Journal of Science, Innovation and Creativity
Vol. 5 No. 1 (2026): ISSN (Online): 2958-454X
DOI: https://doi.org/10.58721/602e6987

Demographic, Socio-Economic, and Professional Determinants of Depression Among Teachers in Resource-Constrained Public Schools in Kenya

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Article History
Received: 2026-03-28
Revised: 2026-07-14
Accepted: 2026-07-18
Published: 2026-07-19

Keywords
Depression
Machine-learning
Mental-health
Teachers

How to cite:
Yegon, G., Ombui, E., & Oduor, C. (2026). Demographic, Socio-Economic, and Professional Determinants of Depression Among Teachers in Resource-Constrained Public Schools in Kenya. *Journal Science, Innovation and Creativity*, *5*(1), 255-272.

Abstract
Teacher depression is a growing occupational health concern in resource-constrained public education systems, yet existing evidence rarely jointly models demographic, socio-economic, and professional risk factors. This study identifies and ranks the factors most strongly distinguishing teachers at elevated depression risk in Kenya's public schools. Survey data were collected from 1,711 public primary, Junior Secondary School (JSS), and secondary school teachers employed by Kenya's Teachers Service Commission (TSC) across multiple counties in Kenya. Depression risk was assessed using the Patient Health Questionnaire-9 (PHQ-9), classified via the standard PHQ-9 ≥10 threshold. An ensemble feature-selection approach combining Random Forest, XGBoost, and CatBoost identified the twenty strongest predictors on which all three algorithms converged; a fixed top-20 threshold was applied for interpretability. 66.1% of teachers met criteria for High Risk. Absence of school-based mental-health resources was the strongest predictor, surpassing all demographic and financial variables. Mid-career tenure (11-15 years) and early-establishing-career age (25-34 years) ranked second and third; acute financial precarity outweighed static financial-literacy measures. Demographic factors accounted for the largest cumulative share of predictive importance (37.5%), followed by institutional support (30.4%), financial precarity (15.1%), professional/workload factors (10.0%), and technology access (7.0%). Cross-sectional design supports associational rather than causal interpretation; findings are confined to the counties sampled and to TSC-employed teachers, excluding contract/intern and BOM teachers. Findings support embedded school-based counselling, structural financial safeguards, and mentorship targeted at at-risk career stages, offering an empirical foundation for context-specific screening and policy interventions in under-resourced educational systems.

Introduction

Teacher depression in resource-constrained regions is a growing crisis with multi-dimensional causes: overcrowded classrooms, delayed salaries, and pay that fails to keep pace with volatile economic conditions are fuelling teacher depression and making the profession unattractive (UNESCO, 2023), even as Sub-Saharan Africa needs to recruit 15 million more teachers by 2030 to meet Sustainable Development Goal targets (UNESCO, 2024). Teachers globally are a high-risk occupational group for psychological distress given the emotional labour, workload, and limited institutional support that characterise the profession (Chiamo et al., 2025). This vulnerability is compounded in Sub-Saharan Africa by systemic resource constraints: roughly a third of teachers and teacher-educators across 14 African countries experienced depression during the COVID-19 period, with a further fifth to a quarter affected by stress-related symptoms (African Union, 2025) — a pandemic-era figure best read as an upper-bound historical baseline, though more recent regional evidence suggests the underlying vulnerability persists (Kisaakye et al., 2024).

Evidence from comparable contexts underscores the scale of the problem: a cross-sectional study in Douala III, Cameroon, found 93.5% of teachers met criteria for psychological distress, alongside high burnout (64%), anxiety (28.4%), and depressive symptoms (28.8%) (Chiamo et al., 2025), and nearly half of surveyed Brazilian basic education teachers scored above the clinical cutoff for probable depression, with structural rather than purely individual vulnerabilities implicated (Feher et al., 2024; Santos et al., 2026). Brazil's specific racial and institutional dynamics do not translate directly to Kenya; this comparison is offered only as evidence that structural patterning of teacher depression recurs across resource-constrained systems generally.

Taken together, these studies suggest teacher depression is patterned by identifiable demographic and occupational factors rather than randomly distributed. Much existing literature, however, originates from higher-income or better-resourced settings, or treats burnout and depression as generalised hazards without isolating specific correlates. In Kenya, public primary, JSS, and secondary schools operate under persistent but unevenly distributed shortages in staffing, remuneration, and institutional support (UNESCO, 2024): some schools retain institutional resources such as counselling services while others do not, and this variability, rather than a uniformly constrained baseline, is what this study treats as central. This study therefore aims to identify and analyse the demographic, socio-economic, and professional factors contributing to depression among public primary, JSS, and secondary school teachers in resource-constrained settings in Kenya. The sample is restricted to TSC-employed teachers; contract/intern and Board of Management (BOM) teachers, who often experience greater job insecurity and lower pay, were not represented, a limitation addressed in Section 3.9.

Global and Regional Burden of Teacher Depression

Depression among teachers is a persistent, under-addressed occupational health concern, with prevalence exceeding the general working population (Education International, 2025; Thomas & Carlson, 2025), and associated factors spanning workload, remuneration, and institutional neglect (Besse et al., 2015; Bete et al., 2022). Reviews of low-resource educational systems report comparable patterns of depressive and chronic-stress symptoms (Kisaakye et al., 2024). Unlike generalised occupational stress, teacher depression develops cumulatively through sustained emotional demand (Thomas & Carlson, 2025), with downstream effects on turnover, absenteeism, and instructional quality (Kidger et al., 2016), intensifying where class sizes are large and mental-health services scarce (Tabassum et al., 2025). Most large studies remain descriptive, rarely disentangling the relative contributions of specific risk factors (AL Awwas et al., 2023)—the gap that motivates this study.

