

Privacy-Preserving Prediction of Psychological Distress Across Schools Using Academic Workload, Bullying, Sleep Quality, and Social Support: A Federated XGBoost Study

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ABSTRACT

Objective: This study aimed to develop and evaluate a privacy-preserving federated XGBoost model for predicting psychological distress among Norwegian upper secondary school students using academic workload, bullying victimization, sleep quality, and perceived social support.

Methods and Materials: A multicenter cross-sectional predictive study was conducted among 2,428 students aged 16–19 years from 12 public upper secondary schools in Norway. Psychological distress was assessed using the Kessler Psychological Distress Scale, while academic workload, bullying victimization, sleep quality, and perceived social support were measured using standardized self-report instruments. Each school retained its raw data locally and participated as an independent node in a federated learning network. Federated XGBoost was trained using locally computed gradient and Hessian statistics transmitted through secure aggregation. Data were divided into training, validation, and independent test subsets. Model performance was evaluated using the area under the receiver operating characteristic curve, area under the precision–recall curve, sensitivity, specificity, balanced accuracy, F1 score, and Brier score. Performance was compared with centralized XGBoost, locally trained XGBoost models, and federated logistic regression.

Findings: Federated XGBoost achieved an area under the receiver operating characteristic curve of .906 and an area under the precision–recall curve of .756 in the independent test sample. The model produced balanced accuracy of .848, sensitivity of .844, specificity of .851, an F1 score of .734, and a Brier score of .112. Its performance did not differ significantly from centralized XGBoost, whereas it significantly outperformed locally trained XGBoost models and federated logistic regression. Academic workload, poor sleep quality, recurrent bullying, low family support, short sleep duration, cyberbullying, and low friend support were the strongest predictors. Leave-one-school-out validation showed stable performance across participating schools.

Conclusion: Federated XGBoost provided accurate and well-calibrated prediction of psychological distress while preserving institutional control over sensitive student data, supporting its potential use as a privacy-conscious screening aid in school mental health systems.

Keywords: psychological distress; federated learning; XGBoost; academic workload; bullying; sleep quality; social support; adolescent mental health

1. Introduction

Psychological distress among adolescents has become an increasingly important concern for schools, families, health professionals, and public authorities because it affects emotional functioning, educational participation, interpersonal relationships, and long-term development. Psychological distress commonly refers to a broad state of emotional suffering characterized by symptoms such as anxiety, sadness, hopelessness, irritability, restlessness, loss of motivation, and difficulty coping with everyday demands. Although these experiences do not necessarily indicate a formally diagnosed psychiatric disorder, persistent or severe distress can interfere substantially with academic performance, school attendance, social engagement, sleep, and health-related behaviors. Evidence from high-school populations indicates that psychological distress is shaped by multiple personal, social, educational, and behavioral factors rather than by a single isolated exposure (Hashim et al., 2026). Research on adolescent mental health similarly emphasizes that emotional difficulties emerge through complex interactions among individual vulnerabilities, family conditions, peer relationships, school environments, social media use, and broader socioeconomic pressures (Lin & Guo, 2024). Consequently, identifying students at elevated risk requires analytical approaches capable of considering several interrelated predictors simultaneously.

Educational environments represent a particularly important context for the development or intensification of distress. Schools are not only places of learning but also major social systems in which students are repeatedly exposed to performance expectations, peer evaluation, interpersonal conflict, competition, and institutional demands. Excessive academic workload, repeated examinations, limited recovery time, pressure to achieve, and fear of educational failure may collectively create sustained psychological strain. Recent ecological research among adolescents has shown that educational stress is closely associated with psychological distress and should be interpreted alongside peer victimization and health-related behaviors (Al-Mamun et al., 2026). Reviews of university and student mental health likewise identify academic pressure, uncertainty about performance, social adjustment, financial concerns, and inadequate coping resources as recurring contributors to psychological problems (Gull et al., 2025; Limone & Toto, 2022). Although much of this evidence has been generated in university settings, the underlying mechanisms are also relevant to upper secondary

students, who must manage demanding coursework while navigating developmental transitions, identity formation, peer relationships, and decisions about higher education or employment.

Academic workload may contribute to distress through several pathways. High task volume and time pressure can reduce opportunities for rest, recreation, physical activity, and supportive social interaction. Students who perceive that educational demands exceed their available resources may experience reduced control, repeated worry, and feelings of inadequacy. Comparable patterns have been documented in other high-demand educational and occupational environments. Studies of physicians, nurses, teachers, and veterinarians show that prolonged exposure to workload, organizational pressure, emotional demands, and insufficient recovery is associated with psychological strain, burnout, and impaired wellbeing (Ghasemi, 2025; Ram & Alharbi, 2025; Yang et al., 2025). Research on veterinarian burnout has further illustrated how chronic occupational stress can produce physiological, psychological, and organizational consequences when demands remain high and protective resources are limited (Steffey, Griffon, Risselada, Buote, et al., 2023; Steffey, Griffon, Risselada, Scharf, et al., 2023). Similarly, anonymous performance evaluation and institutional scrutiny have been linked with stress and distress among higher education teachers (Lakeman et al., 2023). These findings support the broader proposition that sustained performance demands can become psychologically harmful when individuals perceive insufficient control, support, or recovery opportunities.

Sleep quality is another central determinant of adolescent psychological health. Adolescence is already characterized by biological shifts in circadian timing, while early school schedules, academic obligations, social activities, digital-device use, and emotional arousal frequently restrict sleep duration and disrupt sleep continuity. Poor sleep may manifest as prolonged sleep latency, short sleep duration, frequent awakenings, irregular sleep schedules, daytime fatigue, and reduced concentration. A recent narrative review of medical students emphasized that sleep disturbances are consistently associated with impaired quality of life, reduced functioning, and poorer psychological health across diverse settings (Nagabhushan et al., 2026). Longitudinal evidence also indicates that depressive symptoms and insomnia may develop concurrently and reinforce one another during adolescence, suggesting that sleep disturbance is not simply a secondary symptom but may form part of a reciprocal pathway

involving emotional distress (Cheng et al., 2025). In student populations, sleep difficulties have also been associated with academic impairment through their relationships with psychological distress, loneliness, and health-risk behaviors (Chung, 2025).

The relationship between sleep and psychological distress is likely to be bidirectional. Academic worry, interpersonal conflict, and emotional arousal can delay sleep and increase nighttime rumination, whereas insufficient or fragmented sleep can reduce emotional regulation, increase irritability, impair cognitive control, and heighten sensitivity to stress. Sleep disruption may therefore amplify the psychological impact of other school-related adversities. Research examining sexual identity, peer victimization, social support, and sleep quality has shown that adverse peer experiences and reduced support can help explain disparities in adolescent sleep outcomes (Kwon et al., 2025). Other studies have demonstrated that bullying victimization is longitudinally related to poorer sleep and that this pathway may operate through emotional and behavioral mechanisms (Wu et al., 2025). Bullying may also affect sleep indirectly through mobile-phone addiction, while physical activity may modify the severity of this relationship (Wang et al., 2025). These findings suggest that sleep should not be analyzed in isolation but as part of a broader network of academic, interpersonal, behavioral, and emotional influences.

Bullying victimization is among the most damaging school-based experiences associated with adolescent distress. Bullying may involve repeated verbal humiliation, social exclusion, rumor spreading, physical aggression, threats, property-related harm, discriminatory harassment, or abuse conducted through digital platforms. Its defining features generally include repetition, intentional harm, and an imbalance of power between the aggressor and the victim. Research across educational levels has described bullying as a persistent problem that contributes to unsafe and unhealthy learning climates (Abbasi et al., 2023). Studies in elementary-school populations also show that bullying can adversely affect victims' emotional security, participation, and social functioning from an early age (Ghofur et al., 2022; Sari, 2023). Among adolescent girls, bullying may remain hidden because of relational aggression, fear of disclosure, shame, and the normalization of harmful peer behavior, making some experiences difficult for adults to detect (Sharma, 2025). The psychological effects of bullying may therefore be underestimated when schools rely only on formally reported incidents.

