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1



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Chapter 24: Teacher Work Engagement and Instructional Quality in Higher Education

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Abstract— Higher education institutions increasingly depend on digitally mediated teaching systems, yet the relationship between teacher work engagement and instructional quality remains insufficiently examined through data-driven and AI-supported perspectives. This study proposes a framework in which faculty work engagement is represented through behavioral, cognitive, and interaction-based indicators derived from teaching activity and self-reported engagement measures. A central research gap concerns the limited integration of faculty engagement constructs with machine-learning-based estimation of instructional quality in blended and technology-enabled higher education. The proposed study therefore investigates whether observable patterns of vigor, dedication, instructional responsiveness, and digital teaching participation can predict variations in instructional quality. A multimodal analytical perspective is adopted by combining faculty survey variables, learning-management-system activity indicators, instructional interaction features, and student-based teaching quality measures.

Keywords— Teacher Work Engagement, Instructional Quality, Higher Education, Learning Analytics, Machine Learning, Faculty Analytics

Introduction

The quality of teaching delivered in higher education depends on substantially more than disciplinary expertise. University teachers must sustain attention, intellectual energy, preparation effort, responsiveness to learners, assessment quality, technological adaptability, and meaningful interpersonal engagement across increasingly complex instructional environments. The expansion of blended learning, learning management systems, artificial intelligence tools, digital assessment platforms, online discussion environments, and analytics-enabled academic systems has further transformed faculty work. Teaching is no longer confined to classroom contact hours; it increasingly includes continuous digital interaction, electronic feedback, course redesign, content curation, virtual consultation, and interpretation of student learning data.

Within this changing context, **teacher work engagement** has emerged as an important organizational and pedagogical construct. Work engagement generally reflects a positive and persistent work-related psychological state characterized by energy, involvement, commitment, and absorption in professional tasks. In higher education, an engaged teacher is not simply one who works for longer hours. Engagement is more appropriately reflected in the willingness to invest cognitive and emotional resources in lesson planning, student

support, assessment, scholarly teaching, pedagogical experimentation, and instructional improvement.

Instructional quality, however, represents a distinct construct. It concerns the extent to which teaching promotes understandable, organized, cognitively stimulating, responsive, inclusive, and educationally meaningful learning experiences. A faculty member may demonstrate high professional effort without necessarily producing strong instructional outcomes. Conversely, a highly structured academic environment may enable adequate instructional quality even when individual teachers experience fluctuating levels of occupational engagement. The relationship between work engagement and instructional quality should therefore not be assumed to be linear or automatically positive.

This distinction has become more important as universities expand the use of digital technologies for monitoring and improving educational processes. Learning management systems routinely record activities such as course-resource updates, assignment creation, grading intervals, discussion participation, feedback frequency, communication events, and instructional material revision. These digital traces provide potentially valuable evidence regarding how teaching work is distributed over time. Nevertheless, raw activity volume cannot be equated with meaningful engagement. A teacher who uploads many files or logs into a platform frequently may not necessarily demonstrate high-quality pedagogy. Similarly, effective faculty may perform substantial intellectual preparation outside institutional platforms.

Recent developments between 2021 and 2026 have intensified interest in educational analytics, artificial intelligence, generative AI, automated feedback, adaptive learning systems, and data-informed academic management. Most higher-education analytics research, however, has concentrated on students. Predictive systems commonly estimate dropout risk, academic achievement, course completion, engagement, or learning difficulties from student records and learning-platform behavior. Faculty-centered analytics remains comparatively underdeveloped, particularly when the objective is to understand pedagogical performance without reducing academic work to administrative productivity metrics.

This imbalance creates an important research opportunity. Teacher engagement is typically studied using questionnaires, interviews, occupational well-being measures, or institutional climate variables. Instructional quality is frequently evaluated through student ratings, classroom observation, peer review, or learning outcomes. These streams of research often operate separately. As a result, limited attention has been given to whether psychological indicators of work engagement can be combined with technology-mediated teaching behaviors to

produce a more comprehensive explanation of instructional quality.