Demographic Determinants of Teacher Depression

Female educators consistently report higher depressive symptom burden, linked to disproportionate domestic responsibilities alongside full-time teaching (Falebita et al., 2026; Stengård et al., 2021). Career stage and tenure are not uniformly protective: early-career teachers report elevated stress before coping repertoires develop (Nazari & Alizadeh Oghyanous, 2021), while mid-career educators facing stalled advancement constitute a distinct risk group (Carroll et al., 2022). Resource-limited settings show similar demographic clustering of risk by age band and household structure (Maaga & Mokwena, 2023; Mokwena et al., 2026). Most studies, however, treat these characteristics individually rather than jointly modelling their combined predictive contribution.

Socio-Economic Determinants of Teacher Depression

Financial precarity is among the most consistently cited stressors, particularly when remuneration fails to keep pace with cost-of-living pressures, compounding workloads and accelerating burnout (Adasi et al., 2020; Besse et al., 2015; Peele & Wolf, 2020). The JD-R framework explains this amplification: when high demands pair with low control over compensation or progression, psychological cost rises substantially (Wallace, 2017), mediated by interpersonal and resource-based conflict (Kostelić et al., 2024). Compensation-driven dissatisfaction predicts depressive symptoms independently of workload (Singh & Gautam, 2024) and limits capacity for protective behaviours such as physical activity (Davis & Davis, 2023). Socio-economic variables are rarely modelled alongside demographic and professional factors — a gap this study addresses.

Professional and Institutional Determinants of Teacher Depression

Workload structure, administrative support, and relational dynamics are repeatedly identified as primary drivers of teacher depression: low perceived leadership support and limited access to workplace mental-health resources independently predict depressive symptoms (He et al., 2025; Kidger et al., 2016). Intrinsic job satisfaction and emotion-regulation capacity mediate the link between working conditions and wellbeing (Luque-Reca et al., 2022), while manageable class sizes and collaborative planning support job satisfaction (Lau et al., 2025; McJames et al., 2025), and sustained emotional labour without institutional recognition erodes teacher efficacy (Oberg et al., 2025). The collapse of administrative and peer-support structures during emergency remote instruction sharply increased psychological strain, underscoring how central such scaffolding is under ordinary circumstances (Roloff et al., 2022). These professional-level variables, however, are typically studied in isolation, limiting understanding of their relative predictive weight.

Gaps in the Literature and Rationale for the Present Study

Across the reviewed literature, three limitations recur. First, most studies examine demographic, socio-economic, or professional predictors in isolation rather than jointly modelling their interactive contribution (Tabassum et al., 2025). Second, analytic techniques remain largely descriptive or bivariate, limiting capacity to capture non-linear interactions, a constraint increasingly addressed by machine-learning applications in resource-constrained institutional settings (Alharahsheh & Abdullah, 2021; Heffernan et al., 2025). Third, existing evidence rarely accounts for resource variability within constrained systems: studies typically treat “resource constraints” as fixed rather than examining how differential institutional support interacts with individual financial precarity to shape risk; screening frameworks developed in better-resourced settings rarely extend to public-school teachers specifically (Ojeme et al., 2018). These gaps justify an integrated, data-driven analysis of demographic, socio-economic, and professional determinants jointly, within a resource-variable Kenyan public-schooling context, capable of capturing interaction effects that bivariate techniques cannot detect — the contribution of the present study.

Theoretical Framework

This study is anchored in the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2007), which frames occupational wellbeing as a balance between job demands (workload, performance-pressure, financial strain) and job resources (institutional and interpersonal support) that buffer their psychological cost. JD-R was selected because it separates demand- and resource-side constructs, mapping directly onto this study's feature categories: professional/workload and financial precarity variables operationalise demands, while institutional support variables operationalise resources. Prior applications support this mapping: interpersonal and resource-based conflict mediates the relationship between job demands and psychological strain among school employees (Kostelić et al., 2024), and demand-resource imbalance, rather than demand level alone, predicts burnout and suicidal ideation in high-strain occupations (Wallace, 2017). Consistent with JD-R's central proposition that resources moderate rather than merely offset demands, this study's central finding, that the presence or absence of school-based mental-health resources is the strongest predictor of depression risk, is interpreted throughout the Discussion (Section 5) as evidence that resource deficits condition how demands translate into risk, rather than operating as an independent driver.

Methodology

Research Design and Methodological Framework

This study followed a Design-Science Research (DSR) approach, using the DSRM proposed by Peffers et al. (2008) and grounded in the design principles of Hevner et al. (2004) and Gregor and Hevner (2013). The broader doctoral study of which this paper forms part pursues four objectives: (1) identifying and ranking demographic, socio-economic, and professional factors distinguishing depression risk; (2) designing a predictive ensemble model; (3) benchmarking it against single-algorithm baselines; and (4) validating its effectiveness across school contexts. This paper reports exclusively on Objective 1, the problem-identification, feature-engineering, and feature-selection stage. References here to an "ensemble" therefore describe the feature-selection ensemble (Section 3.6) used to rank predictors, not a trained predictive model; the stacking-ensemble artefact itself is constructed and evaluated under Objectives 2-4, outside this paper's scope.

Study Setting and Population

Data were collected from public primary, Junior Secondary School (JSS), and secondary school teachers employed by the Teachers Service Commission (TSC) across multiple counties in Kenya, spanning a mix of urban/peri-urban and rural/peri-urban settings with varying resource availability. This delimitation ensured consistency in employment conditions and institutional structures while excluding private-school teachers, non-TSC staff, and contract/intern and Board of Management (BOM) teachers, which is treated as a sampling-bias limitation in Section 3.9. The sampled counties were deemed sufficiently diverse for model development and validation, although the study does not claim national representativeness. Simple random sampling was used to select participating teachers from consenting schools in each county (the pilot sample size determination is detailed in Section 3.3). The main-study sample of 1,711 teachers reflects the total number of valid, complete responses obtained during the data collection period.

