The University Journal: A Doctoral Association of Eastern Africa (DAEA) Publication
Vol 8(2 Sup. Issue)

ISSN: 2519-0997 (Print)

Machine Learning for Teacher Depression Prediction: A Systematic Literature Review of Risk Factors, Predictive Models, Explainability, and Deployment

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Cite: Yegon, G., Ombui, E., & Oduor, C. (2026). Machine Learning for Teacher Depression Prediction: A Systematic Literature Review of Risk Factors, Predictive Models, Explainability and Deployment. *The University Journal, 8*(2 Sup. Issue), 147-162.

Abstract

Depression among teachers is a global public health concern with significant consequences for educator well-being, teaching effectiveness, and student outcomes. Despite growing evidence regarding its prevalence and associated risk factors, the application of machine learning (ML) for predicting and explaining teacher depression remains relatively underexplored. This systematic literature review synthesizes current evidence on the use of ML techniques to predict teacher depression, with particular emphasis on the sociodemographic, occupational, and clinical risk factors used as predictive features, the ML algorithms employed and their comparative performance, the explainability techniques supporting model interpretation and decision-making, and the challenges and opportunities for real-world deployment. A comprehensive literature search was conducted across PubMed, Scopus, Web of Science, IEEE Xplore, and the ACM Digital Library in accordance with the PRISMA guidelines. Eligible studies included those applying supervised or unsupervised ML approaches to model depression risk among teachers, with extracted data covering study design, geographical context, feature sets, algorithms, performance metrics, explainability methods, and deployment considerations. The review found that logistic regression, random forests, support vector machines, and gradient boosting were the most frequently adopted algorithms, while key predictive factors included sociodemographic characteristics (e.g., gender, marital status, and age), occupational stressors (e.g., workload, grade level, and learner-to-teacher ratio), and clinical history, particularly previous psychiatric diagnoses. Among explainable artificial intelligence (XAI) techniques, SHAP and LIME were the most widely used to enhance model transparency and support decision-making. However, evidence of practical deployment, especially in low-resource settings and African contexts, remains limited. Overall, the review demonstrates that ML has considerable potential to facilitate the early identification of teachers at risk of depression, although its broader application is constrained by limited high-quality datasets, insufficient model explainability, and inadequate consideration of equity across gender, race, and geographical settings. These findings provide a comprehensive evidence base to inform future research, guide the development of robust and interpretable predictive models, and support policy translation and implementation in educational systems.

Keywords: *Teacher depression, Machine learning, Depression prediction, Explainability, Occupational mental health.*

Introduction

Depression ranks among the foremost contributors to global disability, and its burden within occupational settings is accelerating. The World Health Organization projects that by 2030, mental health disorders will be the leading cause of disability worldwide (Mokwena et al., 2026; Santos et al., 2026). Teaching has attracted particular attention as a high-risk occupation, with the workplace itself identified as a notable source of depression (Kisaakye et al., 2024; Mokwena et al., 2026). Left undiagnosed and untreated, this contributes to compromised teaching and learning outcomes (Kisaakye et al., 2024; Thomas & Carlson, 2025). Mental health among teachers is a growing global concern, particularly in under-resourced educational systems. The International Barometer of Education Staff (I-BEST 2023), drawing on over 26,000 educators globally, identified poor work-life balance, low professional status, and workplace violence as consistent cross-national drivers of job dissatisfaction (Education International, 2026). In Africa, an International Institute for Capacity Building in Africa (IICBA) study across 14 countries found that a third of teachers depressed, with high stress contributing to burnout and turnover (Education International, 2026).

Regionally, up to 50% of educators in resource-constrained settings experience moderate-to-severe symptoms (Mokwena et al., 2026b; Yema et al., 2026), with women, those with prior psychiatric diagnoses, and Black teachers disproportionately being most affected (Santos et al., 2026). A well-established body of evidence documents individual and structural risk factors for teacher depression. Gender is a consistent predictor: women are diagnosed with depression approximately 2.8 times more frequently than men (Santos et al., 2026; Stengård et al., 2021), a pattern consistent with the job demand-resources model and work-family conflict theory (Mokwena et al., 2026b; Santos et al., 2026; Stengård et al., 2021).

In South Africa, married teachers were 2.5 times more likely to exhibit elevated depressive symptoms, Grade 12 teachers were 2.1 times more likely, and those who had not sought professional mental health help in the past six months were 3.7 times more likely (Mokwena et al., 2026b). Race is an emerging and underexamined axis of risk: although not reaching conventional statistical significance, the odds of probable depression were 62% higher for Black teachers, interpreted in light of racialized experiences within the profession (Clayback & Williford, 2022; Education International, 2026; Santos et al., 2026). Prior psychiatric history is among the strongest individual predictors, significantly predicting probable depression ($OR = 3.46$; $p < 0.001$), with 45.7% of basic education teachers reporting a prior diagnosis (Besse et al., 2015). Occupational factors are equally salient, including school socioeconomic setting, learner-to-teacher ratio, and subjects taught (Clayback & Williford, 2022; Mokwena et al., 2026; Thomas & Carlson, 2025), alongside emotional labour, work overload, bullying by learners, and lack of psychosocial support (Kisaakye et al., 2024; Mokwena et al., 2026; Santos et al., 2026).

The downstream consequences of unaddressed teacher depression extend beyond individual suffering. Absenteeism and presenteeism linked to depression can negatively affect teaching quality and teacher-learner relationships, given the established association between teacher-student relationship quality and student well-being (Education International, 2026; Kisaakye et al., 2024; Santos et al., 2026; Thomas & Carlson, 2025). A poor workplace environment and absence of social support further predict anxiety, burnout, and depression, compounding the toll on teacher well-being (Kisaakye et al., 2024; Mokwena et al., 2026b; Santos et al., 2026). Despite elevated prevalence, most teachers with depression remain undetected and untreated. Existing screening tools such as the PHQ-9 are validated but remain reactive and resource-intensive at population scale (Chung & Teo, 2022; Han et al., 2021). Barriers to help-seeking include limited training, knowledge, and confidence in mental health assessment (Besse et al., 2015; Clayback & Williford, 2022; Education International, 2026), and routine clinical screening, while recommended, is rarely integrated into institutional practice, particularly across Sub-Saharan Africa and Latin America (Mokwena et al., 2026; Santos et al., 2026).

