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Development and Validation of an AI-Based Decision Support Framework for Optimizing Financial Assistance Allocation in Higher Education

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ABSTRACT

This paper presents an artificial intelligence (AI)-based decision support framework for optimising financial assistance allocation in higher education institutions, with the aim of improving student mental health and well-being. A dataset comprising 5,000 students from various academic programmes was developed, with approximately 15% of the students identified as financially vulnerable and at risk of mental health disorders. Two AI-based models, namely Extreme Gradient Boosting (XGBoost) and Multilayer Perceptron (MLP), were employed for predictive analysis and financial assistance estimation. The results demonstrated that XGBoost outperformed MLP in predictive accuracy, achieving an accuracy of 94.8% and a receiver operating characteristic area under the curve (ROC-AUC) of 0.96, while MLP demonstrated a greater capacity to capture complex nonlinear relationships. The proposed framework estimated an annual institutional financial assistance expenditure of approximately USD 1.06 million, corresponding to an average allocation of USD 1,417 per supported student. The findings highlight the potential importance of targeted financial assistance, including tuition fee subsidies, living allowances, and emergency grants, alongside counselling services, in supporting student well-being, academic continuity, and retention. Overall, the proposed AI-based framework provides a data-driven approach that integrates mental health risk assessment with financial aid decision-making, offering higher education institutions a systematic mechanism for identifying vulnerable students and prioritising financial assistance according to their needs.

1. Introduction

Mental health difficulties among students in higher education institutions present significant challenges to institutional support services, academic continuity, and resource allocation. Previous studies have investigated the prevalence of psychological distress, barriers to seeking professional assistance, and the relationship between student mental health, well-being, and academic experiences [1–5]. Computational approaches incorporating artificial intelligence (AI) have also been

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explored to estimate the economic burden associated with mental health conditions, providing a relevant foundation for integrating institutional resource planning with analytical decision-support systems [6]. Furthermore, existing research emphasises the importance of coordinated institutional responses to address students' mental health needs and promote their overall well-being [7].

Despite these developments, there remains a need for effective decision-support frameworks that systematically address the interconnected challenges of student mental health, financial vulnerability, and institutional resource allocation. Such frameworks must clearly demonstrate how available student information can be transformed into reliable predictions and transparent estimates of financial assistance requirements. Previous studies have examined the relationships between mental health conditions, academic achievement, financial difficulties, and basic-needs insecurity among higher education students [8–14]. Collectively, these investigations highlight the relevance of socioeconomic and academic factors in identifying students who may require additional institutional support. However, the associations reported in these studies do not independently establish that specific financial interventions directly improve student mental health or academic outcomes.

From a predictive modelling perspective, psychological distress, financial vulnerability, eligibility for institutional assistance, and actual financial expenditure represent distinct but potentially interrelated outcomes. Distinguishing among these variables is essential when developing an AI-based framework that integrates student risk classification with financial assistance estimation. A well-structured framework should therefore differentiate between predicting students' vulnerability, determining their eligibility for support, and estimating the financial resources required to address their identified needs. This distinction is necessary to improve the interpretability, reliability, and practical applicability of AI-assisted institutional decision-making.

Recent advances in computational psychological assessment and AI-based machine learning techniques have expanded opportunities to analyse multidimensional student information and identify complex relationships among psychological, socioeconomic, and academic variables [15, 16]. Previous research on AI applications in higher education, particularly in relation to student mental health and well-being, provides a broader methodological foundation for developing predictive and decision-support systems [18–20, 23]. In addition, studies addressing AI implementation and institutional policy highlight the importance of appropriate governance structures, transparent decision-making procedures, and effective implementation strategies when integrating intelligent technologies into educational environments [21, 22].

From a theoretical perspective, human capital theory, the social determinants of health, and behavioural decision theory offer complementary explanations for understanding the relationships among socioeconomic circumstances, educational investment, psychological well-being, and decision-making under uncertainty [24–27]. Integrating these theoretical perspectives with AI-based predictive modelling provides a foundation for examining how student vulnerability can be identified and how institutional financial assistance may be allocated more systematically. Such an approach supports the development of data-driven decision-support frameworks that combine mental health risk assessment, financial vulnerability analysis, and resource allocation planning while recognising the distinction between predicted support needs and empirically demonstrated intervention outcomes.