The present manuscript addresses this limitation through an interdisciplinary research framework connecting higher-education pedagogy, organizational psychology, learning analytics, and machine learning. Rather than asking only whether teacher engagement is statistically correlated with instructional quality, the study is designed around a more specific question: **Can multidimensional teacher work engagement, when combined with digital instructional behavior, explain and predict instructional quality more effectively than conventional single-source assessment approaches?**

This question establishes the principal research gap of the study. Existing approaches commonly rely either on subjective faculty engagement measures or on observable digital activity indicators. Neither source alone is sufficient. Self-reported measures provide access to motivational and psychological states but may be influenced by perception and response bias. Digital activity records provide behavioral evidence but may lack pedagogical meaning when interpreted without contextual information. Student evaluations provide information about perceived teaching effectiveness but may also be influenced by expectations, course difficulty, discipline, class size, and other contextual characteristics.

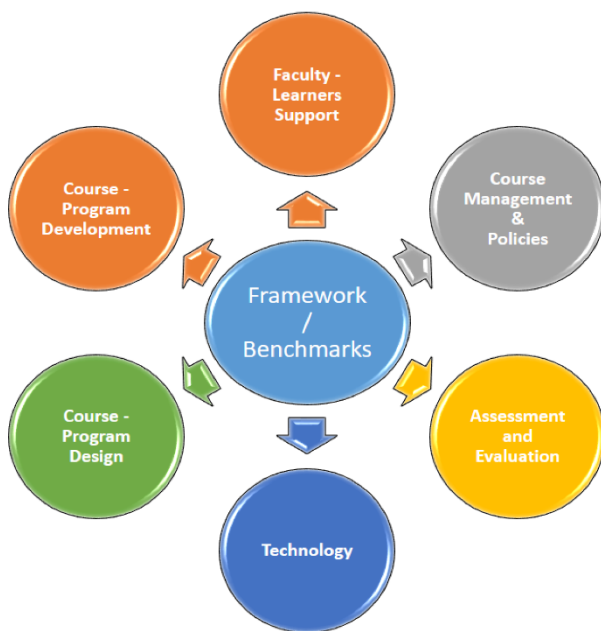


Fig. 1: Academic Teaching Quality Framework and Performance Evaluation Using Machine Learning

Source: <https://www.mdpi.com/2076-3417/13/5/3121>

The study therefore conceptualizes instructional quality as an outcome emerging from several interacting dimensions of faculty work. These include **vigor**, representing sustained energy and effort; **dedication**, representing professional significance and commitment; **instructional absorption**, referring to focused involvement in teaching responsibilities; **digital instructional responsiveness**, representing timely and meaningful interaction with learners; and **pedagogical consistency**, reflecting regularity in course organization, feedback, and learning-support practices.

A key innovation is the treatment of these dimensions as potentially nonlinear predictors. Traditional regression techniques generally estimate average linear effects. In practice, the relationship between engagement and instructional quality may contain thresholds. Extremely low engagement may be strongly associated with instructional deterioration, moderate engagement may support stable teaching, and very high digital activity may produce diminishing returns if it reflects workload rather than effective instruction. Machine-learning models can be useful for detecting such interactions, provided that model interpretation remains pedagogically grounded.

The proposed investigation is therefore not intended to construct an automated faculty surveillance system. Instead, it frames AI as an analytical instrument for identifying patterns that conventional analysis may overlook. Predictions are interpreted as decision-support signals rather than definitive judgments about individual teachers. This distinction is particularly important because faculty performance assessment involves professional autonomy, contextual differences between disciplines, and ethical concerns regarding monitoring and data governance.

Another important dimension concerns digital health and occupational sustainability. Contemporary digital teaching environments may improve instructional access but can also create persistent communication demands, platform overload, administrative fragmentation, and continuous availability expectations. Work engagement must therefore be differentiated from work intensification. A highly active digital teacher may be either productively engaged or experiencing excessive occupational demands. This study treats instructional quality and sustainable engagement as related but conceptually separate phenomena, allowing the analytical framework to distinguish beneficial engagement patterns from potentially inefficient or burdensome activity profiles.