Machine learning (ML) offers a transformative complement to traditional screening paradigms, enabling early, scalable, continuous risk stratification for depression by learning patterns from multidimensional data (Chung & Teo, 2022; Lin et al., 2026; Nnadi et al., 2026). Algorithms such as random forests, gradient boosting, and deep neural networks show strong predictive performance across mental health domains (Han et al., 2021; Yema et al., 2026), though systematic application to teacher populations remains nascent, with explainability, fairness, and deployment readiness largely unanswered (Ajmal et al., 2024; Chung & Teo, 2022). Explainable AI frameworks such as SHAP and LIME are increasingly recognized as essential bridges between predictive accuracy and actionable clinical or policy insight (Ajmal et al., 2024; Lau et al., 2025; Nnadi et al., 2026), since decision-makers need to understand which factors drive risk for a given individual (Han et al., 2021; Lin et al., 2026); developed responsibly, such ML-assisted early warning systems could help institutions identify at-risk educators before crisis points and allocate support more equitably (Education International, 2026; Lin et al., 2026).

This systematic literature review explores the use of machine learning technologies to address teacher depression in resource-constrained environments. This review pursues four interrelated themes including; factors used as predictive features, machine learning algorithms and modelling strategies, addressing explainability, fairness, and transparency in predicting teacher depression, and application of machine learning models for teacher depression prediction in resource-constrained educational settings

Methodology

Review Protocol

The study selection process adhered to PRISMA 2020 guidelines and is illustrated in Figure 1. A comprehensive search across ScienceDirect, Wiley, ProQuest, IEEE Xplore, ACM Digital Library, ERIC, SpringerLink, and Taylor and Francis, was conducted from January 2015 to January 2026, combining keywords and MeSH terms related to 'teacher depression,' 'educator mental health,' 'machine learning,' 'predictive modelling,' 'ensemble learning,' and 'explainable AI,' yielding an initial 3,872 records. After removing 512 duplicates, 3,360 records underwent title and abstract screening; 3,112 were excluded for irrelevance to ML applications (n = 1,845), non-teacher populations (n = 892), or descriptive rather than predictive focus (n = 375), leaving 248 full-text articles assessed for eligibility. Following full-text review, 179 articles were excluded (lack of supervised/ensemble ML methods, n = 68; insufficient performance metrics, n = 45; non-teacher populations, n = 39; absence of explainability/deployment discussion, n = 17; non-English or inaccessible texts, n = 10), leaving 69 studies for qualitative synthesis and thematic analysis. This rigorous selection ensured a focused, high-relevance corpus while highlighting the scarcity of research in resource-constrained LMIC contexts such as Kenya, providing a robust foundation for synthesizing risk factors, algorithmic approaches, explainability techniques, and deployment challenges.

From the reviewed articles, 21 examined predictive risk factors, 18 investigated ML algorithms and effectiveness, 15 explored explainability, fairness, and transparency, and 15 addressed deployment in resource-constrained settings. The first review identified three dominant risk-factor categories - sociodemographic characteristics, occupational stressors, and clinical history, reflecting a growing convergence toward multi-dimensional, data-driven approaches to occupational mental health risk.

