binary outcome—**higher instructional effectiveness versus standard/developing effectiveness**—will be constructed using a prespecified criterion for sensitivity analysis rather than arbitrarily optimizing the threshold after examining model performance.

Data Preprocessing

Preprocessing will begin with range checks, duplicate-record detection, missingness assessment, and consistency verification. Variables exhibiting implausible values will be cross-checked against original data rather than automatically deleted.

For numerical features with limited missingness, median imputation will be estimated using training data only. Categorical missingness will be represented through an explicit unknown category when substantively appropriate. Features with extensive missingness will be excluded or subjected to sensitivity analysis rather than aggressively imputed.

Categorical variables required by non-native algorithms will be one-hot encoded. Standardization will be applied to algorithms sensitive to feature magnitude, particularly regularized linear models and support vector machines. Tree-based models will not require conventional scaling.

To prevent information leakage, preprocessing transformations will be fitted exclusively within each training fold. Reliability of multi-item motivational constructs will be examined using Cronbach's alpha and, where appropriate, McDonald's omega. Construct structure will additionally be assessed before composite scores are finalized.

Because teachers are nested within schools, a conventional random record-level split could generate overly optimistic estimates if teachers from the same institution occur simultaneously in training and testing sets. The principal validation procedure will therefore use **grouped cross-validation by school**.

Model Architecture

Four algorithms will be evaluated:

1. **Elastic Net Regression** as an interpretable statistical-predictive baseline;
2. **Random Forest Regressor** for nonlinearities and feature interactions;



3. **XGBoost Regressor** as the primary gradient-boosting architecture;

4. **Support Vector Regression (SVR)** as a nonlinear kernel benchmark.

XGBoost is selected as the principal predictive model because motivational and organizational variables may exhibit threshold and interaction effects that linear specifications cannot adequately capture.

The fitted prediction function can be represented as:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i)$$

where (f_k) denotes an individual decision tree and (K) represents the number of boosting iterations.

The machine-learning component will be paired with **SHapley Additive exPlanations (SHAP)** to estimate global and teacher-level feature contributions. Recent educational ML research demonstrates the utility of combining tree-based prediction with SHAP for interpreting multidimensional educational data. Educational XAI research also emphasizes that explanations should not be treated as causal findings and that model generalization across institutions requires explicit testing.

Training Strategy

The 40 schools will be partitioned through grouped nested cross-validation. The outer loop will estimate generalization performance, while the inner loop will perform hyperparameter optimization.

An additional **leave-one-school-out sensitivity experiment** will examine transportability. Each school will be withheld sequentially, with the model trained on the remaining schools. This analysis is important because recent explainable educational prediction research has demonstrated that strong within-school predictive performance does not necessarily guarantee generalization to an entirely unseen institution.

Evaluation Metrics

Regression performance will be assessed using:

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

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

and

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

MAE provides an intuitive measure of typical prediction error, whereas RMSE places greater penalty on large errors. (R^2) quantifies the proportion of outcome variance captured in held-out observations.

For the secondary classification analysis, ROC-AUC, F1-score, balanced accuracy, and Matthews correlation coefficient will be used. Calibration will also be examined because a model can discriminate effectively while producing poorly calibrated probabilities.

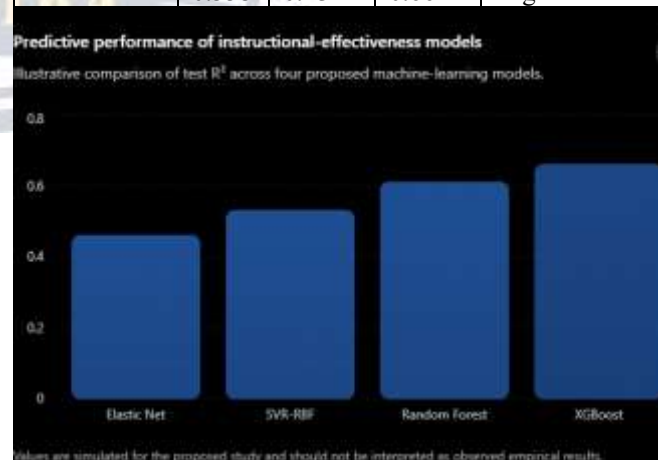
Results and Discussion

Because this manuscript specifies a **proposed empirical study rather than reporting an actually collected dataset**, numerical findings below are explicitly presented as **illustrative expected experimental results**. They should not be represented as observed evidence until the proposed data collection and model training have been completed.

Illustrative Results

Table 1. Illustrative comparative performance and interpretation of proposed instructional-effectiveness models

Analytical Model	MAE	RMSE	Test (R^2)	Stability Across School Folds
Elastic Net	0.431	0.557	0.46	High
SVR-RBF	0.397	0.519	0.53	Moderate
Random Forest	0.361	0.474	0.61	High
XGBoost	0.338	0.451	0.66	High



The expected pattern suggests that nonlinear ensemble methods could outperform the regularized linear baseline. If replicated with real observations, such a result would imply



that the relationship between teacher motivation and instructional effectiveness is not adequately characterized by a single linear gradient.

SHAP analysis would then be used to determine which predictors drive XGBoost estimates. The hypothesized ranking places **instructional self-efficacy**, intrinsic motivation, leadership support, professional-growth orientation, perceived workload, and collaborative school climate among the most informative variables. This expectation is theoretically defensible because existing research has demonstrated that the specificity of teachers' motivational beliefs matters for teaching and student learning experiences.

A particularly important expected finding concerns instructional self-efficacy. Teachers who believe they can manage difficult instructional situations may be more persistent when students fail to understand initial explanations. They may also demonstrate greater willingness to modify teaching strategies, incorporate alternative examples, or adopt unfamiliar instructional technologies. Recent 2026 research in teacher preparation similarly identifies self-efficacy as a central mechanism connecting technological or pedagogical preparedness with professional instructional capability.