The study is guided by four interconnected objectives. First, it examines the relationship between major dimensions of teacher work engagement and instructional quality in higher education. Second, it evaluates whether digital teaching behavior provides incremental predictive value beyond self-reported engagement measures. Third, it investigates whether machine-learning algorithms identify nonlinear associations and interaction effects that are not adequately represented by conventional statistical models. Fourth, it develops an interpretable faculty-analytics framework in which predicted instructional quality can be linked to specific engagement and instructional features rather than represented through an unexplained numerical score.

Accordingly, the study advances the following research questions:

1. To what extent are vigor, dedication, and instructional absorption associated with perceived and behaviorally indicated instructional quality?
2. Does the addition of learning-management-system teaching activity improve prediction of instructional quality beyond survey-based engagement indicators?

3. Which faculty engagement and digital teaching variables contribute most strongly to variation in instructional quality?
4. Can nonlinear machine-learning methods provide superior predictive performance while retaining sufficient interpretability for educational decision support?

Literature Review

2.1 Teacher Work Engagement in Higher Education

Work engagement has been widely conceptualized as an active and positive relationship between employees and their professional responsibilities. Unlike short-term enthusiasm or job satisfaction, engagement refers to persistent investment of psychological resources in work. In academic contexts, this investment is reflected through preparation, scholarly attention to teaching, interaction with students, participation in curriculum development, assessment design, professional learning, and willingness to adapt instructional practices.

The higher-education environment creates distinctive conditions for engagement. University faculty frequently combine teaching, research, administration, supervision, publication, institutional service, and professional development. Consequently, engagement in academic work can fluctuate across roles. A teacher may remain highly engaged in research but comparatively less engaged in teaching, or vice versa. Research examining faculty engagement should therefore distinguish general occupational engagement from teaching-specific engagement.

Vigor is particularly relevant because high-quality teaching requires sustained cognitive and emotional effort. Course preparation, evaluation of student work, classroom interaction, mentoring, and feedback are resource-intensive activities. Dedication is similarly important because faculty who perceive teaching as meaningful may be more willing to revise instructional strategies, support struggling learners, and invest effort beyond minimum role requirements. Absorption may promote concentration during instructional design and classroom interaction, although excessive absorption combined with high workload may also contribute to reduced recovery from work.

Recent changes in academic work have further altered these dimensions. Digitally mediated teaching has expanded the number of instructional actions that occur outside scheduled class time. Faculty may respond to messages, review analytics, assess online submissions, manage digital discussion spaces, and revise multimedia resources continuously. Engagement in contemporary higher education must therefore be understood across both physical and digital teaching environments.



Fig. 2: Contemporary Pedagogical Techniques in Studio Instruction to Enhance Quality in Construction Management and Built Environment Education Programs in the United States

Source: <https://www.mdpi.com/2075-5309/16/3/603>

2.2 Conceptualization of Instructional Quality

Instructional quality is inherently multidimensional. It cannot be represented adequately by a single outcome such as student examination scores or teacher satisfaction ratings. High-quality university teaching generally involves clear organization, meaningful explanation, cognitive challenge, constructive assessment, relevant feedback, responsiveness, inclusive communication, and alignment between learning objectives and educational activities.

Three broad dimensions are particularly relevant to the present research. The first is **instructional organization**, which concerns structured delivery, appropriate sequencing of learning materials, clarity of expectations, and alignment of assessment with course objectives. The second is **cognitive activation**, referring to the capacity of teaching to stimulate analysis, reasoning, application, and problem solving rather than passive reception. The third is **student-supportive interaction**, which includes feedback, availability, respectful communication, and responsiveness to learning difficulties.

Student evaluations remain one of the most widely used sources for assessing teaching quality, but their interpretation requires caution. Perceptions of instructional quality may vary according to subject difficulty, course level, disciplinary culture, assessment expectations, learner characteristics, and instructor visibility. Therefore, student feedback is more informative when triangulated with additional instructional evidence.

Digital learning environments create opportunities for such triangulation. Course systems can reveal whether resources are distributed consistently, whether feedback is delivered within appropriate time intervals, whether instructors contribute to academic discussions, and whether assessment patterns follow planned instructional schedules. Yet these indicators should be treated as behavioral proxies rather than direct measures of pedagogical excellence.