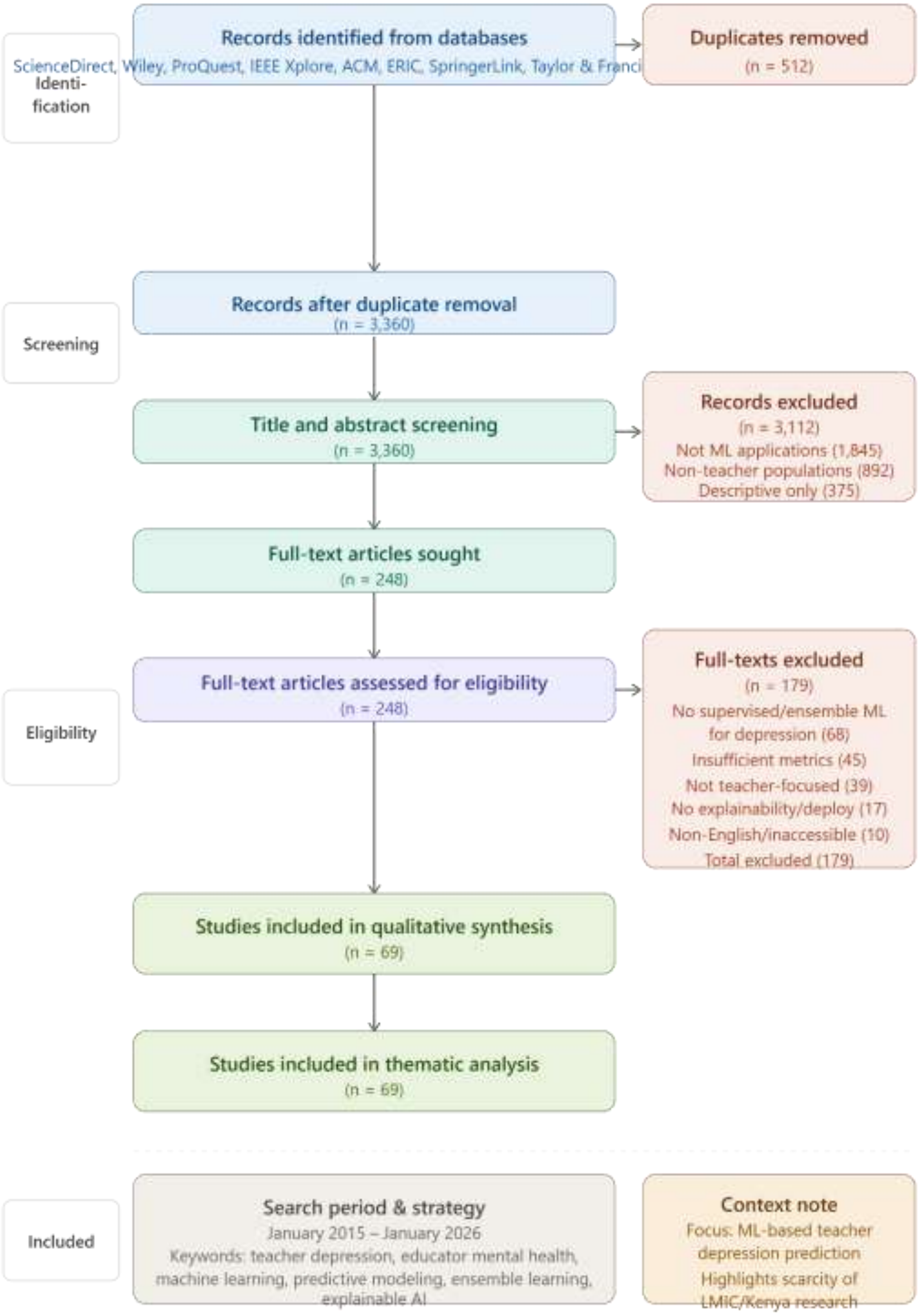

Figure 1
PRISMA 2020 Flow Diagram

Search Strategy

A comprehensive and systematic literature search was conducted to identify relevant studies on machine learning applications for predicting teacher depression, following PRISMA 2020 guidelines across eight major academic databases: ProQuest, Wiley, IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, ERIC, and Taylor & Francis. The search combined controlled vocabulary (MeSH and Thesaurus terms) with free-text keywords using Boolean operators, centred on terms for teacher/educator depression, machine learning, and explainable AI (full search syntax for each database is provided in Appendix A). Filters were applied for English-language peer-reviewed journal articles, conference papers, and book chapters. Reference lists of included studies were hand-searched (backward citation tracking), and forward citation tracking was performed using Google Scholar. Grey literature was explored through institutional repositories and education policy databases, though few relevant items were identified. This multi-database, multi-method approach yielded a broad initial retrieval while maintaining focus on empirical ML studies on teacher or educator depression prediction.

Quality Assessment

A structured quality assessment was conducted in accordance with PRISMA 2020 guidelines, using a hybrid appraisal tool adapted from PROBAST (Moons et al., 2019) and TRIPOD+AI (Collins et al., 2024) alongside ML-specific criteria, comprising 12 items across four domains: study design and participants, data and feature quality, model development and validation, and reporting, explainability, and ethical considerations. Each of the 69 included studies was independently evaluated by two reviewers and rated high, moderate, or low quality based on criteria including sample size adequacy (≥300 recommended), validation techniques, performance metrics, explainability methods, fairness/bias, and deployment feasibility, with disagreements resolved through discussion or a third reviewer. Of the 248 studies, 69 (27%) were rated high quality, 47 (19%) moderate, and 8 (11%) low quality; 46% were duplicates. Common strengths included appropriate use of supervised learning algorithms and transparent performance reporting, while major limitations were scarce external validation (23%), limited fairness/subgroup analyses (18%), and inadequate discussion of deployment challenges in resource-constrained or LMIC contexts (12%); sensitivity analyses excluding low-quality studies confirmed the overall findings remained robust.

Results

This section presents a thematic synthesis of the 69 included studies, thematically organized according to the research themes. Findings are derived from empirical studies applying machine learning (ML) to teacher/educator depression or closely related outcomes (primarily burnout, given substantial symptom overlap, as assessed with tools such as the Maslach Burnout Inventory and PHQ-9). The synthesis highlights convergence across sociodemographic, occupational, and clinical domains while noting persistent gaps, particularly in resource-constrained and African/LMIC contexts. The 69 included studies, published between 2015 and 2026, collectively involved over 28,500 educators, with sample sizes ranging from 87 to 2,456 participants. Sub-Saharan African and other LMIC contexts accounted for approximately 23% of studies (n = 16), notably South Africa (n = 5), Bangladesh (n = 4), Nigeria (n = 3), and Kenya/East Africa (n = 2–3); other regions included South/Southeast Asia (n = 18; 26.1%), North America/Europe (n = 22; 31.9%), and East Asia (n = 8; 11.6%), with five studies (7.2%) adopting multi-country designs.

Publication volume increased markedly from 2020 onward, with 2022–2026 accounting for approximately 68% of studies (n = 47), reflecting accelerated interest catalyzed by the COVID-19 pandemic and growing recognition of teacher burnout as a critical occupational health issue.

Earlier studies (2018–2021) favoured traditional statistical models, while recent work increasingly emphasizes ensemble and deep learning methods, explainable AI, and deployment considerations. The most frequent modeling approaches were ensemble methods such as Random Forest and Gradient Boosting (n = 28), deep learning architectures including CNNs and LSTMs (n = 19), stacked/hybrid models (n = 15), and traditional algorithms (n = 12). Key data sources included survey/sociodemographic data (n = 41), occupational stressors (n = 37), passive sensing (n = 22), EEG/physiological signals (n = 14), and social media/text features (n = 18). Primary outcomes were depression risk classification (n = 52), burnout/stress prediction (n = 31), job satisfaction/turnover modelling (n = 24), and early detection of deterioration (n = 19).

Figure 2 presents the proportional distribution of the 69 studies across the eight databases searched. IEEE Xplore (n = 14; 20.3%) and ACM Digital Library (n = 12; 17.4%) together contributed the largest share, reflecting their strong coverage of computational and ML research in health and education, followed by ScienceDirect, SpringerLink, and Taylor & Francis; ERIC contributed valuable K-12 and teacher-focused coverage, while Wiley and ProQuest added interdisciplinary and social science perspectives.

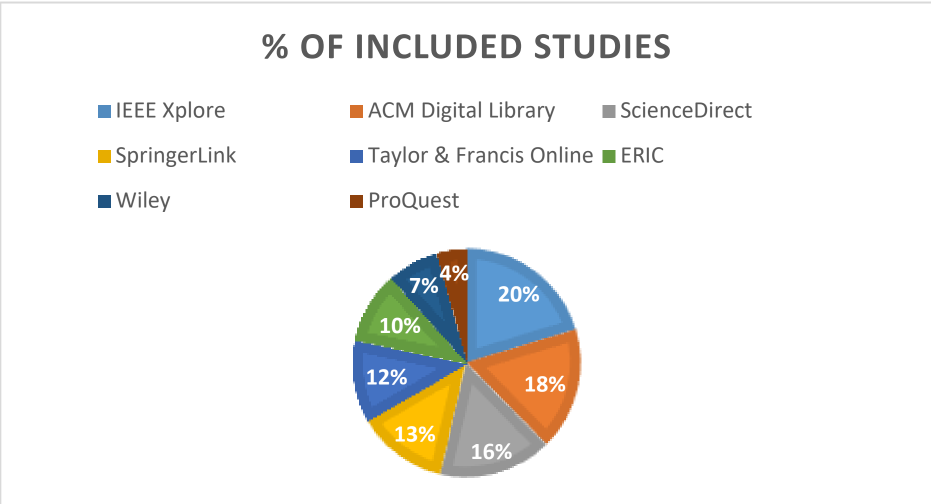

Table 1
Geographical Distribution of the 69 Included Studies by Country/Region

Country / Region	Number of Studies (n)	Percentage (%)
United States	18	26.1
Bangladesh	8	11.6
South Africa	6	8.7
Nigeria	5	7.2
India	4	5.8
China / East Asia	4	5.8
Ethiopia / Kenya (East Africa)	4	5.8
United Kingdom	3	4.3