Data Collection Instrument

Structured surveys, supplemented by external datasets used for validation, were administered to teachers. Depression severity was measured using the Patient Health Questionnaire-9 (PHQ-9), the standard validated screening tool used throughout this study. These validated instruments were paired with a structured questionnaire capturing demographic characteristics (e.g., age category, years in service), socio-economic indicators (e.g., financial stability items), and professional/institutional variables (e.g., performance-related pressure, workload, interpersonal support). Unstructured data sources such as clinical records or social media inputs were deliberately excluded in favour of ethically manageable, practically collectable variables. The instrument was piloted with 67 teachers across three counties (Mombasa, n = 20; Vihiga, n = 25; Meru, n = 22); per-county pilot sample sizes were set using Cochran's (1963) formula in conjunction with the conventional pilot-study guideline of a minimum of six and typically 12–30 participants per stratum. Content and face validity were established through expert review of the instrument prior to piloting, and internal-consistency reliability testing on the pilot data yielded a Cronbach's alpha of 0.78, indicating acceptable reliability.

Variable Operationalisation and Feature-Engineering

Teacher-related stress was operationalised through variables such as unrealistic teaching expectations and concerns about promotion linked to performance ratings. A Social Interaction Index aggregated indicators of financial strain, effectiveness in managing student behaviour, communication quality, and work-life balance. Depression risk was operationalised directly from PHQ-9 scores, the standard validated depression-screening tool, rather than a composite of multiple instruments.

Data Preprocessing

Missing numerical values were imputed using the mean and missing categorical values using the mode; records with irrecoverable missing data or duplicate entries were removed. Non-informative fields, including timestamp, email, name, and mobile-number identifiers, were dropped to reduce redundancy, protect respondent confidentiality, and improve processing efficiency.

Feature-Selection Procedure

Candidate predictors were evaluated using an ensemble feature-selection strategy combining the outputs of three algorithmically distinct models, Random Forest, XGBoost, and CatBoost, each generating an independent importance ranking. Only features appearing consistently across all three rankings were retained, on the principle that convergence across distinct algorithms provides stronger evidence of genuine predictive relevance than a single technique. This intersection process yielded a pool of overlapping predictors, from which a fixed top-20 threshold was applied for interpretability and reporting parsimony, rather than a data-driven cutoff such as an inflexion point in cross-model importance; the resulting twenty most informative predictors were dominated by socio-economic, financial, demographic, and professional/performance-related variables.

Outcome Classification and Class Imbalance Handling

Continuous PHQ-9 scores were binarised into a Low Risk/High Risk classification using the standard PHQ-9 ≥10 threshold. Exploratory analysis revealed pronounced class imbalance favouring the High Risk category; the Synthetic Minority Oversampling Technique (SMOTE) was applied after feature-selection to generate synthetic minority-class examples and prevent classifier bias.

Analytical Approach

The study applied two complementary layers: descriptive analysis of depression-symptom distribution and severity, and the ensemble feature-importance rankings (Section 3.6) as the primary mechanism for identifying which factors most strongly distinguish High Risk from Low Risk teachers. This was preferred over conventional stepwise regression because it captures non-linear relationships and interactions within a high-dimensional, resource-constrained dataset.

Study Limitations Relevant to Interpretation

The study relied on cross-sectional survey data, so the findings should be interpreted as associative rather than causal, and the temporal dynamics of depression onset cannot be captured. Self-reported measures may introduce response bias, and geographic confinement to the sampled counties limits generalisability to urban or other resourced settings. The sample was drawn exclusively from TSC-employed teachers in public primary, JSS, and secondary schools; contract/intern and Board of Management (BOM) teachers, who often experience greater job insecurity and lower pay, were not represented, and findings should not be generalised to these groups. Finally, self-reported measurement using a single validated instrument (PHQ-9), rather than triangulation with clinical assessment, is an inherent constraint of large-scale survey-based screening research generally.

Ethical Considerations

The study adhered to standard ethical research practices, including informed consent and confidentiality safeguards for participating teachers; full procedural detail is provided in the study's ethics documentation.

Results

This chapter presents the empirical results addressing the study's goal of identifying and analysing the demographic, socio-economic, and professional factors contributing to depression among public primary, JSS, and secondary school teachers in resource-constrained Kenyan settings. Section 4.1 characterises the distribution and severity of depression symptoms; Sections 4.2 to 4.4 report demographic, socio-economic, and professional/institutional correlates drawing on the ensemble feature-importance rankings (Section 3.6); Section 4.5 synthesises these into a single cross-model consensus ranking. To remain within the journal's presentation limits, full category-level tables and figures are provided in the Appendix, with the core cross-model ranking retained in the main text.

Sample Characteristics and Depression Severity Distribution

Depression risk classification (Section 3.7), derived from PHQ-9 scores and operationalised via the standard PHQ-9 ≥10 threshold, revealed a pronounced class imbalance: approximately two-thirds of teachers (66.1%) were classified as High Risk, compared with roughly one-third (33.9%) classified as Low Risk (Figure 1; full severity-band breakdown in Appendix Table A2). A finer-grained severity view showed most teachers (66.5%) fell within the high-severity-band (moderately severe to severe symptoms), a further 25.1% recorded moderate symptoms, and 8.4% fell within the low-severity-band, with the overall distribution slightly right-skewed. This pattern indicates that depressive symptomatology in this sample is skewed toward greater severity, reinforcing the rationale for the class-balancing procedure (SMOTE) applied prior to model training.