Early research involving student-generated data demonstrated the potential of behavioural information for investigating psychological well-being and educational outcomes. Wang et al. [28] introduced the StudentLife study, which examined relationships between smartphone-derived behavioural observations and students' mental health. Subsequent research developed machine learning approaches using annual student health surveys, distinguishing between the prediction of mental health difficulties within the same year and the prediction of problems occurring in

subsequent years. Other studies compared predictive algorithms, including sparse logistic regression, support vector machines (SVM), and random forests, using individual and family characteristics, with hyperparameter optimisation employed to improve model performance [29, 30]. Collectively, these investigations demonstrate that the effectiveness of student-risk prediction depends on the observation period, the availability of relevant predictors, and the timing of the prediction.

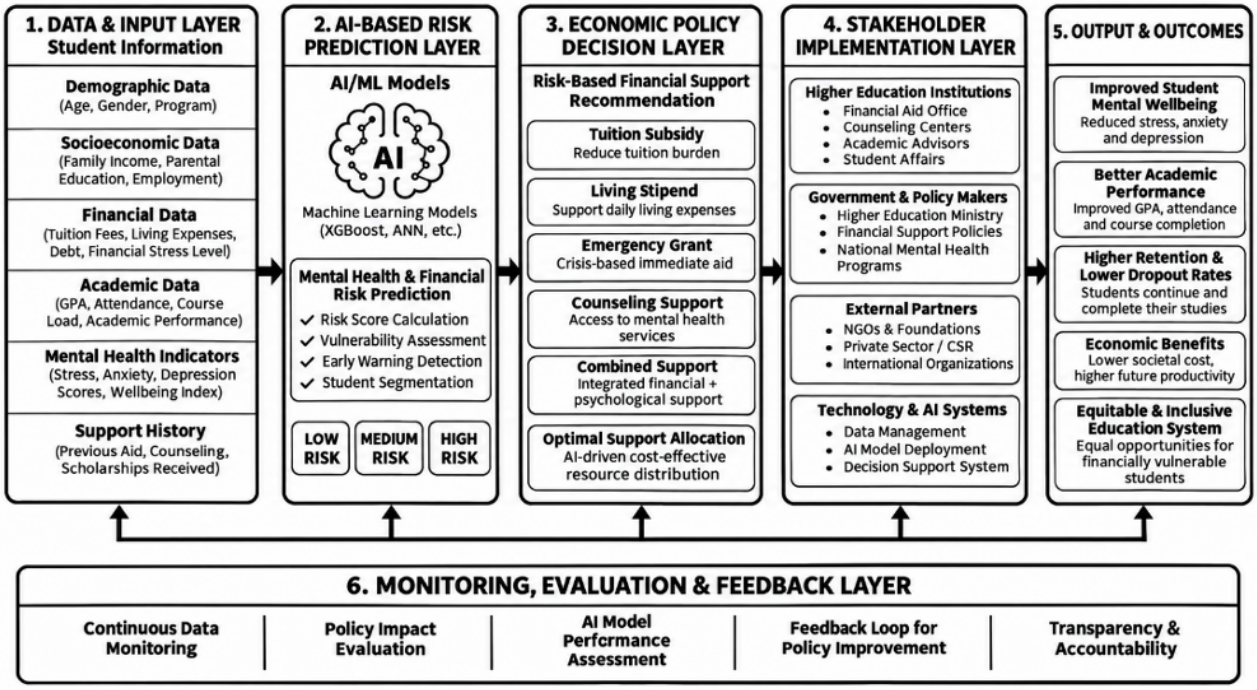


Fig. 1. Proposed AI-Based Decision Support Framework for Student Mental Health Risk Prediction and Institutional Policy Implementation