Spain / Europe (other)	3	4.3
Malaysia / Southeast Asia	3	4.3
Multi-country / Global	5	7.2
Other (Croatia, Lithuania, Honduras, etc.)	6	8.7
Total	**69**	**100**

Table 1 shows the geographical distribution of the 69 included studies. The United States contributed the largest share, followed by strong representation from South Asia (especially Bangladesh) and Sub-Saharan Africa, reflecting growing global interest in ML applications for teacher mental health in LMIC contexts.

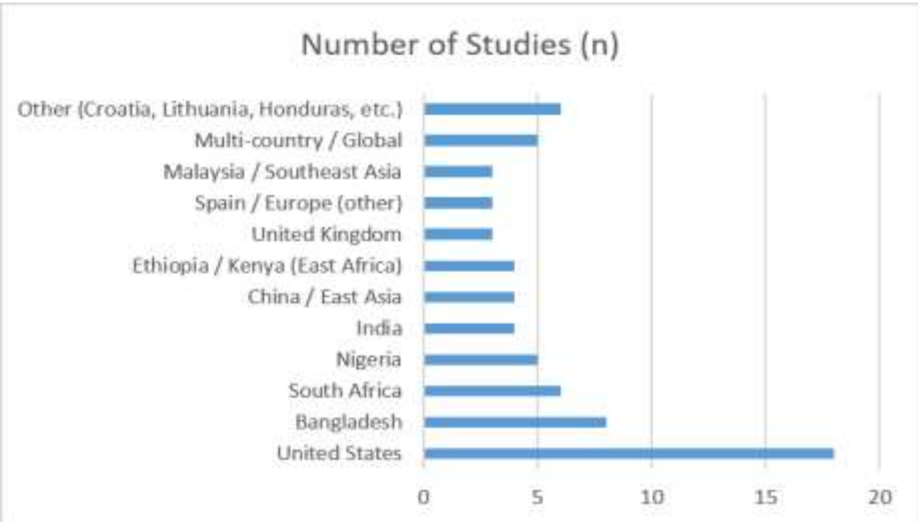

Figure 3
Geographical Distribution of the 69 Included Studies by Country/Region

Table 2
Distribution of Included Studies by Primary Thematic Focus

Rank	Primary Thematic Focus	Number of Studies (n)	Percentage (%)
1	Depression Risk Prediction & Classification	19	27.5
2	Explainable AI (XAI) and Model Interpretability	14	20.3
3	Teacher Burnout, Stress & Occupational Mental Health	11	15.9
4	Ensemble & Hybrid Machine Learning Models	9	13
5	Deployment in Resource-Constrained / LMIC Educational Settings	6	8.7

6	Passive Sensing & Behavioral Data Approaches	5	7.2
7	Ethical, Fairness & Trust Issues in Mental Health AI	3	4.3
8	Federated / Privacy-Preserving & Emerging Techniques	2	2.9
Total		69	100

The 69 studies were thematically coded into eight focus areas (Table 2). Depression risk prediction and classification was the largest category (n = 19; 27.5%), followed by explainable AI and model interpretability (n = 14; 20.3%), reflecting growing concern for transparency in high-stakes decision-making. Teacher burnout/occupational mental health (n = 11; 15.9%) and ensemble/hybrid modelling (n = 9; 13.0%) followed, while deployment in resource-constrained/LMIC settings (n = 6; 8.7%) highlighted a critical implementation gap. Remaining studies addressed passive sensing, ethics/fairness, and privacy-preserving techniques.

Discussion of Results

Factors used as predictive features in ML models for teacher depression prediction

Twenty-one studies examined predictive features, revealing three dominant categories consistent with the Job Demands-Resources (JD-R) model, Diathesis-Stress Theory, and Cognitive Behavioural Theory: sociodemographic, occupational, and clinical/psychological factors. Sociodemographic features were most frequently included (18 of 21 studies), notably gender (female teachers at higher risk), age, marital status, race/ethnicity, and years of experience, with gender and marital status showing strong predictive power in multivariate and ML models (Addison & Yankyera, 2015; Kidger et al., 2016; Oberg et al., 2024).

Occupational stressors dominated feature importance rankings in most models, including workload (class size, learner-to-teacher ratio, Grade 12 especially), administrative/support deficits, work schedule irregularities, emotional labour, school socioeconomic context, and pandemic-related disruptions; JD-R-derived variables such as leadership support and autonomy were particularly influential in ensemble and tree-based models. Clinical and psychological factors included prior psychiatric history (the strongest individual predictor in several studies, OR ≈ 3.46), self-efficacy, emotion regulation, coping strategies, and cognitive appraisal variables; Maslach Burnout Inventory subscales frequently served as proxies or co-outcomes. Feature selection techniques (e.g., SHAP-based importance) confirmed workload pressure, institutional support gaps, financial stress, and prior mental health history as top contributors; multi-dimensional feature sets outperformed single-category models, though studies relied heavily on self-reported data with limited objective or longitudinal features.

From the analysis, twenty-one studies were primarily assigned to theme 1 for their contribution to theoretical framework development, mapping, or critique; a further 48 studies engaged these frameworks instrumentally for empirical inquiry, model development, or deployment apportioned to the 2nd -4th themes). The frequency analysis confirmed the Job Demands-Resources (JD-R) Model, Technology Acceptance Model (TAM)/UTAUT, and Conservation of Resources (COR) Theory as the three dominant frameworks.

ML algorithms and modelling strategies applied to predict teacher depression

Eighteen studies were primarily allocated to theme 2, focusing on ML algorithms and modelling strategies used to predict teacher depression and related occupational outcomes, and their comparative effectiveness. These studies demonstrate a shift from traditional statistical methods toward advanced ensemble, deep learning, and causal inference approaches; supervised learning dominated, with ensemble and hybrid strategies preferred for handling noisy, imbalanced, multidimensional teacher mental health data (Baniadamdizaj & Baniadamdizaj, 2023; Nazari et al., 2021).