Traditional bullying and cyberbullying often overlap, but digital victimization introduces additional risks. Cyberbullying can occur continuously, reach large audiences, preserve humiliating content, and enter spaces that would otherwise provide safety from school-based aggression. Reviews of adolescent cyberincivility show that young people may experience exclusion, harassment, reputational harm, impersonation, and hostile communication across online environments (Kim et al., 2023). Cyberbullying has been associated with reduced emotional wellbeing, increased anxiety, depressive symptoms, and social withdrawal (Hafizi, 2024). The expansion of social media has altered adolescent behavior, identity presentation, peer comparison, and exposure to social feedback, thereby creating new developmental opportunities as well as new psychological challenges (Shi, 2024). Evidence from workplace settings also demonstrates that cyberbullying is associated with adverse psychological outcomes beyond adolescence, highlighting the general capacity of digitally mediated aggression to damage wellbeing (Ikeda et al., 2022).

The effects of school bullying extend across several health domains. Population-based research has shown that traditional and cyberbullying victimization are both related to poorer emotional wellbeing during early adolescence (Halliday et al., 2022). Bullying has also been linked with sadness, sleep difficulties, and suicidal ideation through both direct and indirect pathways (Sutter et al., 2022). Among adolescent female migrants, school bullying has been negatively associated with multidimensional health, suggesting that victimization may be especially consequential for students already managing migration-related or social adaptation pressures (Song et al., 2025). Bullying victimization has also been associated with depressive symptoms through mechanisms involving psychological and social factors (Mei et al., 2021). More recent work indicates that school bullying may contribute to problematic internet use, while emotional resilience can moderate the severity of these associations (Pang et al., 2026). Together, these findings support the inclusion of both traditional and digital victimization indicators when predicting psychological distress.

Social support may protect adolescents from distress by increasing feelings of belonging, emotional security, perceived competence, and access to practical assistance. Supportive family members can help students regulate emotions, interpret stressful events, establish routines, and seek professional help when necessary. Friends may provide

validation, companionship, and protection against social isolation, while supportive teachers and school personnel can facilitate early identification and referral. Research indicates that family and peer support may reduce the impact of peer victimization on adolescent insomnia, although the protective strength of different support sources may vary (Hu et al., 2025). Perceived social support has also been identified as a mediator linking peer victimization with sleep quality and other developmental outcomes (Kwon et al., 2025). These findings indicate that support is not merely an independent predictor of wellbeing but may alter how adolescents respond to bullying, educational stress, and sleep disruption.

The buffering role of support is also consistent with resilience-oriented approaches to bullying prevention. The SHIELD framework emphasizes strengths, healthy relationships, empowerment, supportive environments, and coping resources as central components of interventions addressing bullying and cyberbullying among young people (Dailey & Roche, 2025). Such approaches move beyond identifying deficits and instead consider how individual and contextual assets can reduce harm. Emotional resilience may similarly weaken the association between bullying and maladaptive behavioral outcomes (Pang et al., 2026). Nevertheless, social support should not be treated as sufficient to neutralize severe or repeated victimization. Students exposed to persistent bullying may continue to experience distress even when some protective relationships are available, especially when aggression is widespread, digitally amplified, or embedded within an unhealthy school climate.

The combined effects of workload, bullying, sleep, and social support may be nonlinear and interactive. For example, high academic workload may be manageable for a student who sleeps adequately and receives strong support but may become psychologically overwhelming when combined with chronic sleep deprivation or victimization. Similarly, bullying may have stronger effects among socially isolated students or those already experiencing academic strain. Psychosomatic symptoms among college students have been described as important indicators of accumulated stress and maladaptive responses to educational and emotional pressures (R., 2024). Mental health changes observed during the COVID-19 pandemic further demonstrated how educational disruption, isolation, uncertainty, and altered support structures can interact to affect student wellbeing (King et al., 2022). Problematic internet use and substance-related behaviors may also cluster

with psychological and social risks among emerging adults (Zhou et al., 2024). These interdependencies challenge conventional analyses that assume simple, independent, and linear relationships among predictors.

Most previous studies have examined individual risk factors using correlation, regression, mediation, moderation, or group-comparison methods. These methods are valuable for testing hypotheses and estimating average associations, but they may be less effective when the primary objective is to identify complex predictive patterns at the individual level. Machine-learning methods can incorporate multiple variables, model nonlinear thresholds, identify interactions, and estimate the probability that a student belongs to a high-distress group. Extreme gradient boosting, or XGBoost, is particularly suitable for structured educational and psychological data because it can accommodate continuous and categorical predictors, manage complex relationships, and provide strong predictive performance. It can also generate feature-importance and explanation estimates that clarify which variables contribute most strongly to predictions. However, centralized machine-learning development usually requires institutions to transfer individual-level information to a common database, creating serious concerns when the data include sensitive mental health, bullying, family, and behavioral information.

Privacy is especially important in school-based psychological prediction. Students may be reluctant to disclose distress, victimization, sleep problems, or family difficulties if they believe their identifiable responses could be shared beyond their school or used for disciplinary, academic, or administrative purposes. Centralized data storage also increases the potential consequences of unauthorized access, accidental disclosure, or secondary use. Federated learning offers an alternative approach in which participating schools collaboratively train a shared model while retaining raw student data within their own secured environments. Instead of transferring questionnaire responses and individual outcomes, schools exchange only model-related updates or aggregated statistics. This design can reduce unnecessary movement of sensitive data while enabling institutions to benefit from a larger and more diverse training population.

A federated approach may also improve generalizability across schools. Independently trained local models may perform poorly because individual schools often have limited sample sizes and may differ in student composition, bullying prevalence, educational programs, support services, and workload patterns. Collaborative federated training

allows the model to learn from heterogeneity across institutions without directly pooling student records. At the same time, evaluation must determine whether the federated model performs consistently across schools and demographic subgroups, whether it remains calibrated, and whether privacy preservation produces a meaningful loss of predictive accuracy compared with a centralized benchmark. These questions are important because a high overall accuracy can conceal low sensitivity in specific schools or subgroups.

Current literature provides extensive evidence that academic demands, bullying victimization, sleep impairment, and low social support are individually associated with adverse psychological outcomes. It also demonstrates that bullying may affect sleep, problematic internet use, sadness, and depression; that social support and resilience may modify these pathways; and that educational and occupational stressors can accumulate into broader patterns of distress (Al-Mamun et al., 2026; Sutter et al., 2022; Wang et al., 2025). Yet important gaps remain. Few studies have integrated these domains within one predictive framework, fewer have examined nonlinear interactions across school populations, and privacy-preserving machine-learning designs remain insufficiently represented in adolescent mental health research. Furthermore, prediction should not be used to diagnose students or automate consequential decisions. Its appropriate function is to support screening, identify patterns requiring further assessment, and help schools allocate preventive and counseling resources more effectively.

Norway provides a valuable context for this investigation because upper secondary schools serve diverse academic and vocational populations and operate within a strong institutional framework for education, health, and data protection. A multisite Norwegian design can evaluate whether predictive relationships remain stable across schools while respecting institutional control over sensitive student records. By combining federated XGBoost with interpretable feature analysis, the study can assess both predictive accuracy and the relative contributions of workload, bullying, sleep, and social support. Such an approach may clarify whether privacy-preserving collaboration can approach the performance of centralized modeling while outperforming smaller school-specific models.