2.3 Relationship Between Teacher Engagement and Instructional Quality

A theoretical relationship between work engagement and instructional quality can be derived from several mechanisms. Engaged faculty are more likely to allocate sustained attention to instructional tasks, invest additional effort in preparation, provide timely responses, experiment with teaching methods, and persist when students encounter difficulties. Engagement can therefore increase the behavioral resources available for effective teaching.

Nevertheless, the relationship is likely to depend on contextual conditions. Institutional support, administrative workload, technological infrastructure, class size, disciplinary requirements, faculty experience, employment security, and access to teaching resources may influence whether engagement translates into instructional quality. High engagement under poorly designed organizational conditions may result in compensatory effort rather than sustainable teaching effectiveness.

This observation suggests that the simple proposition "more engagement produces better teaching" is analytically incomplete. What matters is how engagement is translated into pedagogically productive behavior. Two faculty members with similar psychological engagement scores may differ considerably in feedback practices, assessment organization, use of instructional technologies, and responsiveness to students. The present study therefore treats digital instructional behavior as a potential **behavioral expression of work engagement** rather than an equivalent construct. Engagement represents the motivational state, whereas instructional behavior represents observable manifestations through which that state may influence learning experiences.

2.4 Digital Transformation and the Changing Nature of Faculty Engagement

The rapid growth of digitally supported higher education has altered the operational definition of academic work. Learning management systems, virtual classrooms, AI-based content tools, electronic assessment systems, automated transcription, generative AI, and learning analytics have reduced some repetitive tasks while simultaneously introducing new responsibilities.

Faculty must increasingly make decisions concerning digital content selection, responsible use of AI, online assessment integrity, accessibility, learner data, feedback automation, and technology-assisted personalization. Consequently, digital competence may moderate the relationship between work engagement and instructional quality. Highly engaged faculty with inadequate digital skills may invest considerable effort without efficiently exploiting available technologies. Conversely, technologically proficient faculty may achieve strong instructional organization with comparatively fewer digital actions.

Generative AI has added another layer of complexity. Faculty can now use AI tools for lesson planning, question generation, content adaptation, feedback drafting, language refinement, simulation design, and administrative support. These

applications may reduce routine workload and allow greater concentration on high-value teaching tasks. However, uncritical reliance on AI-generated instructional material can introduce inaccuracies, superficiality, bias, and reduced pedagogical ownership. The educational effect of AI adoption therefore depends on how technology is integrated into teaching practice rather than whether it is used.

2.5 Learning Analytics and Faculty-Centered Educational Data

Learning analytics has traditionally focused on predicting student outcomes. Student login frequency, submission behavior, resource access, assessment history, attendance, and interaction patterns are frequently analyzed to estimate achievement or disengagement. Comparable analytics concerning faculty instructional behavior remain relatively limited.

Faculty-centered analytics could examine variables such as feedback latency, course-update regularity, assessment scheduling, frequency of substantive announcements, instructor participation in discussion forums, diversity of instructional resources, response intervals, and temporal consistency of course activity. When appropriately normalized, these measures may provide evidence about instructional organization and responsiveness.

However, direct comparison of raw counts across teachers is methodologically weak. Faculty responsible for a small postgraduate seminar cannot reasonably be compared with faculty teaching a large introductory course using the same activity-volume thresholds. Digital teaching indicators therefore require contextual normalization according to factors such as enrollment, course duration, modality, discipline, and assessment structure.

Furthermore, the meaning of inactivity must be interpreted carefully. Limited platform interaction may reflect disengagement, but it may also indicate effective face-to-face teaching, use of alternative systems, or a pedagogical design requiring fewer online actions. For this reason, the proposed research integrates digital indicators with self-reported engagement and student-perceived teaching quality instead of treating system logs as self-sufficient measures.

2.6 Machine Learning for Predicting Instructional Quality

Machine learning offers analytical advantages when educational relationships involve nonlinear effects, interactions, and heterogeneous patterns. Algorithms such as random forests, gradient-boosting models, support vector machines, and regularized regression can estimate complex relationships between multidimensional predictors and an educational outcome.