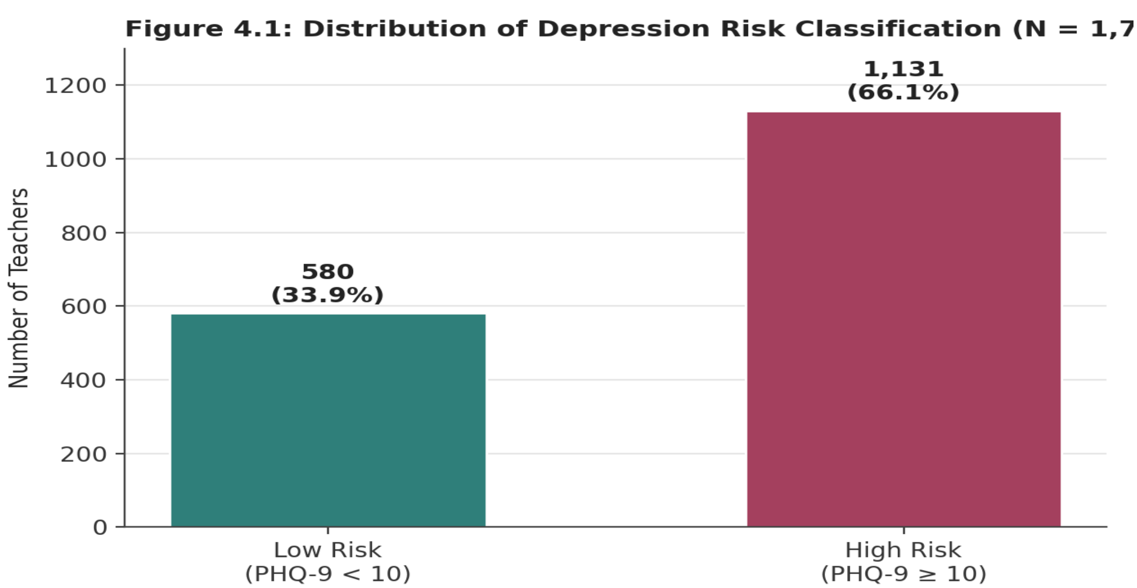

Figure 1: Distribution of Depression Risk Classification (N = 1,711)

Demographic Correlates of Depression Risk

Demographic characteristics, particularly age category and years in service, emerged as consistently strong predictors. Seven demographic predictors appeared among the twenty most informative features (see Appendix Table A3 for the full list). Mid-career teachers with 11-15 years of service returned the second-highest consensus importance score of all twenty retained predictors (0.0516), ahead of every socio-economic and institutional variable except lack of school mental-health resources, consistent with evidence that mid-career educators constitute a distinct risk group rather than benefiting uniformly from accumulated resilience (Carroll et al., 2022). Teachers aged 25-34 ranked third overall (0.0429), suggesting early-to-establishing-career teachers form a second identifiable risk band (Nazari & Alizadeh Oghyanous, 2021). Age bands above 35 years and shorter service tenures contributed smaller but non-negligible importance, while school type and sub-county location contributed modestly.

Socio-Economic and Financial Correlates

Financial precarity indicators were consistently represented among the top predictors, with Fin_A2 (frequency of running out of money before the next paycheck) the strongest of four retained financial variables, ranking sixth overall (full listing in Appendix Table A4). This indicates that acute, recurring financial strain, rather than longer-term indicators such as financial-literacy exposure, is the more salient socio-economic signal of depression risk (Wallace, 2017). The comparatively lower ranking of financial-literacy training (Fin_D4) suggests limited protective value once acute financial strain is accounted for, echoing findings that socio-economic dissatisfaction operates as an active mechanism linking occupational demands to depressive symptoms rather than a background stressor alone (Kostelić et al., 2024).

Professional and Institutional Correlates

Professional and institutional variables, capturing workload pressure, performance-related anxiety, and availability of interpersonal and mental-health support, dominated the upper end of the consensus ranking (full listing in Appendix Table A5). Soc_D1 (absence of school-based mental-health resources or counselling services) recorded the single highest consensus importance score of all twenty retained predictors (0.0762), roughly 1.5 times larger than the second-ranked feature, aligning with evidence that low perceived leadership support and limited access to workplace mental-health resources independently predict depressive symptoms (Kidger et al., 2016). The next-ranked features, lack of parental support (Soc_C1), unrealistic performance expectations (Time_B1), and promotion-related anxiety (Perf_A3), reflect a coherent cluster of relational and performance-pressure stressors (Oberg et al., 2025). The remaining institutional support items collectively reinforce a consistent theme: the absence of a reliable interpersonal support network, whether from colleagues, the school system, or informal networks, is a recurring signal of elevated depression risk.

Relative Importance of Predictors: Cross-Model Consensus Ranking

The study combined feature-importance scores from three algorithmically distinct models, Random Forest, XGBoost, and CatBoost, into a single consensus importance score for each of the twenty retained predictors. Table 1 presents the full ranking.

Table 1: Top 20 Predictors of Teacher Depression Risk — Full Cross-Model Ranking

Rank	Predictor	Category	RF	XGB	CatBoost	Consensus
1	Soc_D1	Institutional Support	0.0782	0.0894	0.061	0.0762
2	Years_in_Service_11-15	Demographic	0.0644	0.0414	0.0489	0.0516
3	Age_Category_25-34	Demographic	0.0487	0.0534	0.0264	0.0429
4	Soc_C1	Institutional Support	0.0358	0.0406	0.0293	0.0352
5	Time_B1	Professional/Workload	0.0304	0.0361	0.0301	0.0322
6	Fin_A2	Financial	0.0138	0.0326	0.0326	0.0264
7	Age_Category_45-54	Demographic	0.0251	0.0256	0.0275	0.0261
8	School_Type_Secondary	Demographic	0.0412	0.0148	0.0205	0.0255
9	Perf_A3	Professional/Workload	0.0177	0.041	0.0159	0.0249
10	Age_Category_35-44	Demographic	0.0339	0.0046	0.0347	0.0244
11	Tech_Platforms_Wearable	Technology Access	0.0138	0.0281	0.0296	0.0238
12	Years_in_Service_5-10	Demographic	0.0236	0.0304	0.0145	0.0228
13	Soc_A2	Institutional Support	0.0188	0.0351	0.0136	0.0225
14	Fin_C2	Financial	0.0118	0.0215	0.033	0.0221
15	Soc_D5	Institutional Support	0.0224	0.0175	0.0232	0.021
16	Fin_D4	Financial	0.0102	0.0301	0.0215	0.0206
17	Sub_County_EMUHAYA	Demographic	0.0077	0.0248	0.0276	0.0201
18	Soc_D4	Institutional Support	0.0224	0.0167	0.0148	0.018
19	Fin_C5	Financial	0.0062	0.0194	0.0248	0.0168
20	Tech_Access_EduSoftware	Technology Access	0.0097	0.0255	0.0139	0.0163

Note. RF = Random Forest; XGB = XGBoost. Consensus = mean of the three per-algorithm importance scores. N = 1,711.