Accordingly, the aim of this study was to develop and evaluate a privacy-preserving federated XGBoost model for predicting psychological distress among Norwegian upper

secondary school students from academic workload, bullying victimization, sleep quality, and perceived social support across multiple schools.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a multicenter, cross-sectional predictive design to develop and evaluate a privacy-preserving machine-learning model for identifying psychological distress among secondary school students in Norway. The study was conducted across 12 public upper secondary schools located in Oslo, Bergen, Trondheim, Stavanger, Tromsø, and Kristiansand. Each participating school was treated as an independent institutional data node within a federated learning network, allowing predictive models to be trained collaboratively without transferring students' individual-level information to a central database. The target population consisted of students enrolled in Grades 11 to 13 during the 2025–2026 academic year. A stratified cluster-sampling procedure was applied to achieve representation across geographical regions, school sizes, academic programs, vocational programs, and grade levels. Schools were initially selected from lists provided by regional education authorities, after which intact classes were randomly invited to participate. A total of 2,684 students received invitations, of whom 2,491 completed the survey. Following the exclusion of 63 participants because of substantial missing data, implausible response patterns, withdrawal of consent, or failure to meet the age and enrollment criteria, the final analytical sample consisted of exactly 2,428 students. The number of students contributed by each school ranged from 148 to 267, ensuring that every institutional node contained an adequate local sample for model training and validation.

Eligible participants were students between 16 and 19 years of age who were formally enrolled in one of the participating schools, possessed sufficient Norwegian-language proficiency to understand the questionnaires, and provided informed consent to participate. Students were excluded when they were temporarily attending the school without formal enrollment, were unable to complete the assessment independently because of severe cognitive or language-related limitations, submitted more than 20% incomplete responses, or completed the questionnaire in an implausibly short period. For students younger than 18 years, consent procedures were implemented in accordance with the requirements of the relevant educational authorities

and ethics regulations. Participation was voluntary, and students were informed that declining participation or discontinuing the survey would have no academic or administrative consequences. Data collection was performed during regular school hours through a secure digital assessment platform. Participants completed the measures individually using school computers, tablets, or personal digital devices under the supervision of trained research assistants and designated school coordinators. No teachers were permitted to view students' responses.

2.2. Measures

Psychological distress was assessed using the 10-item Kessler Psychological Distress Scale. This measure evaluates nonspecific symptoms of anxiety and depression experienced during the previous four weeks, including nervousness, hopelessness, restlessness, depressed mood, effortfulness, and feelings of worthlessness. Each item was rated on a five-point response scale ranging from 1, indicating that the symptom was experienced none of the time, to 5, indicating that it was experienced all of the time. Item scores were summed to produce a total score ranging from 10 to 50, with higher scores representing greater psychological distress. For predictive classification, the continuous score was transformed into a binary outcome based on the established threshold for high psychological distress. Students scoring 30 or higher were classified as experiencing high psychological distress, whereas those scoring below 30 were classified as not experiencing high psychological distress. The continuous total score was retained for descriptive analyses and supplementary sensitivity analyses. Internal consistency was examined separately within each participating school and in the complete analytical sample.

Perceived academic workload was measured using an adapted Academic Workload Scale designed to assess the quantitative and psychological demands associated with schoolwork. The instrument contained 10 items addressing the volume of assignments, frequency of examinations, time pressure, difficulty of simultaneously managing multiple academic tasks, perceived expectations for achievement, insufficient time for recovery, and concerns about meeting academic deadlines. Students responded to each item on a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. A total academic workload score was calculated by averaging the item responses, with higher values indicating greater perceived academic demands. In

addition to the overall score, individual item responses were retained as potential model features because different dimensions of workload, such as examination pressure and insufficient completion time, could have distinct associations with psychological distress. The Norwegian-language version was reviewed by specialists in educational psychology and adolescent mental health to ensure linguistic clarity and contextual appropriateness.

Bullying victimization was assessed using selected items from the revised Olweus Bully/Victim Questionnaire. Students were first provided with a standardized definition of bullying that emphasized intentionality, repetition, and an imbalance of power. They subsequently reported the frequency with which they had experienced verbal bullying, social exclusion, rumor spreading, physical aggression, property-related bullying, discriminatory harassment, and electronic or social-media-based bullying during the previous two months. Responses were recorded on a five-category frequency scale ranging from no exposure to several times per week. A general victimization score was computed by summing the item responses, with higher scores indicating more frequent and diverse bullying experiences. A categorical indicator of recurrent bullying was also constructed, identifying students who reported exposure at least two or three times per month. Traditional bullying and cyberbullying features were retained separately in the predictive dataset to permit the model to detect potentially different patterns of association with psychological distress.

Sleep quality was evaluated using the Pittsburgh Sleep Quality Index, which measures subjective sleep characteristics during the preceding month. The instrument assesses subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. The seven component scores were summed to generate a global score ranging from 0 to 21, with higher scores indicating poorer sleep quality. A global score greater than 5 was used to identify students with poor sleep quality. To improve the predictive resolution of the machine-learning model, the global score, component scores, usual sleep duration, estimated sleep latency, frequency of nighttime awakening, and daytime tiredness were included as candidate predictors. Students also reported typical bedtime and wake time on school days and non-school days, enabling the calculation of differences in sleep timing and an approximate indicator of social jetlag.

Perceived social support was assessed using the Multidimensional Scale of Perceived Social Support. The 12-item instrument measures perceived emotional and practical support from family members, friends, and significant others. Responses were provided on a seven-point Likert scale ranging from 1, very strongly disagree, to 7, very strongly agree. Mean scores were calculated for family support, friend support, significant-other support, and overall perceived social support. Higher scores reflected stronger perceptions that supportive individuals were available when needed. The three domain scores and selected individual items were included in the predictive analysis to determine whether specific sources of support contributed differently to the classification of psychological distress.

A demographic and educational information form was used to collect data on age, gender, grade level, academic or vocational study program, parental educational level, perceived family economic status, migration background, living arrangement, school attendance, average academic performance, and participation in extracurricular activities. Participants also reported whether they had received psychological counseling or mental health treatment during the previous year. These variables were primarily used to characterize the sample and assess potential differences between participating schools. A restricted set of non-identifying demographic variables was included as covariates in supplementary models to evaluate whether the principal predictors retained their predictive value after accounting for background characteristics. Before the main data collection, the digital questionnaire was pilot-tested with 42 students from a school that did not participate in the final study. The pilot assessment examined item clarity, questionnaire completion time, technical performance, and acceptability. Minor linguistic modifications were made following feedback, but no substantive changes were introduced to the standardized instruments.

2.3. Data Analysis

Initial data preparation and descriptive analyses were performed separately within each participating school to maintain the decentralized structure of the study. Local preprocessing scripts were standardized and distributed to all school nodes to ensure that variable coding, exclusion criteria, missing-data procedures, feature engineering, and outcome definitions were applied consistently. Continuous variables were examined for out-of-range values, extreme

distributions, and implausible response combinations. Categorical variables were checked for coding errors and sparse categories. Participants with more than 20% missing questionnaire data were excluded before model development. For the remaining participants, missing continuous values were imputed locally using the median value calculated from the training portion of the relevant school dataset, whereas missing categorical values were replaced with the most frequent local category. Imputation parameters were estimated exclusively from training data and subsequently applied to validation or test observations to prevent information leakage. Continuous predictors were not required to be standardized for tree-based modeling; however, harmonized ranges and coding conventions were used across all schools. Descriptive statistics, including means, standard deviations, frequencies, percentages, medians, and interquartile ranges, were generated locally and transferred only in aggregated form for the preparation of overall sample summaries.