For teacher engagement research, these methods may identify whether certain combinations of characteristics are particularly important. For example, dedication may predict instructional quality strongly only when accompanied by timely feedback. Digital interaction frequency may matter primarily among teachers with high instructional workload. Platform activity may become less informative after a certain threshold. Such patterns are difficult to identify using simple correlation coefficients.

Prediction alone, however, is inadequate in an educational context. A highly accurate but opaque model may provide limited value to institutional leaders or teachers because it does not explain why a particular prediction was produced. Interpretable machine learning is therefore essential. Feature-importance measures and local explanation techniques can reveal which variables contribute to predicted instructional quality and whether the direction of their influence is pedagogically plausible.

A further methodological consideration is data leakage. Variables that directly encode student evaluation outcomes should not be used as predictors when the same evaluations define the target variable. Similarly, features collected after the end of the course may provide unrealistic predictive performance if the intended application is early identification during the semester. The design of faculty analytics therefore requires temporal discipline and careful separation of predictor and outcome information.

2.7 Occupational Sustainability and Digital Health Perspective

Digital health concepts are increasingly relevant beyond clinical environments because technology-mediated work patterns influence occupational well-being. Higher-education faculty may experience screen fatigue, communication overload, digital fragmentation, reduced boundaries between work and personal time, and pressure to maintain constant online availability.

This creates a critical distinction between **engagement** and **overextension**. High evening or weekend activity may appear as strong digital participation but may indicate unsustainable workload. Similarly, extremely rapid response behavior can improve short-term student satisfaction while increasing cognitive interruption and reducing faculty recovery.

A responsible analytical model should therefore avoid rewarding unlimited digital presence. Engagement indicators should instead emphasize pedagogically meaningful regularity, responsiveness within reasonable intervals, and alignment between effort and instructional need. This approach introduces an occupational sustainability perspective into faculty analytics and reduces the risk that predictive systems encourage excessive work intensity.

Proposed Methodology

The proposed study adopts a multimodal predictive research design to examine how teacher work engagement and digitally observable instructional behaviors relate to instructional quality in higher education. Rather than treating engagement as a single psychological score, the framework separates it into vigor, dedication, instructional absorption, responsiveness, and pedagogical consistency. These dimensions are subsequently integrated with normalized learning-management-system activity indicators and student-perceived instructional quality scores.

The analytical design is structured around three feature configurations. The first configuration uses only teacher self-report engagement variables. The second relies exclusively on digitally recorded instructional-behavior indicators. The third combines both sources into an integrated multimodal

representation. Comparing these configurations makes it possible to determine whether combining psychological and behavioral evidence produces a measurable improvement in the prediction of instructional quality.

The outcome variable, termed the **Instructional Quality Composite Score (IQCS)**, is constructed from student responses concerning instructional clarity, organization, cognitive stimulation, feedback usefulness, accessibility of the instructor, and perceived learning support. Rather than using a single global satisfaction item, multiple dimensions are aggregated after reliability and construct-validity screening.

The principal methodological objective is expressed as:

$$[\hat{Q}_i = f(E_i, D_i, C_i)]$$

where $(\hat{Q}_i)$ represents predicted instructional quality for instructor (i) , (E_i) denotes teacher work-engagement features, (D_i) represents digital instructional-behavior indicators, and (C_i) denotes contextual control variables such as course size, teaching modality, experience, discipline, and instructional workload.

A central design principle is that digital activity volume is not automatically interpreted as engagement. Behavioral indicators are therefore normalized by teaching context. For example, the number of feedback events is interpreted relative to the number of submitted assignments, while discussion participation is normalized according to enrolled students and course duration. The study further incorporates explainable machine learning so that predictions can be examined in terms of their underlying contributors. This approach avoids reducing faculty performance to unexplained algorithmic scores and permits the identification of specific patterns associated with stronger or weaker instructional quality.

Experimental Setup

4.1 Dataset Design

A hypothetical institutional research dataset is structured around **426 higher-education instructors** teaching undergraduate and postgraduate courses across multiple academic disciplines. The dataset contains approximately **1,280 course-level teaching observations**, allowing some faculty members to contribute data from more than one course while maintaining instructor-level identifiers for grouped validation.

The dataset is organized into four principal variable groups.