Aggregating the twenty predictors by category shows that demographic factors accounted for the largest cumulative share of consensus importance (37.5%, across seven predictors), followed by institutional support factors (30.4%, five predictors, concentrated overwhelmingly in Soc_D1 alone), financial predictors (15.1%, four predictors), professional/workload predictors (10.0%, two predictors), and technology access indicators (7.0%, two predictors). Table 2 summarises this category-level breakdown.

Table 2: Category-Level Aggregation of Consensus Feature-Importance

Category	Predictors in Top 20	Cumulative Consensus Importance	% of Total
Demographic	7	0.2134	37.5%
Institutional Support	5	0.1729	30.4%
Financial	4	0.0859	15.1%
Professional/Workload	2	0.0571	10.0%
Technology Access	2	0.0401	7.0%
Total	20	0.5694	100.0%

While demographic predictors are the most numerous among the top twenty, no single demographic feature approaches the importance of Soc_D1: the single strongest individual driver of depression risk in this sample remains institutional, the structural absence of school-based mental-health support (cross-model agreement on the top five predictors is illustrated in Appendix Figure A5). All three algorithms independently ranked Soc_D1, Years_in_Service_11-15, and Age_Category_25-34 among the four most important features despite differing internal mechanics, confirming that the determinants identified in Sections 4.2-4.4 are not artefacts of a particular modelling choice. Together, the results show that teacher depression risk in this sample is jointly patterned by institutional deficits (chiefly the absence of mental-health resources), demographic position (mid-career tenure and early-establishing-career age), acute financial precarity, and performance/relationship-based workplace pressures, directly addressing Objective 1 by ranking, by empirical strength, the factors that most reliably distinguish High Risk from Low Risk teachers.

Discussion

This chapter interprets the findings in relation to the demographic, socio-economic, and professional determinants of depression among teachers in resource-constrained Kenyan settings, organised around the predictor domains identified in the consensus ranking: demographic risk profile (5.1), institutional and social support gaps (5.2), financial precarity (5.3), and combined policy implications (5.4). Section 5.5 considers limitations.

Interpreting the Demographic Risk Profile

Years in service (11-15 years) and age category (25-34 years) emerged as the second- and third-most important predictors overall, surpassed only by the absence of school-based mental-health resources, indicating that career stage and age carry as much predictive weight as the conditions under which teachers work. This is consistent with evidence that the tenure-strain relationship is non-linear: accumulated experience shapes wellbeing through grit and coping resources rather than tenure alone (Nazari & Alizadeh Oghyanous, 2021), and where such resources are depleted, mid-career teachers become a distinct risk group. The 25-34 age band is conceptually distinct, capturing broader life-stage pressures rather than career-cycle position alone. Gender did not appear among the twenty retained predictors, despite evidence that the psychological cost of workload is not uniform across gender groups (Falebita et al., 2026); this more plausibly reflects that gender effects are expressed indirectly through the retained age, tenure, and workload variables rather than as an independent main effect.

The Role of Institutional and Social Support Gaps

The single strongest predictor of depression risk was Soc_D1, the absence of school-based mental-health resources, with consensus importance roughly 1.5 times larger than any other feature. This reframes the remaining findings: institutional and professional variables appear to constitute the dominant structural condition against which other risk factors operate, consistent with job demands-resources framing, in which the psychological cost of a demand is amplified or dampened by available resources (Kostelić et al., 2024; Luque-Reca et al., 2022). Lack of parental support, unrealistic performance expectations, limited collegial support, and having no one to turn to when overwhelmed reinforce a single pattern: a multi-layered erosion of support, absent institutionally, thin among peers, and inconsistent at the parental interface. The abrupt collapse of administrative and peer-support structures during emergency remote teaching elsewhere sharply increased psychological strain precisely because it removed relied-upon scaffolding (Roloff et al., 2022); the present findings suggest such scaffolding was largely absent in these schools to begin with, echoing the levers associated with job satisfaction elsewhere (McJames et al., 2025) and the time-poverty mechanism by which subjective inability to meet expectations erodes satisfaction independently of workload (Zhou et al., 2025).

Financial Precarity as a Structural Stressor

Among the four financial predictors, Fin_A2 (frequency of running out of money before the next paycheck) was by a clear margin the most important, ranking ahead of borrowing behaviour, financial-literacy training, and skipped meals or essential purchases. Financial-literacy training ranked lowest, suggesting the depression risk associated with financial hardship is not primarily a knowledge deficit but a structural condition of income insufficiency relative to recurring cost-of-living. This is consistent with evidence that dissatisfaction rooted in inadequate compensation predicts depressive symptomatology independently of workload and calls for policy-level rather than individual-level intervention (Singh & Gautam, 2024), and parallels findings among public-school teachers in Jimma, Ethiopia (Bete et al., 2022). Financial hardship also plausibly narrows the coping behaviours available to teachers under strain, since financial constraints limit capacity to engage in protective behaviours such as physical activity (Davis & Davis, 2023), compounding rather than operating independently of the institutional and social support gaps discussed above.

Implications for Policy and School-Based Mental-Health Support

Taken together, these findings point toward a coherent set of policy priorities. First, because Soc_D1 was the strongest predictor overall, embedding accessible, school-based mental-health resources and counselling should be treated as a first-order intervention; ICT4D-based screening frameworks demonstrate feasibility in comparably resource-constrained settings without requiring specialist clinical staff at every school (Ojeme et al., 2018). Second, the financial findings argue against a purely educational response to hardship: policy responses should prioritise structural measures, timely salary disbursement, emergency salary-advance mechanisms, or targeted allowances over financial-education programming alone (Singh & Gautam, 2024). Third, mid-career teachers and those aged 25-34 constitute identifiable, targetable subgroups whose risk stems partly from stalled progression rather than inexperience, so structured mentorship and transparent promotion pathways may do more than generic stress-management workshops. Finally, with two-thirds of the sample classified as High Risk, a screening rather than purely reactive model of support is warranted, potentially building on the predictive, feature-ranked approach used here; because the present design is cross-sectional, this remains a forward-looking implication requiring the longitudinal validation described in Section 5.5.