The primary predictive model was developed using federated extreme gradient boosting, referred to as federated XGBoost. In this framework, each school functioned as a separate client that retained its raw student-level data. A secure coordinating server initialized the global model and managed iterative communication among the participating nodes. During each training round, the schools calculated local gradient and Hessian statistics based on their own observations. These encrypted and aggregated statistics were communicated to the coordinating server, which used them to identify optimal tree splits and update the shared ensemble model. Raw feature values, questionnaire responses, outcome labels, and individual predictions were never transmitted between schools or uploaded to the central server. Secure aggregation procedures prevented the server from inspecting the contribution of an individual student or reconstructing a school's underlying records. Communication between nodes and the coordinating server was protected through encrypted channels, and each school was authenticated before participating in the training process.

The dataset at each school was divided into training, validation, and testing subsets using stratified sampling to preserve the local proportion of students with high psychological distress. Seventy percent of observations were assigned to local training sets, 15% to local validation sets, and 15% to local test sets. The partitions were generated with a fixed random seed and were kept unchanged throughout model development. The training subsets were used to

estimate the federated model, the validation subsets were used for hyperparameter selection and early stopping, and the local test subsets were reserved for final evaluation. To examine the capacity of the model to generalize to a school that had not contributed data during model training, an additional leave-one-school-out validation procedure was conducted. In each iteration, data from 11 schools were used to train the federated model, and the remaining school served as an external institutional test site. This process was repeated until every school had been used once as the held-out site.

Hyperparameters were tuned through a federated validation procedure that evaluated candidate combinations without pooling individual-level data. The tuned parameters included the number of boosting rounds, maximum tree depth, learning rate, minimum child weight, subsampling proportion, column-sampling proportion, gamma, and L1 and L2 regularization coefficients. The primary optimization objective was binary logistic loss. Because the number of students classified as having high psychological distress was expected to be smaller than the number classified as not having high distress, class imbalance was addressed through a class-weight parameter derived from the distribution of the outcome in the federated training data. Early stopping was applied when the aggregated validation loss failed to improve across 30 consecutive boosting rounds. The final hyperparameter configuration was selected based primarily on the mean validation area under the receiver operating characteristic curve, while calibration and sensitivity were also considered to avoid selecting a model that performed well only in ranking students but produced poorly calibrated risk estimates.

Predictive performance was assessed using the area under the receiver operating characteristic curve, the area under the precision–recall curve, accuracy, balanced accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and F1 score. The area under the precision–recall curve was emphasized because it is particularly informative when the target condition is less frequent than the non-distress category. A decision threshold was initially selected using the aggregated validation data by maximizing the Youden index, although an alternative threshold prioritizing sensitivity was examined because failure to identify students experiencing substantial distress may carry greater practical consequences than false-positive classification. Model calibration was evaluated using the Brier score, calibration intercept, calibration slope, and graphical comparisons of predicted and observed

probabilities. Performance indices were calculated independently at each school and subsequently combined using sample-size-weighted averaging. Ninety-five percent confidence intervals were estimated through repeated stratified bootstrap resampling conducted locally at each node, with only aggregated bootstrap estimates communicated to the coordinating server.

The performance of federated XGBoost was compared with that of local XGBoost models trained independently at each school and a conventional centralized XGBoost benchmark created within a controlled analytical environment using a fully de-identified research copy of the data where legally and ethically permissible. The centralized benchmark was included solely to quantify the potential performance cost associated with privacy-preserving decentralized training and was not used for the primary analysis. Federated logistic regression was also developed as a more interpretable baseline. All comparison models used equivalent training and testing partitions and the same predictor set. Differences in the area under the receiver operating characteristic curve between competing models were evaluated using paired bootstrap procedures based on predictions from the same test observations.

Feature importance was examined using gain-based importance and federated approximations of Shapley additive explanation values. Local explanation values were calculated within each school and aggregated at the summary level, without transmitting student-level explanations. Global importance rankings were used to determine the relative contributions of academic workload, bullying victimization, sleep quality, social support, and demographic covariates to psychological distress prediction. Dependence patterns were evaluated to identify whether risk changed linearly or nonlinearly across predictor values. Interaction effects of substantive interest, including interactions between bullying and social support, workload and sleep quality, and bullying and sleep quality, were examined through aggregated interaction importance. Individual-level explanation outputs were not shared with schools or used for disciplinary or academic decision-making.

Several sensitivity analyses were conducted. The model was re-estimated using the continuous psychological distress score as a regression outcome, using alternative cutoffs for high distress, excluding students who reported recent psychological treatment, and restricting the predictor set to the four principal domains. Models were also evaluated separately across gender, grade level, academic and

vocational programs, and geographical regions to examine potential disparities in performance. Differences in sensitivity, specificity, calibration, and false-positive rates across subgroups were inspected as indicators of algorithmic fairness. A model was considered potentially inequitable when it demonstrated consistently lower sensitivity or substantial miscalibration in a subgroup despite adequate overall performance. Statistical analyses, local preprocessing, federated model training, and explainability procedures were implemented using Python and compatible privacy-preserving machine-learning libraries. All analyses used two-tailed criteria where inferential tests were applied, and statistical significance was defined as $p < .05$.

3. Findings and Results

Of the 2,684 students invited to participate, 2,491 completed the digital assessment, corresponding to an initial response rate of 92.8%. After applying the predetermined eligibility and data-quality criteria, 63 questionnaires were excluded because of excessive missing data, implausibly short completion times, inconsistent response patterns, or withdrawal of consent. The final analytical sample therefore consisted of 2,428 students from 12 Norwegian upper secondary schools. The participants ranged in age from 16 to 19 years, with a mean age of 17.42 years and a standard deviation of 0.87. A total of 1,298 participants were girls, representing 53.5% of the sample, 1,091 were boys, representing 44.9%, and 39 identified as nonbinary or another gender identity, representing 1.6%. Regarding grade level, 854 students were enrolled in Grade 11, accounting for 35.2% of the sample, 819 were enrolled in Grade 12, accounting for 33.7%, and 755 were enrolled in Grade 13, accounting for 31.1%. Academic study programs were attended by 1,556 students, or 64.1%, whereas 872 students, or 35.9%, were enrolled in vocational programs. A migration background was reported by 493 students, representing 20.3% of the sample. Most participants, including 1,774 students or 73.1%, lived with two parents or guardians, while 489 students, or 20.1%, lived primarily with one parent or guardian, and 165 students, or 6.8%, reported another living arrangement.

With respect to socioeconomic characteristics, 303 students, representing 12.5% of the sample, perceived their family economic status as below average, 1,694 students, representing 69.8%, described it as average, and 431 students, representing 17.8%, described it as above average. At least one parent or guardian had completed tertiary education for 1,493 participants, or 61.5% of the sample. A total of 389 students, representing 16.0%, reported receiving psychological counseling, school-based mental health support, or another form of mental health treatment during the previous year. Based on the predetermined Kessler Psychological Distress Scale cutoff score of 30 or higher, 597 students were classified as experiencing high psychological distress. This corresponded to an overall prevalence of 24.6%, while the remaining 1,831 students, or 75.4%, were classified as not experiencing high psychological distress. High psychological distress was identified among 379 girls, corresponding to 29.2% of all girls, 204 boys, corresponding to 18.7% of all boys, and 14 students identifying as nonbinary or another gender, corresponding to 35.9% of that group. Because the number of gender-diverse students was comparatively small, estimates for this subgroup were interpreted cautiously.