Beyond mental health assessment, educational predictive analytics has increasingly addressed student retention and dropout risks through AI-based modelling techniques. Previous studies have applied machine learning algorithms to retention management and examined how the characteristics and quality of institutional datasets influence predictive performance. Other investigations have explored student dropout prediction using institutional academic records, demonstrating the potential value of routinely collected educational information for identifying students at risk of discontinuing their studies [31, 32]. Romero and Liao [33] further investigated university dropout and scholarship receipt using statistical and machine learning models, establishing a connection between educational prediction and financial assistance considerations. These contributions support the incorporation of academic and socioeconomic variables into institutional decision-support systems. Nevertheless, predictive performance should be distinguished from empirical evidence demonstrating the effectiveness of interventions implemented on the basis of model predictions.

Drawing on these previous investigations, the proposed AI-based decision-support framework is presented in Figure 1. The framework integrates several interrelated research areas, including student mental health, financial stress, financial assistance policies, AI-based prediction, and institutional AI policy development. The theoretical and methodological foundations supporting these components are summarised in Table 1.

Table 1
Key Research Areas and Supporting References for the Proposed AI-Based Student Support Framework

Key research area	Supporting references
Student mental health	[1, 6]
Financial stress	[9, 12]
Financial support policy	[13, 14]
AI-based prediction	[15, 16]
AI policy framework	[21–23]

The application of AI-based algorithms to healthcare expenditure prediction provides a relevant methodological foundation for integrating predictive analytics with institutional resource planning. Previous studies have reviewed and empirically compared supervised machine learning approaches for estimating healthcare expenditure, demonstrating that predictive performance may vary across different expenditure groups [34, 35]. Other investigations have developed neural network models for predicting annual population healthcare costs using insurance records and proposed two-stage super learner approaches that separately estimate the probability of expenditure and the expected expenditure amount conditional on expenditure occurring [36, 37]. Although these studies do not provide direct evidence regarding the effectiveness of university financial assistance, they offer transferable modelling principles for defining monetary prediction targets, addressing heterogeneous expenditure distributions, and validating predicted costs against observed expenditure.

The present study employs Extreme Gradient Boosting (XGBoost) and Multilayer Perceptron (MLP) models as complementary approaches to predictive analysis using structured student data. XGBoost is a regularised ensemble learning algorithm that combines boosted decision trees to capture complex nonlinear relationships and interactions among predictor variables [38]. In contrast, MLP is an artificial neural network architecture that learns hierarchical representations through interconnected layers using backpropagation. Regularisation techniques, including dropout, can be employed to reduce overfitting and improve the generalisation of neural network models [39, 40]. Both XGBoost and MLP are capable of modelling nonlinear associations, although their relative predictive performance depends on dataset characteristics, feature distributions, model configurations, and training procedures. Consequently, their comparative effectiveness must be established empirically using consistent evaluation datasets and performance metrics rather than inferred solely from their architectural differences. Although MLP can capture complex nonlinear relationships through its hidden layers, this characteristic does not necessarily guarantee superior predictive performance.

Reliable AI model development also requires careful consideration of data preprocessing, class imbalance, feature selection, and probability calibration. The Synthetic Minority Over-sampling Technique (SMOTE) provides a mechanism for generating synthetic minority-class observations to address imbalanced classification datasets, while feature selection techniques help identify informative predictors and reduce unnecessary redundancy [41, 42]. To minimise data leakage and ensure unbiased performance estimation, preprocessing procedures, including resampling, feature selection, and feature scaling, should be fitted exclusively within the training partitions and subsequently applied to validation or test data. Furthermore, classification accuracy and probability calibration represent distinct dimensions of predictive performance. This distinction is particularly important when estimated risk probabilities are used to inform institutional financial assistance planning. Explainable AI techniques, such as SHapley Additive exPlanations (SHAP), can further

support model interpretability by quantifying the contributions of individual features to specific predictions, although these explanations should not be interpreted as evidence of causal relationships [43, 44].