Limitations

Several limitations qualify the interpretation of these findings. The cross-sectional design means all reported relationships are associational rather than causal; comparable East African public-school research faced the same constraint (Bete et al., 2022). Consensus feature-importance synthesises non-linear, ensemble-based measures of predictive contribution rather than the coefficients and confidence intervals of conventional inferential statistics, better suited to identifying which factors matter most in combination than to quantifying isolated effect sizes. Gender did not survive the intersection-based feature-selection procedure despite evidence that workload-related psychological cost is not uniform across gender groups (Falebita et al., 2026; He et al., 2025); future analyses should examine gender as a moderating rather than purely additive variable. The retained technology access variables ranked among the lowest of the twenty predictors, but their presence suggests a digital-divide dimension warranting dedicated investigation (Heffernan et al., 2025). Finally, geographic confinement to the selected counties, self-reported measurement, and reliance on a single point-in-time PHQ-9 assessment mean the findings should be generalised cautiously to urban, private-school, or differently resourced populations not represented here. Notwithstanding these limitations, consistency with comparable studies in other resource-constrained settings (Bete et al., 2022; Ojeme et al., 2018) suggests the core pattern identified is unlikely to be an artefact of this sample alone.

Conclusion

This study set out to identify and analyse the demographic, socio-economic, and professional factors contributing to depression among public primary, JSS, and secondary school teachers in resource-constrained settings in Kenya, corresponding to Objective 1 of the broader doctoral design-science study introduced in Section 3.1. Using an ensemble feature-selection approach applied to survey data from 1,711 teachers employed by the Teachers Service Commission, the study found that depression risk in this population is patterned, predictable, and dominated by a small number of identifiable factors rather than distributed evenly or idiosyncratically. This paper reports the factor-identification stage of that broader study; the validated stacking-ensemble predictive artefact itself is designed, benchmarked, and evaluated under the study's remaining objectives and is not claimed here. The absence of school-based mental-health resources emerged as the single strongest predictor, followed closely by mid-career tenure (11-15 years) and early-to-establishing-career age (25-34 years), with acute financial precarity and a cluster of professional and interpersonal support deficits completing the picture of a compounding, multi-layered risk structure.

The value of this study lies less in confirming that teacher depression is prevalent, a finding already well established internationally, and more in demonstrating which specific, actionable factors matter most when demographic, socio-economic, and professional variables are modelled jointly rather than in isolation. This study was calibrated to the realities of resource-constrained Kenyan public schools, where staffing shortages, delayed remuneration, and limited infrastructure are active determinants of teacher wellbeing, not background conditions. Identifying the absence of school-based mental-health resources as the dominant predictor, ahead of every demographic and financial variable considered, provides a concrete, evidence-based starting point for intervention rather than a diffuse call for “more support.” The cross-model consensus approach, in which Random Forest, XGBoost, and CatBoost independently converged on the same top predictors, further strengthens confidence that these findings reflect genuine structural patterns rather than artefacts of a single modelling choice.

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Appendix: Supplementary Tables and Figures

The tables and figures below present the full category-level breakdowns referenced in Chapter Four. They are provided as supplementary material to keep the main text within the journal's table-and-figure limit.

Table A1: Distribution of Binary Depression-Risk Classification

Risk Category	PHQ-9 Criterion	n	% of Sample
Low Risk	PHQ-9 < 10	580	33.90%
High Risk	PHQ-9 ≥ 10	1,131	66.10%
Total	–	1,711	100.00%

Table A2: PHQ-9 Depression Severity Band Distribution

Severity Band	PHQ-9 Range	n	% of Sample
Low (Minimal-Mild)	0-9	144	8.40%
Moderate	10-14	430	25.10%
High (Mod. Severe-Severe)	15-27	1,137	66.50%
Total	–	1,711	100.00%

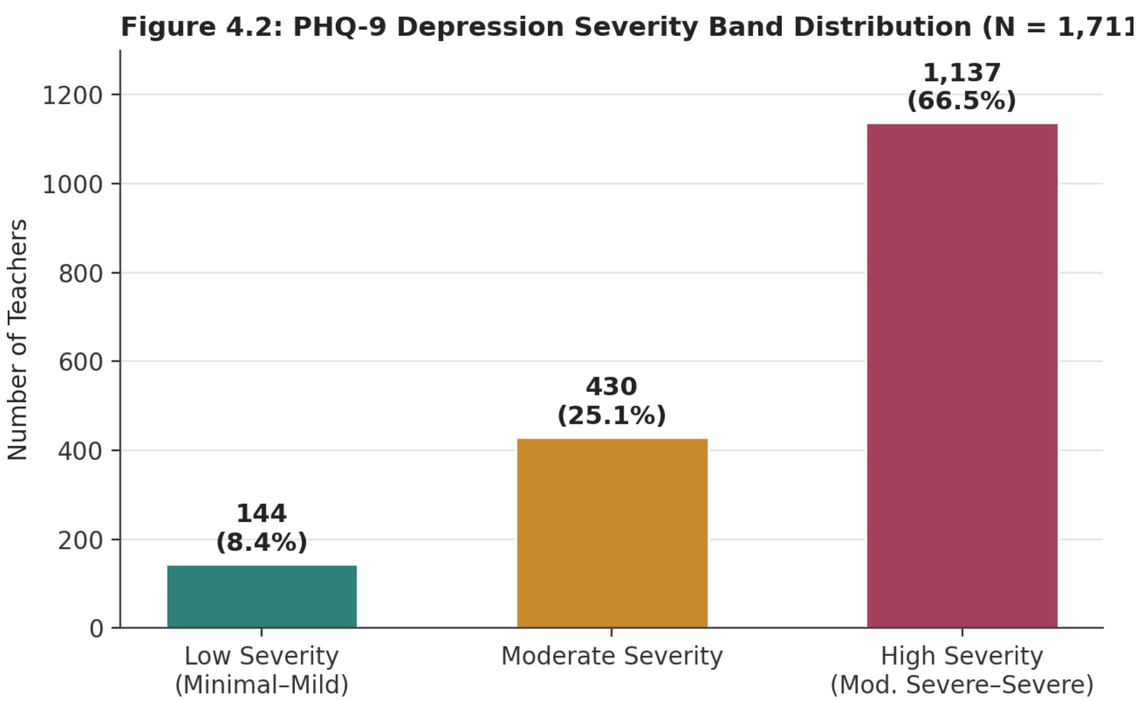

Figure A1: PHQ-9 Depression Severity Band Distribution (N = 1,711)