The final sample was divided into mutually exclusive model-development subsets according to the prespecified stratified partitioning procedure. The training subset contained 1,699 students, including 418 students with high psychological distress; the validation subset contained 364 students, including 89 students with high psychological distress; and the independent test subset contained 365 students, including 90 students with high psychological distress. The prevalence of high distress was therefore 24.6% in the training subset, 24.5% in the validation subset, and 24.7% in the test subset. No statistically significant differences were observed among the three subsets in age, gender distribution, grade level, study program, migration background, family economic status, or prevalence of high psychological distress, indicating that the stratified partitioning procedure produced comparable samples for model development and evaluation. The number of participants contributed by individual schools ranged from 148 to 267, and the school-specific prevalence of high psychological distress ranged from 19.1% to 30.4%.

Table 1

Descriptive Statistics, Internal Consistency, and Differences in Principal Study Variables According to Psychological Distress Classification

Variable	Possible range	Total sample, M (SD)	No high distress, M (SD), n = 1,831	High distress, M (SD), n = 597	Welch's t	Cohen's d	Cronbach's α
Academic workload	1–5	3.28 (0.78)	3.08 (0.70)	3.90 (0.66)	25.97***	1.19	.89
Bullying victimization	0–28	4.72 (4.37)	3.63 (3.42)	8.07 (5.19)	19.56***	1.13	.91
Global sleep-quality score	0–21	6.79 (3.32)	5.78 (2.75)	9.88 (3.00)	29.58***	1.46	.83
Perceived social support	1–7	5.12 (1.11)	5.38 (0.97)	4.31 (1.12)	–20.92***	–1.06	.94
Psychological distress	10–50	23.66 (7.94)	20.05 (5.11)	34.74 (3.65)	—	—	.92

As presented in Table 1, students classified as experiencing high psychological distress reported substantially less favorable scores across all four principal predictor domains. Their mean academic-workload score was 3.90, compared with 3.08 among students without high distress. The difference was statistically significant, $t(1066.63) = 25.97$, $p < .001$, and the standardized mean difference of 1.19 indicated a large effect. The largest between-group difference was found for sleep quality. Students with high psychological distress had a mean global sleep-quality score of 9.88, whereas the corresponding mean among students without high distress was 5.78, $t(944.23) = 29.58$, $p < .001$, Cohen's $d = 1.46$. Thus, the high-distress group reported substantially poorer sleep, including longer sleep latency, shorter sleep duration, more frequent sleep disturbances, and greater daytime dysfunction. The mean bullying-victimization score was also markedly higher in the high-distress group, with a mean of 8.07 compared with 3.63

in the group without high distress, $t(771.67) = 19.56$, $p < .001$, Cohen's $d = 1.13$. Recurrent bullying, defined as victimization occurring at least two or three times per month, was reported by 248 students with high distress, or 41.5%, and 223 students without high distress, or 12.2%. This difference was statistically significant, $\chi^2(1) = 248.24$, $p < .001$, and students exposed to recurrent bullying had approximately 5.12 times the odds of being classified as experiencing high psychological distress compared with students not reporting recurrent bullying. Conversely, perceived social support was significantly lower among students with high distress. Their mean social-support score was 4.31, compared with 5.38 among students without high distress, $t(905.53) = -20.92$, $p < .001$, Cohen's $d = -1.06$. All instruments demonstrated satisfactory to excellent internal consistency, with Cronbach's alpha coefficients ranging from .83 for the global sleep-quality measure to .94 for perceived social support.

Table 2

Predictive Performance of Federated XGBoost and Comparison Models in the Independent Test Sample

Model	AUROC (95% CI)	AUPRC (95% CI)	Balanced accuracy	Sensitivity	Specificity	PPV	NPV	F1 score	Brier score
Federated XGBoost	.906 (.872–.940)	.756 (.699–.812)	.848	.844	.851	.650	.944	.734	.112
Centralized XGBoost benchmark	.913 (.880–.946)	.768 (.713–.822)	.857	.856	.858	.664	.948	.748	.108
Locally trained XGBoost models	.847 (.809–.884)	.634 (.574–.692)	.776	.756	.796	.553	.909	.639	.151
Federated logistic regression	.856 (.819–.893)	.657 (.598–.714)	.781	.778	.785	.543	.915	.639	.146

The federated XGBoost model demonstrated strong discrimination in the independent test sample, producing an AUROC of .906 and an AUPRC of .756. The AUPRC was substantially higher than the high-distress prevalence of .247 in the test sample, indicating that the model provided considerably greater precision across sensitivity levels than

would be expected from a noninformative classifier. At the decision threshold of .31 selected from the validation data, the model correctly identified 76 of the 90 students with high psychological distress, corresponding to a sensitivity of .844. It correctly classified 234 of the 275 students without high distress, resulting in a specificity of .851. The resulting

confusion matrix contained 76 true-positive classifications, 234 true-negative classifications, 41 false-positive classifications, and 14 false-negative classifications. The positive predictive value was .650, indicating that 65.0% of students classified as being at high risk met the psychological-distress criterion, whereas the negative predictive value was .944, indicating that 94.4% of students classified as not being at high risk were correctly classified. The balanced accuracy of .848 and F1 score of .734 demonstrated that the model maintained an appropriate balance between identifying distressed students and limiting false-positive predictions.

The centralized XGBoost benchmark achieved an AUROC of .913, which was only .007 higher than the AUROC of federated XGBoost. The paired bootstrap confidence interval for this difference extended from $-.002$ to $.016$, and the difference was not statistically significant, $p = .118$. Similarly, the differences between the federated and centralized models in sensitivity, specificity, F1 score, and Brier score were small. These findings indicated that retaining individual-level data within schools imposed little measurable reduction in predictive performance. In contrast, federated XGBoost significantly outperformed the sample-size-weighted average of the independently trained local XGBoost models. The AUROC difference was .059, with a 95% bootstrap confidence interval from .031 to .087, $p < .001$. The federated model also provided a 12.2-percentage-point improvement in AUPRC, a 7.2-percentage-point improvement in balanced accuracy, and a reduction of .039 in the Brier score relative to the local models. This finding demonstrated that collaborative learning across schools improved prediction compared with requiring each school to rely only on its own smaller local sample.

Federated XGBoost also performed significantly better than federated logistic regression. The difference in AUROC

was .050, with a 95% confidence interval from .024 to .077, $p < .001$, while the difference in AUPRC was .099. The improved performance of federated XGBoost suggested that nonlinear relationships and interactions among workload, bullying, sleep characteristics, and social support contributed meaningfully to the prediction of psychological distress. Calibration analysis showed that federated XGBoost produced a calibration intercept of .02 and a calibration slope of .96, indicating close correspondence between predicted and observed probabilities and only limited overfitting. In leave-one-school-out validation, the AUROC ranged from .872 to .921 across the 12 held-out schools, while the AUPRC ranged from .681 to .792 and the Brier score ranged from .104 to .129. The relatively narrow variation across held-out schools indicated that the model generalized to institutions that had not contributed data during the corresponding training iteration.

Subgroup analyses provided no evidence of a major performance disparity across the principal demographic and educational groups. The AUROC was .899 among girls and .903 among boys, while sensitivity differed by 3.7 percentage points and specificity differed by 4.2 percentage points between these groups. The AUROC was .909 among students in academic programs and .897 among those in vocational programs. Across Grades 11 to 13, AUROC values ranged from .898 to .914, and calibration slopes ranged from .92 to 1.01. Performance was also similar among students with and without a migration background, with an AUROC difference of .018. Estimates for students identifying as nonbinary or another gender were unstable because only 39 such students were included in the full sample and very few were represented in the independent test subset. Consequently, no definitive conclusion regarding algorithmic fairness for this subgroup was drawn.