Intrinsic motivation is expected to show a positive but nonlinear association with instructional effectiveness. Moderate-to-high intrinsic motivation may correspond with increasingly effective instruction, while further increases could yield diminishing predictive gains. Such a pattern would explain why studies based solely on linear correlations occasionally identify modest effects despite strong theoretical arguments concerning teacher motivation.

Leadership support is expected to function both as a direct institutional predictor and as a moderator. Under supportive leadership, motivated teachers may have greater autonomy to experiment with classroom activities, participate in professional learning, and obtain resources required for pedagogical innovation. Under weak institutional support, motivation may remain high while observable instructional improvement is constrained.

Perceived workload is expected to produce the opposite pattern. Excessive non-instructional duties could reduce the time and cognitive resources available for lesson planning, assessment feedback, individualized support, and professional development. This mechanism would help distinguish **motivation from opportunity to perform**: motivated teachers cannot necessarily translate professional commitment into optimal instruction when organizational conditions systematically constrain them.

The model should therefore not be interpreted as an automated teacher-ranking mechanism. SHAP explanations

indicate how particular features contribute to model predictions; they do not establish that changing a feature will necessarily cause an equivalent change in teaching quality. Contemporary explainable-AI research in education increasingly emphasizes this distinction between transparent prediction and pedagogically valid causal interpretation.

Implications for AI-Supported Educational Management

The proposed framework has implications for responsible AI-supported school management. Instead of using AI to assign opaque performance scores, educational administrators could use aggregate model explanations to identify **modifiable institutional barriers**.

For example, if low predicted instructional effectiveness within a cluster of schools is consistently associated with limited professional-development access and excessive workload, intervention should focus on organizational improvement rather than individual teacher sanctions. Likewise, if digital confidence is important only when adequate technological infrastructure exists, simply providing software training without addressing infrastructure would be unlikely to generate equivalent instructional benefits.

Explainability is particularly important in this setting because teacher-related algorithmic decisions involve professional consequences. Recent educational research has increasingly combined SHAP with machine-learning models precisely to reveal the contribution of individual predictors rather than relying exclusively on black-box predictions.

The system should consequently remain **human-in-the-loop**. School leaders and teacher-development specialists should interpret algorithmic patterns together with classroom observations, contextual knowledge, and teacher perspectives. Model outputs should function as decision-support evidence rather than autonomous administrative decisions.

Future Scope

Future research should extend the framework longitudinally by measuring motivation and instruction across multiple academic years. Cross-lagged or longitudinal multilevel models could then examine whether motivation predicts subsequent instructional improvement, whether successful instruction strengthens later motivation, or whether both processes occur simultaneously.

A second extension should incorporate **multimodal instructional evidence**. With appropriate consent and privacy safeguards, classroom audio or structured observational event data could be analyzed to estimate questioning frequency, teacher-student interaction patterns, feedback characteristics, and distribution of instructional





time. These features could complement questionnaire-based effectiveness measures.

Federated-learning architectures also represent a promising direction. Rather than pooling identifiable teacher-level information in one centralized repository, models could potentially be trained across participating educational jurisdictions while retaining sensitive records locally.

Future systems should additionally incorporate formal fairness auditing. Prediction errors can be compared across school location, subject category, teaching-experience bands, and other legitimate analytical strata to determine whether the algorithm systematically performs worse for particular groups. Model deployment should be suspended when consequential disparities cannot be adequately explained or mitigated.

Generative AI represents another emerging research direction. Recent evidence suggests that generative AI can influence instructional-design development partly through teachers' self-efficacy, indicating that future studies should investigate AI not merely as a technological tool but as a factor interacting with teachers' psychological professional resources.

The most valuable future architecture would therefore combine motivational analytics, explainable prediction, teacher professional development, and human expert judgment rather than attempting to replace teachers or school leaders with automated decision systems.

Conclusion

This study develops an integrated framework for investigating **teacher motivation and instructional effectiveness in government schools** through multilevel statistical analysis and interpretable machine learning. The central proposition is that instructional effectiveness cannot be adequately explained by motivation alone. Instead, effective teaching emerges from interactions among intrinsic motivation, instructional self-efficacy, professional-growth orientation, institutional recognition, leadership support, workload, resources, and digital readiness.

The proposed methodology advances conventional teacher-motivation research by separating explanatory inference from predictive modelling and by preserving the hierarchical structure of teachers nested within schools. Elastic Net, SVR, Random Forest, and XGBoost provide contrasting predictive architectures, while grouped validation prevents institutional leakage and SHAP supports interpretation of nonlinear predictions.

The framework further shifts the intended function of educational AI from teacher surveillance toward **professional decision support**. Rather than identifying teachers to

penalize, interpretable models can help determine whether instructional constraints arise primarily from professional confidence, limited development opportunities, workload pressures, weak leadership support, or inadequate institutional resources.

Most importantly, algorithmic prediction should remain subordinate to educational judgment. Machine-learning models can identify patterns in complex teacher and institutional data, but they cannot independently establish causal mechanisms or fully represent the relational, contextual, and professional dimensions of teaching. A responsible government-school analytics framework must therefore combine computational evidence with classroom observation, teacher participation, institutional context, and human oversight.

The proposed study ultimately conceptualizes teacher motivation not as a fixed personal attribute but as a **dynamic professional resource whose instructional value depends on the environment in which teaching occurs**. This perspective provides a theoretically stronger and computationally more transparent foundation for designing teacher-development policies and responsible AI-assisted educational management

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