Table A3: Demographic Predictors of Depression Risk, Ranked by Consensus Importance

Predictor	Description	Consensus Importance	Overall Rank (of 20)
Years_in_Service_11-15	11-15 years of teaching service	0.0516	2
Age_Category_25-34	Teacher aged 25-34 years	0.0429	3
Age_Category_45-54	Teacher aged 45-54 years	0.0261	7
School_Type_Secondary	Employed at a secondary school	0.0255	8
Age_Category_35-44	Teacher aged 35-44 years	0.0244	10
Years_in_Service_5-10	5-10 years of teaching service	0.0228	12
Sub_County_EMUHAYA	School located in Emuhaya sub-county	0.0201	17

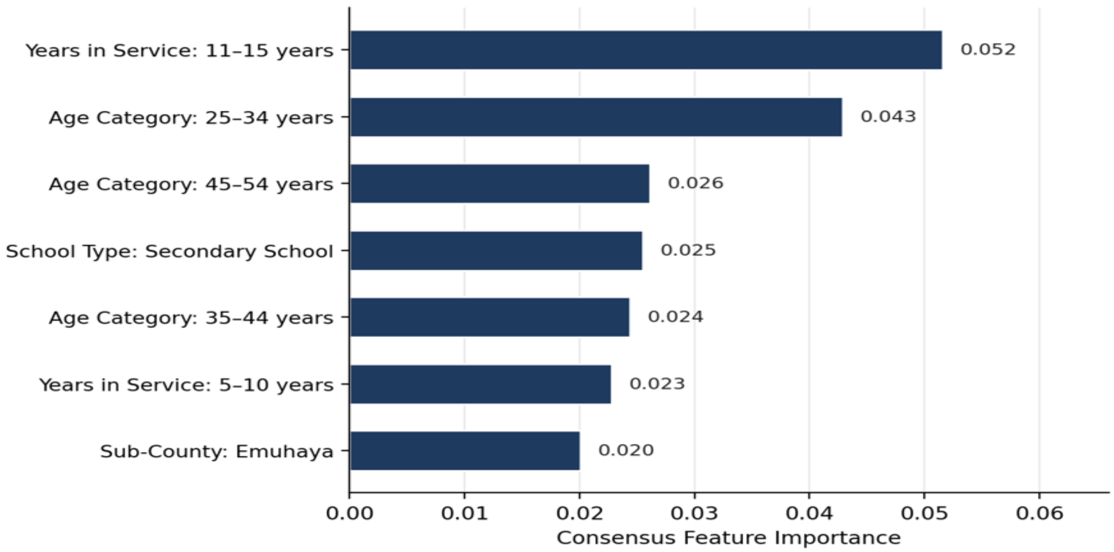

Figure A2: Demographic Predictors Ranked by Consensus Importance

Table A4: Socio-Economic and Financial Predictors of Depression Risk

Predictor	Description	Consensus Importance	Overall Rank (of 20)
Fin_A2	Frequently runs out of money before next paycheck	0.0264	6
Fin_C2	Borrows from family, friends, or institutions for basic needs	0.0221	14
Fin_D4	Has received financial-literacy training	0.0206	16
Fin_C5	Has skipped meals or essential purchases due to financial constraints	0.0168	19

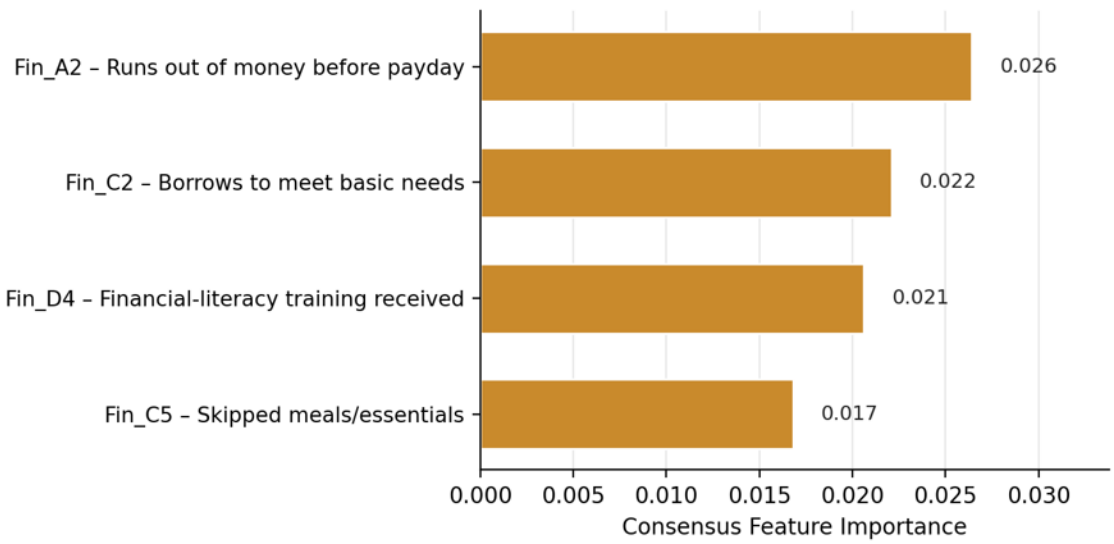

Figure A3: Socio-Economic / Financial Predictors Ranked by Consensus Importance

Table A5: Professional and Institutional Predictors of Depression Risk

Predictor	Description	Consensus Importance	Overall Rank (of 20)
Soc_D1	School offers no mental-health resources or counselling services	0.0762	1
Soc_C1	Parents do not support teacher in managing student behaviour	0.0352	4
Time_B1	Expected to meet unrealistic teaching/performance targets	0.0322	5
Perf_A3	Worries about non-promotion due to low performance ratings	0.0249	9
Soc_A2	Colleagues rarely help when overwhelmed with work	0.0225	13
Soc_D5	No one to turn to when feeling overwhelmed or stressed	0.021	15
Soc_D4	Feels unsupported when dealing with job-related emotional distress	0.018	18