Table 3

Relative Feature Importance and Direction of Association in the Federated XGBoost Model

Rank	Predictor	Relative importance (%)	Predominant relationship with predicted distress
1	Academic-workload total score	21.7	Higher workload increased predicted risk, particularly above scores of approximately 3.6
2	Global sleep-quality score	18.9	Poorer sleep quality increased predicted risk, with a marked increase above a score of 7
3	Recurrent bullying victimization	13.8	Recurrent victimization produced a substantial increase in predicted risk
4	Perceived family support	9.6	Stronger family support reduced predicted risk
5	Average sleep duration	7.1	Sleep duration below approximately 7 hours increased predicted risk
6	Cyberbullying frequency	6.3	More frequent cyberbullying increased predicted risk
7	Perceived friend support	5.5	Stronger friend support reduced predicted risk

8	Social jetlag	4.2	Greater differences between school-day and non-school-day sleep timing increased predicted risk
9	Examination and deadline pressure	3.8	Greater examination pressure and time pressure increased predicted risk
10	Sleep-related daytime dysfunction	3.3	More frequent fatigue and daytime impairment increased predicted risk
11	School absence	2.2	More frequent absence was associated with increased predicted risk
12	Perceived family economic status	1.4	Below-average economic status was associated with a modest increase in predicted risk
13	Gender	1.1	Female and gender-diverse categories contributed modestly to higher predicted risk relative to the male category
14	Grade level	0.7	Higher grade level showed a weak positive contribution
15	Migration background	0.4	Contribution was small and did not show a consistent directional pattern

The feature-importance analysis indicated that the four principal conceptual domains accounted for most of the predictive information used by the federated XGBoost model. Academic workload was the most influential individual feature and accounted for 21.7% of total normalized importance. Shapley additive explanation patterns showed a gradual increase in predicted distress across lower and moderate workload scores, followed by a steeper increase when the academic-workload score exceeded approximately 3.6 on the five-point scale. Students reporting simultaneous examination demands, insufficient time to complete assignments, and difficulty recovering between academic tasks received particularly elevated predicted probabilities. Examination and deadline pressure contributed an additional 3.8% of total feature importance, demonstrating that specific time-pressure experiences added predictive information beyond the general workload score.

The global sleep-quality score was the second most influential feature, accounting for 18.9% of normalized importance. Predicted risk increased substantially once the global sleep-quality score exceeded approximately 7 and was especially elevated among students with scores above 10. Average sleep duration contributed another 7.1%, while social jetlag and sleep-related daytime dysfunction contributed 4.2% and 3.3%, respectively. Students who slept fewer than approximately 7 hours on school nights, reported difficulty awakening, experienced daytime fatigue, or had a difference of more than 2 hours between school-day and weekend sleep timing were assigned higher predicted probabilities of distress. These findings indicated that both global sleep impairment and specific behavioral dimensions of sleep contributed independently to prediction.

Bullying-related variables also occupied prominent positions in the feature ranking. Recurrent bullying was the third most important predictor and accounted for 13.8% of normalized importance, while cyberbullying accounted for an additional 6.3%. The increase in predicted distress was

most pronounced when students reported repeated exposure rather than isolated incidents. Verbal humiliation, social exclusion, rumor spreading, and digitally mediated harassment were the bullying indicators most frequently associated with positive Shapley values. Social support showed an inverse relationship with predicted distress. Family support accounted for 9.6% of feature importance and friend support accounted for 5.5%. Predicted risk declined progressively as social-support scores increased, with the strongest protective pattern occurring when family-support and friend-support scores exceeded approximately 5.5 on the seven-point scale.

The model also identified meaningful interactions among the principal predictors. The strongest interaction was observed between academic workload and poor sleep quality. High workload was associated with a moderate increase in predicted distress when sleep quality was relatively favorable, but the predicted probability rose sharply when high workload co-occurred with a global sleep-quality score above 7. A second prominent interaction occurred between bullying victimization and perceived social support. Students exposed to recurrent bullying but reporting strong family or friend support had lower predicted probabilities than students experiencing a comparable frequency of bullying with low support. Nevertheless, strong support did not completely eliminate the elevated risk associated with recurrent victimization. The third notable interaction involved bullying and sleep quality, with the combination of recurrent victimization and severe sleep disturbance producing a greater increase in predicted distress than either factor alone. Among demographic variables, gender, grade level, perceived family economic status, and migration background collectively accounted for only 3.6% of normalized importance, demonstrating that the model's predictions were driven primarily by potentially modifiable psychological, social, academic, and behavioral characteristics rather than demographic background.

Figure 1

Receiver Operating Characteristic, Precision–Recall, and Calibration Curves for the Federated XGBoost Model in the Independent Test Sample