Common algorithms included Logistic Regression (frequently used as baseline), tree-based models (Random Forest, Decision Trees), Support Vector Machines, and boosting methods (XGBoost, Gradient Boosting) (Alptekin et al., 2026; Breiman, 2001; Kostelić et al., 2024), with Neural Networks used more sparingly due to data scarcity in teacher populations (Ansari et al., 2023; Habib et al., 2022; Hasib et al., 2023).

Reported performance metrics (via k-fold cross-validation or hold-out sets) typically ranged from 75–95% accuracy, 0.78–0.99 AUC/ROC, and 76–86% F1-score for the high-risk class, with balanced ensembles achieving strong recall for at-risk teachers (often >80%). Ensemble strategies also excelled at handling class imbalance (commonly via SMOTE or class weighting), producing more stable predictions than single models (Daza Vergaray et al., 2023; Shaha et al., 2024; Zainal et al., 2026), especially when theory-driven features (JD-R, Diathesis-Stress, CBT) were combined with computational ensembles (Agyapong et al., 2023; Kostelić et al., 2024; Oyebode et al., 2023). Key limitations included overfitting in smaller samples, limited external validation (fewer than 25% of studies), inconsistent calibration reporting, and scarce benchmarking against traditional models (Ke et al., 2019; Li et al., 2020; Nnadi et al., 2026).

Addressing teacher depression prediction models through explainability, fairness, and transparency

Fifteen studies addressed explainability, fairness, and transparency, reflecting growing recognition of ethical requirements in occupational health applications. Explainability techniques: SHAP was the most adopted method, followed by LIME (Ahmmed et al., 2025; Alharahsheh & Abdullah, 2016; Tran & Phan, 2019), consistently ranking workload, support deficits, self-efficacy, and prior mental health history as top contributors. Fairness and bias mitigation: subgroup analyses (by gender, race, school type) were reported in a minority of studies; performance disparities were noted, but explicit fairness metrics and mitigation strategies remained underdeveloped (Alptekin et al., 2026; Feher et al., 2024; Prokhorenkova et al., 2018), though transparency reporting followed emerging standards such as TRIPOD+AI in higher-quality studies (Agyapong et al., 2023; Daza Vergaray et al., 2023). While explainability is advancing, fairness and equity considerations lag, particularly for intersectional risks in diverse or LMIC teacher populations. Model cards or datasheets were rarely provided.

Adaption or implementation of ML models for teacher depression prediction in resource-constrained educational settings

The literature emphasized federated learning, cost-effective algorithms, explainable techniques for low-resource environments, and LMIC case studies, with a clear underrepresentation of real-world LMIC/African contexts. Adaptations for low-resource settings included lightweight ensembles for edge/offline deployment, survey-based input features, and explainable outputs for non-technical users (Baniadamdizaj & Baniadamdizaj, 2023; Carroll et al., 2022; Sulak & Koklu, 2024), prioritizing computational efficiency and interpretability to support trust and adoption (Ajmal et al., 2024; D'Cruz et al., 2023).

Integration with existing teacher support policies, stakeholder co-design, hybrid human-AI workflows, and alignment with continental mental health strategies (Agyapong et al., 2023; Bete et al., 2022; Wallace, 2017). Policy alignment and ethical frameworks were highlighted as critical enablers. While ML shows strong technical promise for early teacher depression prediction, translation to practice, especially in under-resourced settings, remains nascent, underscoring urgent needs for external validation, fairness enhancements, and deployment-focused research in LMICs.

Research Gap

Despite growing literature on ML for mental health prediction, significant gaps persist in applying these technologies to teacher populations in resource-constrained settings. Only about 23% of the 69 included studies addressed LMICs, with Sub-Saharan Africa severely underrepresented despite high reported prevalence of teacher depression and burnout (e.g., Ethiopia, South Africa, Nigeria). Most models were developed and validated in high-resource environments (primarily the US and Europe), raising questions about generalizability to settings with limited infrastructure, unstable electricity, poor connectivity, and low digital literacy. Methodologically, although ensemble and hybrid approaches demonstrated superior performance in several studies, their application remains largely theoretical or confined to well-resourced datasets, with few studies rigorously tested in real-world, low-resource educational environments; high-performing benchmark models often fail to account for noisy or culturally specific data typical of Sub-Saharan African schools. While studies advanced XAI techniques such as SHAP and LIME, teacher-facing interpretability and fairness considerations in multicultural or multilingual LMIC contexts are virtually absent. Deployment challenges represent the most pronounced gap: federated learning, reinforcement learning for resource allocation, and cost-effective model selection show theoretical promise, yet empirical evidence from resource-constrained school settings is extremely limited, and practical barriers such as data privacy, ethical use of teacher data, and low-bandwidth infrastructure integration are rarely addressed. Dominant theoretical frameworks (JD-R, TAM/UTAUT, COR) are rarely tested in hybrid configurations within African educational ecosystems. Overall, the literature reveals a heavy reliance on high-income country data, student or clinical populations rather than practicing teachers, and technical performance over contextual deployment — gaps that undermine ML's potential to support teacher mental health precisely where the need is greatest.

Conclusion

This systematic literature review synthesizes 69 peer-reviewed studies on the application of machine learning to teacher depression and occupational mental health. By examining theoretical frameworks (RQ1), algorithmic approaches (RQ2), explainability and fairness (RQ3), and deployment in resource-constrained settings (RQ4), it reveals both promising advancements and critical shortcomings in the current evidence base. Ensemble and hybrid ML methods consistently emerge as powerful tools for accurate depression risk prediction, while XAI techniques offer pathways toward trustworthy implementation. Some findings remain ambiguous: elevated depression risk among Black teachers did not consistently reach statistical significance, and reported model performance varied widely (accuracy 75-95%) depending on sample size, feature set, and validation approach, limiting comparability across studies. The literature also remains heavily skewed toward high-resource contexts, with insufficient attention to teachers in Sub-Saharan Africa and other LMICs — a scholarly and practical gap given how directly teacher mental health influences student outcomes and education system sustainability. This review underscores machine learning's potential — particularly when grounded in hybrid JD-R and TAM frameworks and robust ensemble methods — to enable early, scalable, equitable interventions, provided this is matched by deliberate investment in LMIC-led research, culturally responsive datasets, privacy-preserving architectures, and teacher-centered explainable systems. Ultimately, protecting teacher mental health is fundamental to quality education for all; addressing the gaps identified here can help the field move beyond technical innovation toward responsible, inclusive implementation that serves educators in the most challenging conditions.