Journal of Science, Innovation and Creativity
Vol. 5 No. 1 (2026): ISSN (Online): 2958-454X
DOI: https://doi.org/10.58721/602e6987

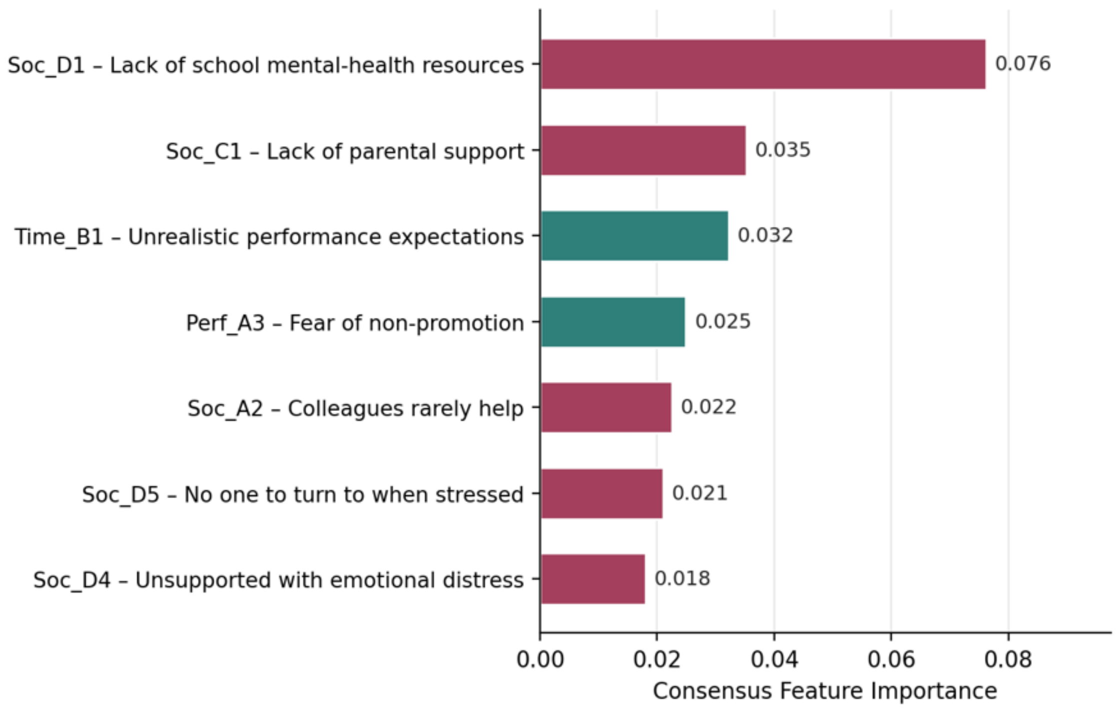

Figure A4: Professional & Institutional Predictors Ranked by Consensus Importance

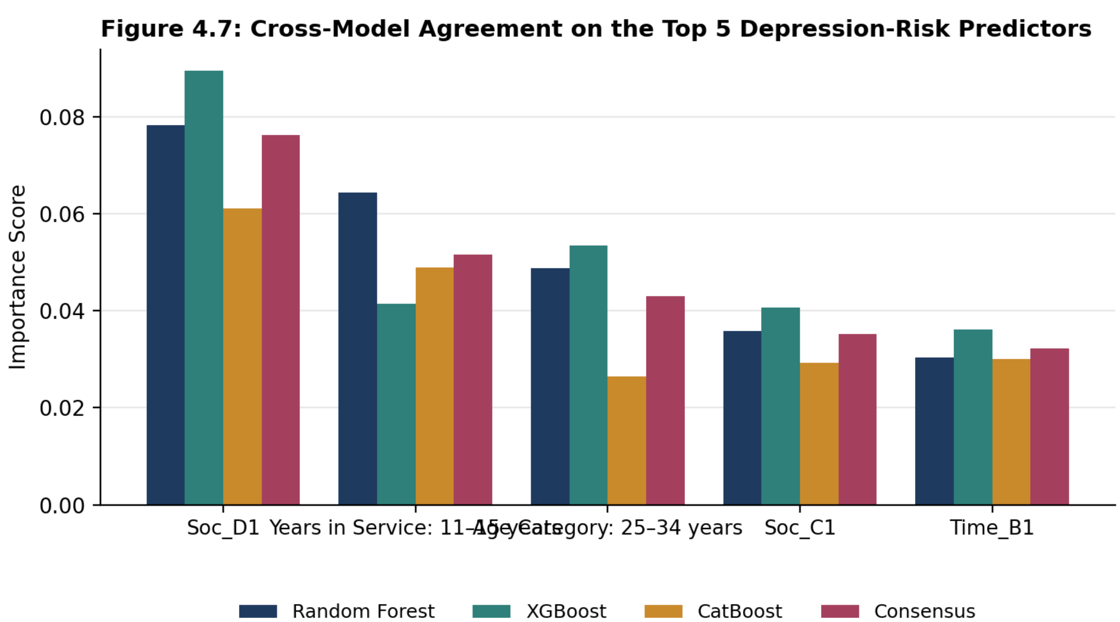

Figure A5: Cross-Model Agreement on the Top 5 Depression-Risk Predictors