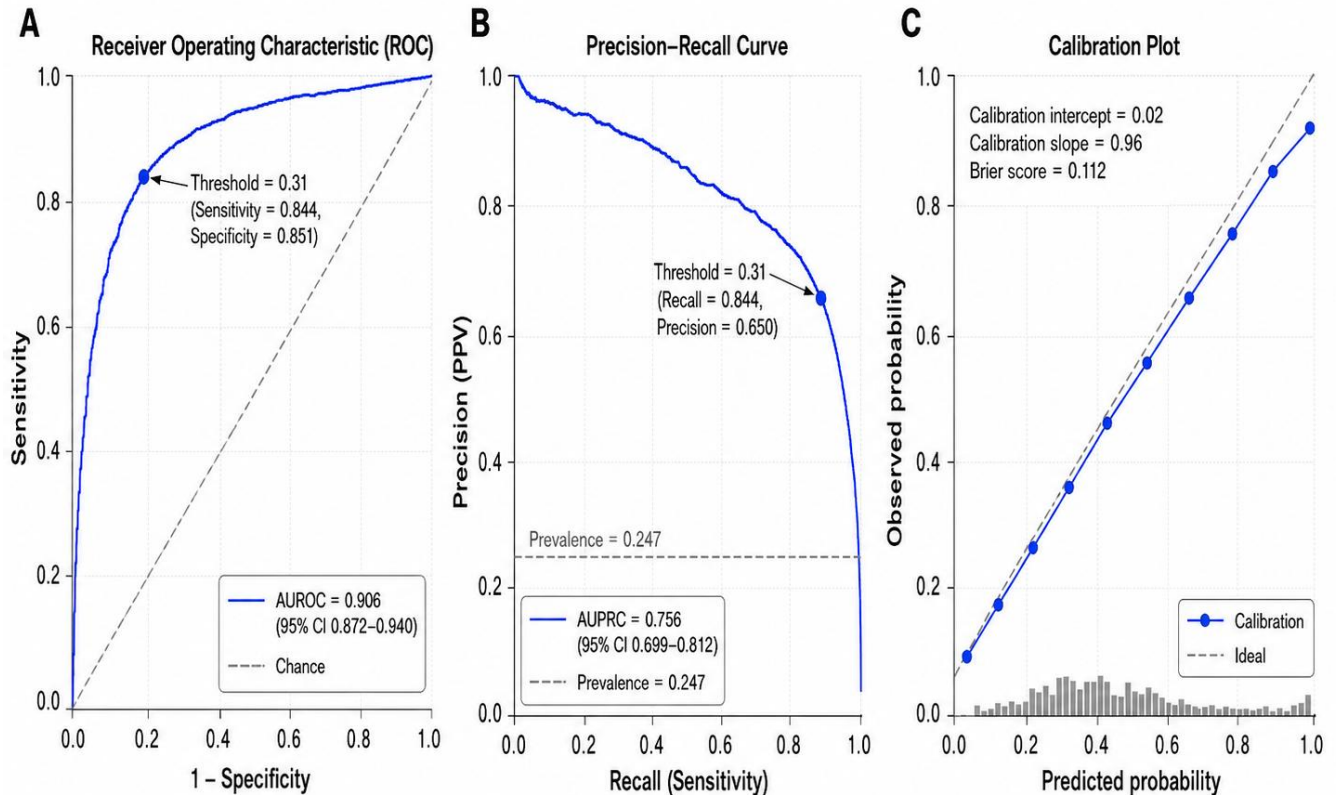


Figure 1 demonstrates the discrimination and calibration of the final federated XGBoost model. The receiver operating characteristic curve remained well above the diagonal reference line across the full range of classification thresholds, consistent with the AUROC of .906. The precision–recall curve also remained substantially above the horizontal prevalence reference of .247, particularly across sensitivity values between .60 and .90. At the prespecified probability threshold of .31, the model achieved a sensitivity of .844 and a specificity of .851. Lowering the threshold to .24 increased sensitivity to .900 but reduced specificity to .756, whereas increasing the threshold to .42 improved specificity to .909 but reduced sensitivity to .722. These threshold-dependent results showed that the model could be adapted to different implementation priorities. A school screening program seeking to minimize missed cases could employ the more sensitive threshold, whereas a setting with limited follow-up resources could use a higher threshold to reduce false-positive referrals.

The calibration curve closely followed the ideal 45-degree line across most of the predicted-probability range.

For students with predicted probabilities below .20, the mean predicted and observed risks differed by less than two percentage points. Predictions between .20 and .60 also showed close agreement with observed high-distress prevalence. A small degree of overprediction was observed among students with predicted probabilities above .70, although this region contained a relatively small proportion of the test sample. The calibration intercept of .02, calibration slope of .96, and Brier score of .112 collectively indicated that the model generated reliable probability estimates rather than merely ranking students according to relative risk. The concentration of true-positive cases in the upper predicted-risk categories further demonstrated that the model successfully differentiated students with elevated distress from those with lower levels of risk. Overall, the curves supported the conclusion that federated XGBoost achieved strong discrimination, useful precision, and satisfactory calibration while allowing the participating schools to retain all individual-level student data within their local institutional environments.

4. Discussion

The present study developed and evaluated a privacy-preserving federated XGBoost model for predicting psychological distress among 2,428 Norwegian upper secondary school students using academic workload, bullying victimization, sleep quality, and perceived social support. The findings showed that students classified as experiencing high psychological distress reported substantially higher academic workload, more frequent bullying victimization, poorer sleep quality, and lower perceived social support than students without high distress. All between-group differences were large, with the strongest standardized difference observed for sleep quality, followed by academic workload, bullying victimization, and social support. The federated XGBoost model demonstrated strong predictive performance in the independent test sample, achieving an area under the receiver operating characteristic curve of .906, an area under the precision–recall curve of .756, balanced accuracy of .848, sensitivity of .844, and specificity of .851. Its performance was statistically comparable to that of the centralized XGBoost benchmark and superior to both independently trained local XGBoost models and federated logistic regression. Feature-importance analysis further showed that academic workload was the most influential predictor, followed by global sleep quality, recurrent bullying victimization, family support, sleep duration, cyberbullying, and friend support. The findings therefore support the value of integrating educational, interpersonal, behavioral, and protective factors within a nonlinear predictive framework while retaining sensitive student data within participating schools.

The pronounced difference in academic workload between students with and without high psychological distress indicates that educational demands were central to the emotional difficulties identified in this sample. Students in the high-distress group reported greater assignment volume, examination pressure, deadline congestion, insufficient recovery time, and perceived inability to meet academic expectations. This finding is consistent with ecological evidence showing that educational stress is a major correlate of adolescent psychological distress and that its effects should be considered alongside peer victimization and health-related behaviors (Al-Mamun et al., 2026). It also aligns with research identifying academic pressure, uncertainty, and cumulative educational demands as important contributors to mental health problems among students (Gull et al., 2025; Limone & Toto, 2022). The

nonlinear importance pattern observed in the present study is particularly informative. Predicted distress increased progressively at lower workload levels but rose more sharply when workload scores exceeded approximately 3.6, suggesting that academic demands may become especially harmful after students perceive that their coping capacity has been exceeded.

This pattern can be interpreted through a cumulative stress perspective. Academic workload may not be harmful solely because of the number of tasks students must complete, but because it reduces time available for sleep, recreation, physical activity, social contact, and emotional recovery. Similar mechanisms have been described in high-demand occupational contexts, where persistent workload, organizational pressure, and inadequate recovery contribute to psychological strain and burnout (Ram & Alharbi, 2025; Yang et al., 2025). Reviews of teacher and veterinarian mental health likewise emphasize that chronic demands become particularly damaging when individuals lack control, support, or opportunities for recovery (Ghasemi, 2025; Steffey, Griffon, Risselada, Buote, et al., 2023; Steffey, Griffon, Risselada, Scharf, et al., 2023). Although adolescents differ from adult professionals, the underlying imbalance between demands and available resources may be comparable. The present results extend this reasoning to upper secondary students by showing that workload was not merely associated with distress at the group level but also contributed more predictive information than any other individual variable.

Sleep quality produced the largest standardized difference between the high-distress and non-distressed groups and was the second most influential predictor in the federated model. Students with high distress reported longer sleep latency, shorter sleep duration, more frequent sleep disturbances, greater daytime dysfunction, and larger discrepancies between school-day and non-school-day sleep schedules. This finding is consistent with evidence that sleep disruption is strongly associated with impaired psychological functioning and reduced quality of life in student populations (Nagabhushan et al., 2026). It also corresponds with longitudinal research indicating that insomnia and depressive symptoms may develop together and reinforce one another across adolescence (Cheng et al., 2025). Sleep difficulty may therefore function both as an expression of existing distress and as a mechanism that increases vulnerability to further emotional deterioration.

Several processes may explain the strong predictive role of sleep. Inadequate or fragmented sleep can impair

emotional regulation, concentration, impulse control, and stress tolerance, making students more reactive to academic pressure and interpersonal conflict. At the same time, worry about school performance, bullying experiences, and social rejection may increase cognitive arousal at night and delay sleep onset. The observed interaction between workload and sleep quality supports this reciprocal interpretation. High workload was associated with elevated distress, but its effect became substantially stronger among students with poor sleep. This result is consistent with evidence linking sleep difficulties with academic impairment through psychological distress, loneliness, and related behavioral factors (Chung, 2025). It also reflects findings that peer victimization can contribute to poor sleep through emotional and behavioral pathways (Wang et al., 2025; Wu et al., 2025). Thus, sleep appears to operate as both an independent predictor and an amplifier of other school-related risks.

Bullying victimization was another major predictor of psychological distress. Students in the high-distress group reported more than twice the mean bullying score of those without high distress, and recurrently victimized students had substantially greater odds of meeting the high-distress criterion. This finding aligns with a broad literature documenting the emotional consequences of repeated peer aggression across childhood, adolescence, and higher education (Abbasi et al., 2023; Ghofur et al., 2022; Sari, 2023). Population-based studies have shown that both traditional and cyberbullying are associated with poorer emotional wellbeing (Halliday et al., 2022), while other research has linked bullying to sadness, sleep problems, and suicidal ideation through direct and indirect pathways (Sutter et al., 2022). The present study reinforces these findings by demonstrating that recurrent bullying remained one of the most influential predictors even when academic workload, sleep, support, and demographic variables were considered simultaneously.