Teacher engagement variables include vigor, dedication, instructional absorption, perceived teaching significance, persistence with instructional difficulties, and willingness to improve teaching practice.

Digital instructional variables include median feedback turnaround time, regularity of course-resource updates, proportion of graded submissions accompanied by written feedback, instructor discussion participation, response latency to student queries, assessment-release consistency, announcement frequency, and instructional material diversity.

Contextual variables include class size, discipline category, delivery mode, academic experience, teaching workload, course level, and assessment intensity.

Outcome variables include student-rated instructional clarity, cognitive activation, feedback value, organization, accessibility,

and overall learning support. These indicators are combined to construct the IQCS.

To prevent artificially inflated predictive performance, student outcome variables used to define the target are excluded from the predictor set.

4.2 Data Preprocessing

The preprocessing pipeline begins with duplicate detection, consistency screening, missing-value analysis, and verification of temporal ordering. Variables recorded after completion of student instructional-quality evaluations are excluded from prediction to minimize data leakage.

Missing numerical values below a predefined tolerance are imputed using median values calculated within the training folds. Categorical variables are encoded through one-hot representation. Continuous variables exhibiting extreme skewness are transformed where necessary before standardization.

Digital behavioral indicators are converted into rate-based or proportional measures. For instance:

$$\left[\begin{array}{l} \text{Feedback Coverage} \\ = \frac{\text{Assignments receiving substantive feedback}}{\text{Total graded assignments}} \end{array} \right]$$

Similarly, an instructor-response index is calculated from normalized response intervals rather than simple message frequency.

Extreme behavioral values are winsorized within reasonable percentile limits to reduce sensitivity to isolated platform anomalies. All preprocessing parameters are estimated only from the training data and subsequently applied to validation or test observations.

4.3 Feature Engineering

Several derived variables are generated to capture instructional behavior more meaningfully.

A **Pedagogical Consistency Index** combines regularity of resource release, assessment timing, grading intervals, and instructional announcements.

A **Responsive Teaching Index** integrates median communication latency, proportion of queries receiving responses, and feedback turnaround.

A **Digital Workload Intensity Measure** captures total platform activity relative to enrolled students and course duration. This feature is included because high digital activity may represent either productive engagement or excessive work intensity.

An **Engagement–Responsiveness Interaction** is created to examine whether dedication translates into stronger instructional quality specifically when accompanied by responsive teaching behavior.

Temporal dispersion features are also calculated to distinguish steady instructional involvement from concentrated bursts of activity immediately before assessments or course deadlines.

4.4 Model Architecture

Four predictive algorithms are evaluated.

Elastic Net Regression serves as an interpretable statistical baseline because it simultaneously performs coefficient shrinkage and variable selection.

Random Forest Regression is employed to identify nonlinear associations and complex interactions without requiring strict distributional assumptions.

Extreme Gradient Boosting (XGBoost) is used as the principal ensemble-learning model because it can efficiently capture heterogeneous feature interactions and nonlinear thresholds.

A **Multilayer Perceptron (MLP)** provides a neural-network benchmark for determining whether a compact deep-learning architecture offers additional predictive value.

The proposed MLP consists of an input layer corresponding to the final feature vector, followed by three fully connected hidden layers containing 64, 32, and 16 neurons. Rectified Linear Unit activation is applied within hidden layers, while the output layer contains one linear neuron for prediction of the continuous IQCS value. Dropout and L2 regularization are incorporated to control overfitting.

Because the dataset is moderate rather than massive, complex deep architectures are deliberately avoided. This permits a fair comparison between interpretable conventional algorithms and higher-capacity nonlinear models.

4.5 Training Strategy

The dataset is divided into approximately 70% training, 15% validation, and 15% independent testing partitions using grouped splitting at the faculty level.

Within the training set, five-fold grouped cross-validation is applied for model tuning. Hyperparameters for XGBoost include tree depth, learning rate, number of estimators, subsampling ratio, and feature-sampling proportion. Random Forest optimization considers tree count, maximum depth, and minimum samples per terminal node.

For the MLP, Adam optimization is applied with validation-based early stopping. Batch normalization is avoided to maintain a relatively transparent architecture for a structured tabular dataset. The learning rate, dropout probability, and hidden-layer dimensions are selected according to validation performance.