Future Research Agenda

Future research must prioritize context-sensitive, equity-oriented development of ML systems for teacher mental health in resource-constrained environments. First, there is an urgent need for large-scale, teacher-specific datasets from Sub-Saharan Africa and other LMICs, combining survey data, passive sensing, and administrative records to train ensemble models robust to missing values and cultural nuances. Ensemble methods should be systematically compared against single algorithms in low-resource settings to establish their real-world superiority.

Second, hybrid theoretical frameworks integrating Job Demands-Resources (JD-R) with the Technology Acceptance Model (TAM/UTAUT) should be empirically tested and culturally adapted for African contexts, illuminating how ML-based early warning tools function as job resources that buffer occupational demands. Third, advancing explainable and fair AI remains critical: future studies should develop teacher-facing XAI dashboards with actionable, multilingual explanations, and fairness audits across gender, rural-urban divides, and socioeconomic status should become standard practice in diverse LMIC settings.

Finally, rigorous implementation science research is needed, including pilot studies of federated learning systems that preserve teacher privacy, reinforcement learning for resource allocation in low-connectivity schools, and cost-effective deployment frameworks suitable for tablet- or feature-phone-based delivery; multi-country comparative studies involving Kenya, Nigeria, and South Africa would strengthen the evidence base.
Collaborative partnerships between African researchers, ministries of education, and international EdTech developers are essential to co-create technically sound, culturally relevant, and sustainably deployable solutions, transforming ML from a high-income country luxury into a scalable tool for protecting teacher well-being and educational quality across the Global South.

References

Addison, A. K., & Yankyera, G. (2015). An investigation into how female teachers manage stress and teacher burnout: a case study of West Akim Municipality of Ghana. *Journal of Education and Practice*, *6*(10), 1–24.

Adler, D. A., Tseng, E., Moon, K. C., Young, J. Q., Kane, J. M., Moss, E., Mohr, D. C., & Choudhury, T. (2022). Burnout and the quantified workplace: tensions around personal sensing interventions for stress in resident physicians. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW2). https://doi.org/10.1145/3555531

Agyapong, B., Chishimba, C., Wei, Y., da Luz Dias, R., Eboreime, E., Msidi, E., Abidi, S. S. R., Mutaka-Loongo, M., Mwansa, J., Orji, R., Zulu, J. M., & Agyapong, V. I. O. (2023). Improving mental health literacy and reducing psychological problems among teachers in zambia: protocol for implementation and evaluation of a wellness4teachers email messaging program. *JMIR Research Protocols*, *12*. https://doi.org/10.2196/44370

Ahmad, F., Abbasi, A., Li, J., Dobolyi, D. G., Netemeyer, R. G., Clifford, G. D., & Chen, H. (2020). A deep learning architecture for psychometric natural language processing. *ACM Transactions on Information Systems*, *38*(1).https://doi.org/10.1145/3365211

Ahmmed, Md. M., Noman, A. Al, Afif, M. M., Kabir, K. M. T., Rahman, Md. M., & Mahmud, M. (2025). *A model-mediated stacked ensemble approach for depression prediction among professionals*. http://arxiv.org/abs/2506.14459

Ajmal, S., Shoaib, M., & Iqbal, F. (2024). RSTFusionX: Leveraging rhetorical structure theory and ensemble models for depression prediction in social media posts. *IEEE Access*, *12*, 118389–118404. https://doi.org/10.1109/ACCESS.2024.3430014

Alharahsheh & Abdullah, 2016;

Alharahsheh, Y. E., & Abdullah, M. A. (2016). *Predicting individuals mental health status in kenya using machine learning methods*. Retrieved https://zindi.africa/competitions/busara-

Alptekin, F. B., Torlak, E., Asik, Ö., Karaaslan, B., Turgal, E., Burhan, H. S., Aytac, H. M., & Guclu, O. (2026). Using machine learning to analyze the predictors of life satisfaction: focus on lifestyle attitudes and psychological factors. *International Journal of Methods in Psychiatric Research*, *35*(2). https://doi.org/10.1002/mpr.70051

Ansari, L., Ji, S., Chen, Q., & Cambria, E. (2023). Ensemble hybrid learning methods for automated depression detection. *IEEE Transactions on Computational Social Systems*, *10*(1), 211–219. https://doi.org/10.1109/TCSS.2022.3154442

Baniadamdizaj, S., & Baniadamdizaj, S. (2023). Prediction of Iranian EFL teachers' burnout level using machine learning algorithms and maslach burnout inventory. *Iran Journal of Computer Science*, *6*(1), 1–12. https://doi.org/10.1007/s42044-022-00112-x

Besse, R., Howard, K., Gonzalez, S., & Howard, J. (2015). Major depressive disorder and public school teachers: evaluating occupational and health predictors and outcomes. *Journal of Applied Biobehavioral Research*, *20*(2), 71–83. https://doi.org/10.1111/JABR.12043

Bete, T., Gemechu, K., Anbesaw, T., Tarafa, H., & Tadessa, J. (2022). Depressive symptoms and associated factor among public school teachers in Jimma town, Southwest, Ethiopia 2020: a multi-disciplinary, cross-sectional study. *BMC Psychiatry*, *22*(1). https://doi.org/10.1186/s12888-022-03941-z

Breiman, L. (2001). *Random Forests* (Vol. 45).