Fairness and rigorous validation are equally important when AI-generated predictions inform institutional resource allocation. Previous research has demonstrated that historical healthcare expenditure may represent a biased proxy for underlying healthcare needs when access to services differs across population groups. Similarly, historical financial assistance records may reflect institutional eligibility rules, administrative decisions, or budgetary constraints rather than the full extent of students' financial vulnerability [45]. Previous methodological studies have also highlighted the importance of precision–recall analysis for evaluating classification models with imbalanced datasets and the risk of overly optimistic performance estimates when model selection and performance evaluation are not adequately separated [46]. These findings emphasise the need to assess predictive discrimination, probability calibration, subgroup-level errors, and monetary estimation accuracy through a clearly documented validation procedure.

Building on these theoretical and methodological foundations, the present study investigates an AI-based decision-support framework that integrates student mental health risk prediction with annual financial assistance estimation. The proposed five-layer framework for student risk prediction and institutional resource planning is illustrated in Figure 2. Using a dataset comprising 5,000 students, the study compares the predictive performance of XGBoost and MLP and translates estimated student-level financial assistance requirements into projected annual institutional expenditure. Specifically, the study examines the accuracy of AI-based models in identifying students who meet the specified risk criteria and evaluates the potential usefulness of financial assistance estimates for institutional budget planning and resource allocation. Through this integrated approach, the proposed framework aims to support transparent, evidence-informed decision-making while distinguishing predictive model performance from the actual effectiveness of financial support interventions.

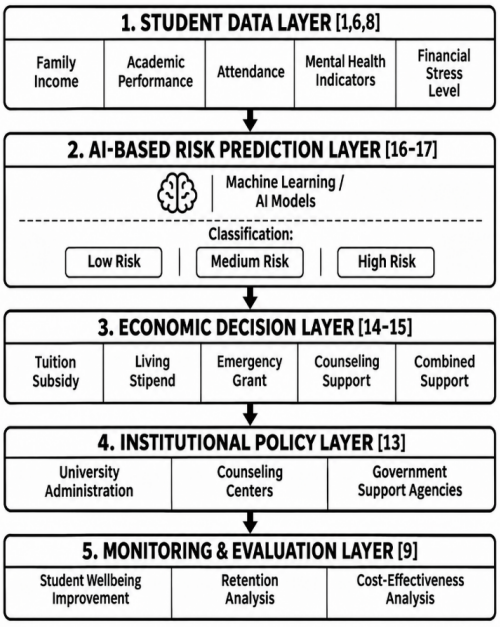


Fig. 2. Five-layer AI-based decision support framework for student risk prediction

2. Dataset and Methodology

A dataset comprising 5,000 higher education students was developed using data augmentation techniques. Approximately 15% of the students in the dataset were classified as being at risk of mental health disorders. The dataset included students from various academic programmes, including Engineering, Health Sciences, Business Education, Applied Sciences, Arts and Social Sciences, and Information Technology. This multidisciplinary representation provided a basis for examining student mental health risks across different academic disciplines and evaluating the applicability of the proposed AI-based predictive framework.