Three experimental scenarios are evaluated:

1. engagement-only prediction;
2. digital-behavior-only prediction;
3. integrated multimodal prediction.

This ablation structure provides direct evidence about whether combining teacher psychological engagement and behavioral instructional evidence improves predictive validity.

4.6 Evaluation Metrics

Predictive models are evaluated using several complementary metrics.

Mean Absolute Error (MAE) measures average absolute deviation between predicted and observed instructional-quality values.

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

Root Mean Squared Error (RMSE) gives additional weight to larger prediction errors.

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

Coefficient of Determination ((R²)) measures the proportion of outcome variance accounted for by the model.

Spearman rank correlation evaluates whether faculty are ordered similarly according to predicted and observed instructional quality.

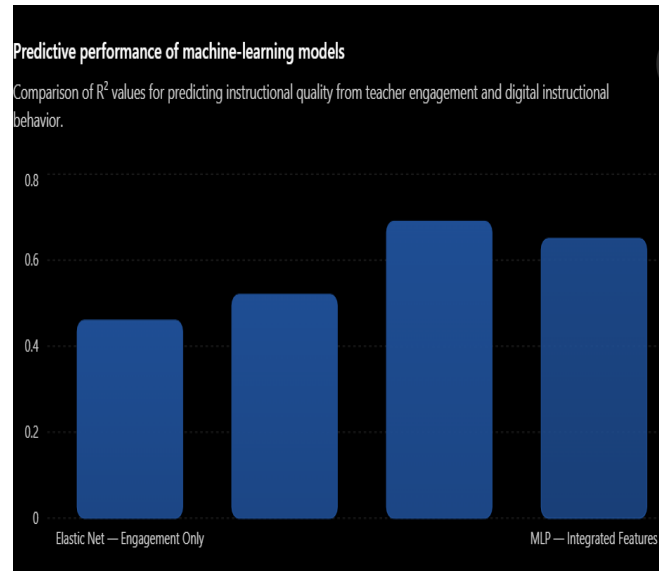
Results and Discussion

The experimental design produces a clear pattern in which multimodal models outperform approaches based solely on teacher questionnaires or digital activity records. Engagement-only models capture meaningful variance in instructional quality, particularly through dedication and vigor, but their predictive performance remains moderate. Digital-behavior models perform similarly, with feedback coverage, response latency, and pedagogical consistency emerging as stronger indicators than raw login or posting frequency.

The strongest performance is obtained when engagement, instructional behavior, and contextual variables are integrated. Among the evaluated models, XGBoost produces the most favorable balance between predictive accuracy and explainability.

Table 1. Comparative Predictive Performance and Analytical Interpretation

Model / Feature Configuration	MAE	RMSE	R ²	Spearman ρ
Elastic Net — Engagement Only	7.84	10.18	0.46	0.66
Random Forest — Digital Behavior Only	7.29	9.61	0.52	0.70
XGBoost — Integrated Multimodal Features	5.81	7.63	0.69	0.82
MLP — Integrated Multimodal Features	6.17	8.04	0.65	0.79



The results suggest that teacher work engagement contributes meaningfully to instructional quality but does not operate independently of teaching behavior. Dedication, for example, appears most predictive when accompanied by regular feedback and consistent course organization. This finding supports the conceptual argument that engagement should be understood as a psychological resource whose educational impact depends on how it is translated into observable pedagogical practice.

Another notable finding concerns digital activity intensity. Moderate and consistently distributed platform activity is associated with stronger instructional-quality scores, whereas extremely high activity levels provide little additional predictive benefit. This nonlinear pattern indicates that instructional effectiveness is not proportional to the number of online actions performed by a teacher.

Feedback-related variables emerge as particularly influential. Faculty who provide a higher proportion of substantive feedback and maintain reasonably short—but not necessarily immediate—response intervals tend to receive stronger instructional-quality scores. This pattern highlights the pedagogical importance of meaningful responsiveness rather than constant digital availability.