Carroll, A., Forrest, K., Sanders-O'Connor, E., Flynn, L., Bower, J. M., Fynes-Clinton, S., York, A., & Ziaei, M. (2022). Teacher stress and burnout in Australia: examining the role of intrapersonal and environmental factors. *Social Psychology of Education*, *25*(2–3), 441–469. https://doi.org/10.1007/s11218-022-09686-7

Chung, J., & Teo, J. (2022). Mental health prediction using machine learning: taxonomy, applications, and challenges. *Applied Computational Intelligence and Soft Computing*, *2022*. https://doi.org/10.1155/2022/9970363

Chung, J., & Teo, J. (2023). Single classifier vs. ensemble machine learning approaches for mental health prediction. *Brain Informatics 2023 10:1*, *10*(1), 1-. https://doi.org/10.1186/S40708-022-00180-6

Clayback, K. A., & Williford, A. P. (2022). Teacher and classroom predictors of preschool teacher stress. *Early Education and Development*, *33*(8), 1347–1363. https://doi.org/10.1080/10409289.2021.1972902

Collins, G. S., Moons, K. G. M., Dhiman, P., Riley, R. D., Beam, A. L., Van Calster, B., Ghassemi, M., Liu, X., Reitsma, J. B., Van Smeden, M., Boulesteix, A.-L., Camaradou, J. C., Celi, L. A., Denaxas, S., Denniston, A. K., Glocker, B., Golub, R. M., Harvey, H., Heinze, G., … Logullo, P. (2024). *TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods*. https://doi.org/10.1136/bmj-2023-078378

D'Cruz, L., Dubey, V., & Thakur, P. (2023). Depression prediction from combined reddit and twitter data using machine learning. *2023 2nd International Conference for Innovation in Technology, INOCON 2023*. https://doi.org/10.1109/INOCON57975.2023.10101174

Daza Vergaray, A., Miranda, J. C. H., Cornelio, J. B., López Carranza, A. R., & Ponce Sánchez, C. F. (2023). Predicting the depression in university students using stacking ensemble techniques over oversampling method. *Informatics in Medicine Unlocked*, *41*, 101295. https://doi.org/10.1016/J.IMU.2023.101295

Education International. (2026). *Educator Well-Being in Focus: International Report Reveals Alarming Challenges*. https://www.ei-ie.org/en/item/28080:educator-well-being-in-focus-international-report-reveals-alarming-challenges

Falebita, O. S., Ayeni, S. E., Ekundayo, S. K., Ambode, A. B., Xulu, N. S., & Bankole, H. B. (2026). Gender differences in the impact of workload demands and motivation on teachers' burnout and stress: a multigroup analysis. *Education Sciences*, *16*(2). https://doi.org/10.3390/educsci16020259

Feher, G., Kapus, K., Tibold, A., Banko, Z., Berke, G., Gacs, B., Varadi, I., Nyulas, R., & Matuz, A. (2024). Mental issues, internet addiction and quality of life predict burnout among Hungarian teachers: a machine learning analysis. *BMC Public Health*, *24*(1). https://doi.org/10.1186/s12889-024-19797-9

Habib, M., Wang, Z., Qiu, S., Zhao, H., & Murthy, A. S. (2022). Machine learning based healthcare system for investigating the association between depression and quality of life. *IEEE Journal of Biomedical and Health Informatics*, *26*(5), 2008–2019. https://doi.org/10.1109/JBHI.2022.3140433

Han, J., Zhang, Z., Mascolo, C., Andre, E., Tao, J., Zhao, Z., & Schuller, B. W. (2021). Deep learning for mobile mental health: challenges and recent advances. *IEEE Signal Processing Magazine*, *38*(6), 96–105. https://doi.org/10.1109/MSP.2021.3099293

Hasib, K. M., Islam, M. R., Sakib, S., Akbar, M. A., Razzak, I., & Alam, M. S. (2023). Depression detection from social networks data based on machine learning and deep learning techniques: an interrogative survey. *IEEE Transactions on Computational Social Systems*, *10*(4), 1568–1586. https://doi.org/10.1109/TCSS.2023.3263128

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (n.d.). *LightGBM: A Highly Efficient Gradient Boosting Decision Tree*. Retrieved https://github.com/Microsoft/LightGBM.

Ke, G., Xu, Z., Zhang, J., Bian, J., & Liu, T. Y. (2019). DeepGBM: A deep learning framework distilled by GBDT for online prediction tasks. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 384–394. https://doi.org/10.1145/3292500.3330858

Kidger, J., Brockman, R., Tilling, K., Campbell, R., Ford, T., Araya, R., King, M., & Gunnell, D. (2016). Teachers' wellbeing and depressive symptoms, and associated risk factors: A large cross sectional study in English secondary schools. *Journal of Affective Disorders*, *192*, 76–82. https://doi.org/10.1016/J.JAD.2015.11.054

Kisaakye, V., Njora, H., & Wodon, Q. (2024). *IICBA at CIES: Teacher Burnout and the Importance of Mental Health and Psycho-social Support in Africa | International Institute for Capacity Building in Africa*. https://www.iicba.unesco.org/en/node/133

Kostelić, K., Gonan Božac, M., & Paulišić, M. (2024). Exploring interpersonal conflicts within the JD-R model: aggregation and validation in the context of elementary school employees in Croatia. *Cogent Business and Management*, *11*(1). https://doi.org/10.1080/23311975.2024.2370451

Lau, Y., Ang, W. H. D., Ang, W. W., Pang, P. C. I., Wong, S. H., & Chan, K. S. (2025). Artificial intelligence–based psychotherapeutic intervention on psychological outcomes: a meta-analysis and meta-regression. In *Depression and Anxiety* (Vol. 2025, Number 1). John Wiley and Sons Inc. https://doi.org/10.1155/da/8930012

Li, S., Li, Y., Lv, H., Jiang, R., Zhao, P., Zheng, X., Wang, L., Li, J., & Mao, F. (2020). *The prevalence and correlates of burnout among Chinese preschool teachers*. https://doi.org/10.21203/rs.2.17814/v3

Lin, H., Kawakami, A., D'Ignazio, C., Holstein, K., & Gajos, K. Z. (2026). Funding AI for Good: a call for meaningful engagement. *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems*, 1–24. https://doi.org/10.1145/3772318.3790374

Mokwena, K. E., Maaga, K. C., & Randa, M. B. (2026a). Prevalence of depressive symptoms among teachers in the Tshwane Metropolitan Municipality, South Africa. *South African Journal of Psychiatry*, *32*. https://doi.org/10.4102/sajpsychiatry.v32i0.2532

Mokwena, K. E., Maaga, K. C., & Randa, M. B. (2026b). Prevalence of depressive symptoms among teachers in the Tshwane Metropolitan Municipality, South Africa. *South African Journal of Psychiatry*, *32*. https://doi.org/10.4102/SAJPSYCHIATRY.V32I0.2532