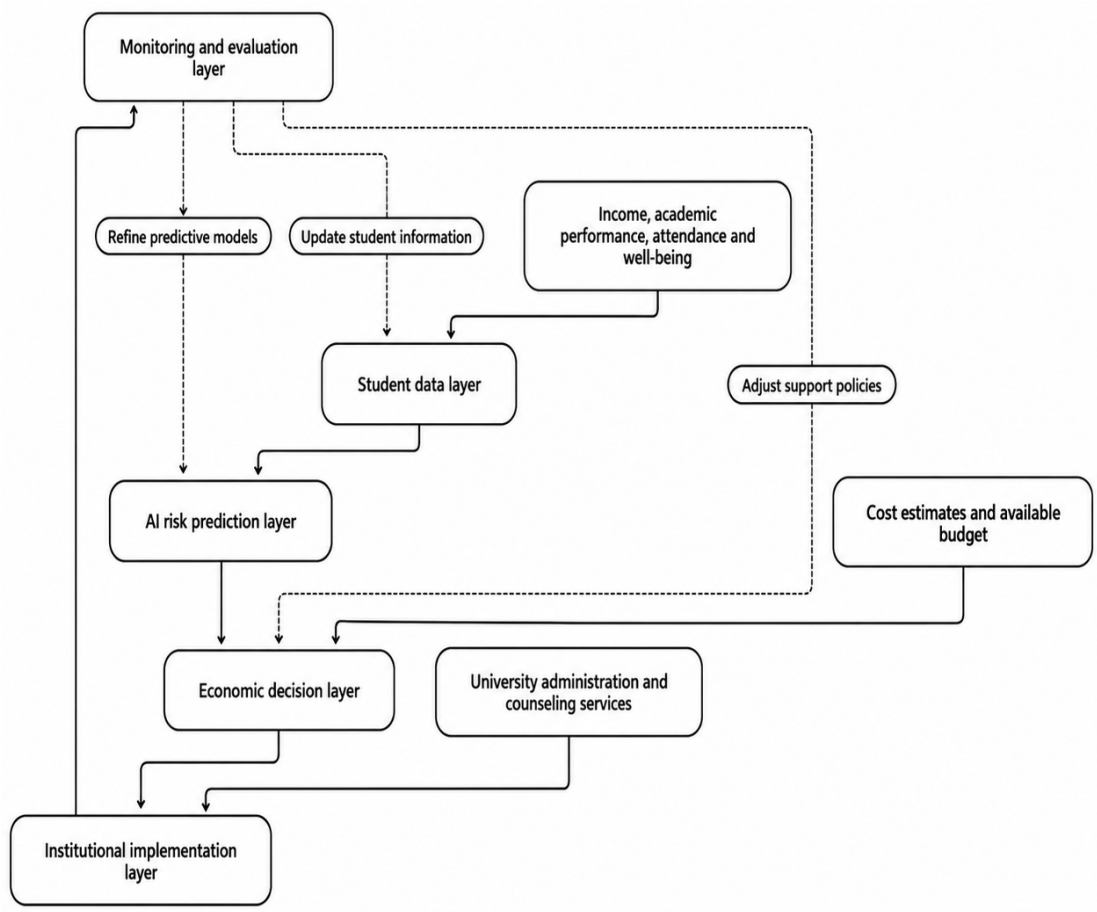


Fig. 3. Data pipeline design and five-layer architecture integrating student information, predictive analytics, financial decisions and institutional implementation

The key variables included in the dataset were gender, income classification, mental health scores, academic performance, attendance records, financial stress levels, and types of financial assistance. These variables were incorporated into the proposed AI-based framework to support student mental health risk prediction and financial assistance estimation. The data processing pipeline and the proposed five-layer architecture, which integrate student information, financial assistance decision-making, and institutional policy implementation, are illustrated in Figure 3.