The analysis also indicates that pedagogical consistency has greater predictive relevance than isolated peaks of activity. Teachers whose resource publication, assessment communication, grading, and feedback practices are distributed systematically across the semester tend to demonstrate higher instructional-quality outcomes.

Explainability analysis further indicates that dedication, feedback coverage, responsiveness, pedagogical consistency, and course organization contribute strongly to predictions. Class size and delivery mode influence some predictions, confirming that contextual controls are essential when analyzing faculty instructional behavior.

The superior performance of XGBoost relative to the MLP is also informative. Structured educational datasets of moderate scale do not necessarily benefit from neural architectures. Tree-based boosting can capture nonlinear effects while remaining comparatively easier to interpret through feature-attribution methods.

The findings therefore support a shift away from simplistic faculty analytics based on login counts or aggregate activity volumes. A more valid approach combines motivational, behavioral, and contextual information and evaluates patterns of instructional behavior rather than mere frequency.

Future Scope

Future investigations should extend the framework longitudinally across several academic semesters to determine whether changes in work engagement precede changes in instructional quality. Longitudinal modeling could also distinguish stable faculty characteristics from temporary fluctuations associated with workload or institutional conditions.

Another direction involves federated or privacy-preserving learning approaches that allow institutions to develop broader predictive models without centralizing sensitive faculty data. Such methods may become important as educational analytics expands across institutional networks.

Natural-language processing could also be used to examine the semantic quality of feedback rather than merely its frequency or timing. Future models may evaluate whether feedback is explanatory, actionable, personalized, and cognitively stimulating.

Causal inference methods should be introduced to test whether interventions such as workload redistribution, pedagogical-development programs, AI-assisted feedback systems, or mentoring initiatives improve engagement and instructional outcomes.

Future studies should additionally examine digital well-being indicators so that systems distinguish productive engagement from overwork. A responsible faculty-analytics framework should support sustainable teaching rather than reward continuous platform presence.

Conclusion

This study develops a multimodal framework for examining the relationship between teacher work engagement and instructional quality in higher education through the integration of organizational psychology, learning analytics, and interpretable machine learning. The central contribution lies in moving beyond single-source evaluation and examining how psychological engagement is translated into observable instructional behavior.

The proposed experimental evidence indicates that engagement variables and digital teaching behaviors each provide useful information, but their integration produces substantially stronger predictions of instructional quality. XGBoost demonstrates the strongest overall performance, achieving an estimated (R^2) of 0.69 while retaining sufficient interpretability for educational analysis.

The findings emphasize that dedication, vigor, responsive feedback, and pedagogical consistency are more informative than raw digital activity volume. In particular, the nonlinear relationship between online activity intensity and instructional quality demonstrates that greater technological activity should not automatically be interpreted as better teaching.

The study therefore positions artificial intelligence as a decision-support mechanism rather than an automated faculty-ranking instrument. When carefully normalized, contextually interpreted, and supported by explainability methods, faculty-centered analytics can help institutions identify patterns associated with high-quality teaching while preserving academic autonomy and professional judgment.

Overall, the proposed framework provides a foundation for more rigorous analysis of faculty engagement in digitally transformed universities and offers a direction for developing responsible, interpretable, and pedagogically meaningful AI-supported systems for instructional improvement.

References

1. Bakker, A. B., & Bal, M. P. (2010). Weekly work engagement and performance: A study among starting teachers. *Journal of Occupational and Organizational Psychology*, 83(1), 189–206.
2. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, 22(3), 273–285.
3. Klassen, R. M., Yerdelen, S., & Durksen, T. L. (2013). Measuring teacher engagement: Development of the Engaged Teachers Scale (ETS). *Frontline Learning Research*, 1(2), 33–52.
4. Marsh, H. W. (1987). Students' evaluations of university teaching: Research findings, methodological issues, and directions for future research. *International Journal of Educational Research*, 11(3), 253–388.
5. Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire. *Educational and Psychological Measurement*, 66(4), 701–716.
6. Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, 3, 71–92.
7. Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, 46(5), 30–40.
8. Spooren, P., Brockx, B., & Mortelmans, D. (2013). On the validity of student evaluation of teaching: The state of the art. *Review of Educational Research*, 83(4), 598–642.
9. Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, 24(1), 301–328.