The importance of cyberbullying in the model also deserves attention. Digital victimization accounted for additional predictive information beyond recurrent bullying as a general category. Cyberbullying can extend exposure beyond the physical boundaries of school, increase audience size, preserve humiliating content, and reduce opportunities for victims to disengage from aggression. Research on adolescent cyberincivility has identified exclusion, hostile communication, impersonation, and reputational harm as common experiences with potentially serious psychological consequences (Kim et al., 2023). Cyberbullying has also been associated with anxiety, depressive symptoms, social

withdrawal, and reduced emotional wellbeing (Hafizi, 2024). Changes in adolescent social behavior under conditions of intensive social-media use may further increase opportunities for social comparison, public judgment, and repeated peer surveillance (Shi, 2024). The current results therefore support assessing digital and face-to-face victimization separately rather than treating bullying as a single undifferentiated construct.

The model identified a particularly strong interaction between bullying and sleep quality. Students exposed to recurrent victimization and poor sleep received markedly higher predicted probabilities of distress than students exposed to either factor alone. This pattern is consistent with studies showing that bullying can disturb sleep directly and indirectly (Wang et al., 2025; Wu et al., 2025). Repeated victimization may produce nighttime rumination, vigilance, fear of future encounters, or continued exposure through digital communication. Poor sleep may then weaken emotional control and increase the subjective impact of subsequent bullying. The interaction therefore suggests a self-reinforcing cycle in which victimization disrupts sleep and sleep loss reduces resilience to victimization-related stress. Similar multi-pathway effects have been identified in research linking bullying with depressive symptoms, problematic internet use, and broader health impairment (Mei et al., 2021; Pang et al., 2026; Song et al., 2025).

Perceived social support showed a strong inverse relationship with psychological distress. Students with high distress reported substantially lower family, friend, and overall support than their peers without high distress. Family support was the fourth most influential model feature, and friend support also contributed meaningfully. These findings agree with research showing that support from family and peers may reduce the impact of victimization on adolescent insomnia and psychological functioning (Hu et al., 2025). They are also consistent with longitudinal evidence indicating that perceived social support can mediate associations among social identity, peer victimization, and sleep quality (Kwon et al., 2025). Supportive relationships may reduce distress by providing emotional validation, practical help, protection from isolation, and encouragement to seek assistance.

The interaction between bullying and social support further clarifies this protective function. Students exposed to recurrent bullying but reporting stronger family or friend support had lower predicted distress than similarly victimized students with weak support. However, support did not completely eliminate the increased risk associated

with repeated victimization. This finding is compatible with strength-based resilience models, which emphasize supportive relationships, empowerment, healthy environments, and coping resources as buffers against bullying-related harm (Dailey & Roche, 2025). It also supports evidence that resilience can moderate the consequences of bullying without necessarily removing them entirely (Pang et al., 2026). Schools should therefore avoid interpreting support as a substitute for preventing victimization. Protective relationships may reduce harm, but they cannot justify leaving persistent bullying unaddressed.

The superior performance of federated XGBoost relative to federated logistic regression suggests that psychological distress was predicted through nonlinear and interactive relationships that could not be fully represented by a conventional additive model. This is consistent with the conceptual complexity of adolescent mental health, which is shaped by interacting personal, educational, behavioral, and social influences (Lin & Guo, 2024). The model captured thresholds in workload and sleep quality, as well as interactions among workload, sleep, bullying, and support. Such findings are difficult to represent adequately through models that assume linearity and independent predictor effects. The relatively small contribution of demographic factors further indicated that prediction was driven mainly by modifiable experiences rather than fixed background characteristics.

The federated model also performed nearly as well as the centralized XGBoost benchmark. The difference in AUROC was only .007 and was not statistically significant. This result is important because it demonstrates that privacy-preserving collaboration across schools did not impose a substantial predictive penalty. At the same time, the federated model clearly outperformed models trained independently at each school. The improvement likely occurred because federated learning allowed the algorithm to benefit from a larger and more heterogeneous population while preserving local control of student records. The leave-one-school-out results further showed that performance remained stable when the model was evaluated in schools that had not contributed data during the relevant training iteration. This supports the potential transportability of the approach across educational settings with different student compositions and local conditions.

The strong negative predictive value of .944 is particularly relevant for school-based screening. The model was highly effective at identifying students unlikely to meet the high-distress criterion, while sensitivity of .844 indicated

that most high-distress cases were detected. Nevertheless, the positive predictive value of .650 means that the model should not be interpreted as a diagnostic instrument. Approximately one third of students classified as high risk did not meet the predetermined distress threshold. These students may still have experienced subthreshold difficulties, but model predictions must be followed by human assessment. The appropriate role of the system is therefore to support screening and prioritize further evaluation rather than to label students, determine treatment, or automate educational decisions.

5. Conclusion

The subgroup findings were generally reassuring because discrimination and calibration were similar across gender, grade level, study program, and migration background. However, the small number of gender-diverse students prevented reliable fairness assessment for that subgroup. This limitation is important given evidence that minority social identities may be associated with differences in victimization, support, and sleep (Kwon et al., 2025). Fairness should therefore be understood as an ongoing evaluation requirement rather than a property established by one analysis. The model's relatively low dependence on demographic features is encouraging, but similar overall accuracy does not guarantee equal consequences when prediction is implemented in real school systems.

6. Limitations & Suggestions

This study had several limitations. Its cross-sectional design prevented causal conclusions about whether workload, bullying, poor sleep, and low support produced psychological distress or whether distressed students perceived and reported these experiences differently. All principal variables were measured through self-report, which may have introduced recall bias, common-method variance, and social-desirability effects. Although the sample included 12 schools from several Norwegian cities, it may not fully represent rural schools, private institutions, students who were absent during data collection, or adolescents who had discontinued education. The binary distress outcome was based on a screening threshold rather than a clinical diagnosis. The centralized comparison model was created only where ethically and legally permissible and should not be interpreted as the preferred operational design. In addition, the feature-importance and Shapley estimates described predictive contributions rather than causal effects.

The relatively small number of students identifying outside binary gender categories limited subgroup evaluation, and unmeasured factors such as family conflict, neurodevelopmental conditions, trauma exposure, personality, physical health, and access to mental health care may also have affected distress.

Future studies should employ longitudinal designs to determine how changes in workload, bullying, sleep, and social support precede changes in psychological distress over time. Repeated assessments across academic terms would help identify periods of heightened risk, such as examination seasons or school transitions. Research should also test the model in rural regions, private schools, lower secondary schools, and educational systems outside Norway. Larger samples of gender-diverse students and other potentially vulnerable groups are required for more reliable fairness analyses. Future models could incorporate passive or minimally invasive indicators such as attendance patterns, sleep timing, or school-calendar intensity, provided that strict consent, data minimization, and governance procedures are maintained. Comparative research should evaluate alternative federated algorithms, differential privacy, secure multiparty computation, and personalized federated learning. Prospective implementation studies are also needed to determine whether model-supported screening improves referral, early intervention, and student outcomes without increasing stigma or unnecessary surveillance.

Schools should use the findings to strengthen coordinated prevention rather than to focus exclusively on individual students. Academic schedules should be reviewed to reduce unnecessary deadline clustering, excessive examination pressure, and insufficient recovery time. Sleep education should be integrated into student health programs and linked with realistic workload management rather than presented only as a matter of personal responsibility. Schools should establish confidential and accessible procedures for reporting both traditional and cyberbullying, followed by timely investigation and support. Family, peer, counseling, and teacher support systems should be strengthened, especially for students exposed to repeated victimization or persistent academic strain. Any predictive model should function only as an aid to trained professionals, with transparent governance, informed consent, restricted access, regular bias audits, and clear prohibitions against disciplinary or academic use. Students identified as potentially at risk should receive a confidential, supportive human assessment before any action is taken.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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