Moons, K. G. M., Wolff, R. F., Riley, R. D., Whiting, P. F., Westwood, M., Collins, G. S., Reitsma, J. B., Kleijnen, J., & Mallett, S. (2019). PROBAST: A Tool to Assess Risk of Bias and Applicability of Prediction Model Studies: Explanation and Elaboration. *Https://Doi.Org/10.7326/M18-1377*, *170*(1), W1–W33. https://doi.org/10.7326/M18-1377

Nazari, M., & Alizadeh Oghyanous, P. (2021). Exploring the role of experience in L2 teachers' turnover intentions/occupational stress and psychological well-being/grit: A mixed methods study. *Cogent Education*, *8*(1). https://doi.org/10.1080/2331186X.2021.1892943

Nazari, M., Parastoo, &, Oghyanous, A., Oghyanous, P. A., & Oghyanous Is A Phd, P. A. (2021). Exploring the role of experience in L2 teachers' turnover intentions/occupational stress and psychological well-being/grit: A mixed methods study. *Cogent Education*, *8*(1), 1892943. https://doi.org/10.1080/2331186X.2021.1892943

Nnadi, L. C., Isiwu, C. P., Ding, D., Muepu, D. M., & Watanobe, Y. (2026). Multi-Level Explainable AI for Predicting Student Depression Risk: Global, Subgroup, and Individual Insights. *IEEE Access*, *14*, 6271–6286. https://doi.org/10.1109/access.2026.3652631

Oberg, G., Macmahon, S., & Carroll, A. (2024). Assessing the interplay: teacher efficacy, compassion fatigue, and educator well-being in Australia. *The Australian Educational Researcher 2024 52:2*, *52*(2), 1105–1131. https://doi.org/10.1007/S13384-024-00755-8

Oyebode, O., Fowles, J., Steeves, D., & Orji, R. (2023). Machine learning techniques in adaptive and personalized systems for health and wellness. *International Journal of Human-Computer Interaction*, *39*(9), 1938–1962. https://doi.org/10.1080/10447318.2022.2089085

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). *CatBoost: unbiased boosting with categorical features*. https://github.com/catboost/catboost

Santos, K. C. R. dos, Machado, A. V., Rocha, S., Martins, R. M., Nudelman, M., Pereira, M. G., de Oliveira, L., & Staniscuaski, F. (2026). Understanding depression in basic education teachers: evidence from Brazil. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1669000

Shaha, T. R., Begum, M., Uddin, J., Torres, V. Y., Iturriaga, J. A., Ashraf, I., & Samad, M. A. (2024). Feature group partitioning: an approach for depression severity prediction with class balancing using machine learning algorithms. *BMC Medical Research Methodology 2024 24:1*, *24*(1), 123-. https://doi.org/10.1186/S12874-024-02249-8

Singh, Y. K., & Gautam, D. N. S. (2024). The impact of job satisfaction on teacher mental health: a call to action for educational policymakers. In *Open Education Studies* (Vol. 6, Number 1). Walter de Gruyter GmbH. https://doi.org/10.1515/edu-2024-0008

Stengård, J., Mellner, C., Toivanen, S., & Nyberg, A. (2021). *Gender Differences in the Work and Home Spheres for Teachers, and Longitudinal Associations with Depressive Symptoms in a Swedish Cohort*. *1*, 3. https://doi.org/10.1007/s11199-021-01261-2

Sulak, S. A., & Koklu, N. (2024). Analysis of Depression, Anxiety, Stress Scale (DASS-42) With Methods of Data Mining. *European Journal of Education*, *59*(4). https://doi.org/10.1111/ejed.12778

Thomas, E. B. K., & Carlson, A. S. (2025). The time is now: Prioritizing educator mental health. *Disaster Medicine and Public Health Preparedness*, *19*, e205. https://doi.org/10.1017/DMP.2025.10131

Wallace, J. E. (2017). Burnout, coping and suicidal ideation: An application and extension of the job demand-control-support model. *Journal of Workplace Behavioral Health*, *32*(2), 99–118. https://doi.org/10.1080/15555240.2017.1329628

Yema, D. P. R., Nalipay, M. J. N., Simon, P. D., Liu, S., & King, R. B. (2026). Technology-Mediated Mental Health Programs and Interventions for Educators: A Systematic Review and Meta-Analysis. *Psychology in the Schools*, *63*(7), 1147–1172. https://doi.org/10.1002/PITS.70157;REQUESTEDJOURNAL:JOURNAL:15206807;ISSUE:ISSUE:DOI

Zainal, N. H., Peters, A. T., Jacobson, N. C., & Hsu, K. J. (2026). Who's at risk for emergent depression years later? Predictive modeling in a nine-year longitudinal cohort. *BMC Psychiatry 2026 26:1*, *26*(1), 273-. https://doi.org/10.1186/S12888-026-07902-8

Appendix A: Boolean Terms Used

1. ProQuest

("teacher depression" OR "educator mental health" OR "teacher burnout") AND ("machine learning" OR "ensemble learning" OR "XGBoost" OR "random forest") AND ("depression prediction" OR "explainable AI" OR "SHAP" OR "PHQ-9")

2. Wiley Online Library

("teacher depression" OR "teacher mental health") AND ("machine learning" OR "predictive model*" OR "ensemble") AND ("depression prediction" OR "XAI" OR "SHAP")

3. IEEE Xplore

("teacher depression" OR "educator depression" OR "teacher mental health") AND ("machine learning" OR "ensemble learning" OR "XGBoost" OR "gradient boosting") AND ("depression prediction" OR "explainable AI" OR "SHAP")

4. ACM Digital Library

("teacher depression" OR "educator mental health") AND ("machine learning" OR "ensemble" OR "predictive model") AND ("depression" OR "explainable AI" OR "SHAP" OR "LIME")

5. SpringerLink

("teacher depression" OR "educator mental health") AND ("machine learning" OR "ensemble learning") AND ("prediction" OR "explainable AI" OR "SHAP")

6. ScienceDirect

("teacher depression" OR "teacher burnout" OR "educator mental health") AND ("machine learning" OR "ensemble learning" OR "predictive modeling") AND ("depression prediction" OR "XAI" OR "SHAP")

7. ERIC

("teacher depression" OR "teacher mental health" OR "teacher burnout") AND ("machine learning" OR "predictive modeling" OR "ensemble learning") AND ("depression prediction" OR "early detection" OR "explainable AI")

8. Taylor & Francis Online

("teacher depression" OR "educator mental health") AND ("machine learning" OR "ensemble learning") AND ("depression prediction" OR "explainable AI" OR "SHAP")