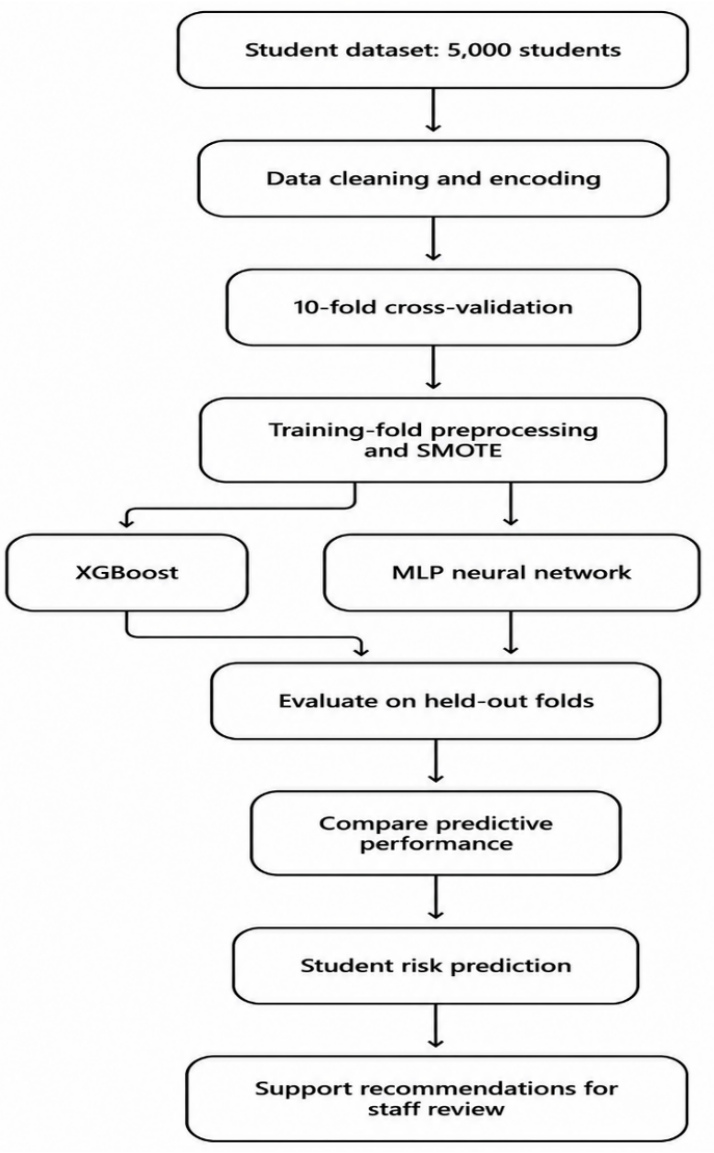


Fig. 4. AI-based decision-support workflow

The proposed data processing pipeline comprised sequential stages of data acquisition, preprocessing, AI model training, predictive analysis, financial assistance decision-making, and cost estimation. During preprocessing, data cleaning procedures were applied to identify and address missing values, inconsistent observations, and outliers. Feature normalisation and label encoding were subsequently performed to improve model stability, computational efficiency, and compatibility with machine learning algorithms. The study developed an AI-based decision-support framework to optimise financial assistance allocation in higher education institutions, with the broader objective of supporting student mental health and well-being through targeted financial assistance mechanisms. The overall AI-based decision-support workflow is illustrated in Figure 4.

To address class imbalance in the identification of students at risk of mental health disorders, the Synthetic Minority Over-sampling Technique (SMOTE) and balanced sampling strategies were implemented. Two AI-based predictive models, namely Extreme Gradient Boosting (XGBoost) and an artificial neural network based on the Multilayer Perceptron (MLP) architecture, were incorporated

into the proposed framework. XGBoost was employed for structured-data classification and feature importance analysis, while the MLP model was designed to capture complex nonlinear relationships among the input variables. The MLP architecture comprised an input layer, two hidden layers with Rectified Linear Unit (ReLU) activation functions, dropout regularisation layers, and a sigmoid output layer for binary mental health risk classification.

The proposed system workflow integrated student data acquisition, preprocessing, model training, risk prediction, financial assistance recommendation, and subsequent monitoring and evaluation. The model development process incorporated 10-fold cross-validation, L2 regularisation, early stopping, and dropout techniques to minimise overfitting and improve generalisation performance. Classification performance was evaluated using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). Meanwhile, regression-based financial assistance estimation was assessed using mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2).

Computational complexity analysis indicated that XGBoost required lower training costs and shorter execution times than the MLP model under the evaluated configurations. The MLP architecture, however, provided the capacity to learn complex nonlinear patterns through its interconnected hidden layers. Furthermore, annual financial assistance requirements, average expenditure per supported student, and variations across academic programmes, gender groups, and income categories were analysed to support institutional resource planning, financial assistance allocation, and policy-level decision-making.

3. Development of the AI Framework for Predictive Analysis and Financial Support Estimation

Building on the dataset characteristics, preprocessing procedures, and model architectures described in the preceding section, the proposed AI-based framework integrates predictive modelling with financial assistance estimation and institutional decision-making. Within this framework, XGBoost and MLP serve as alternative modelling approaches for identifying relationships between student characteristics and the specified prediction outcomes. XGBoost captures complex relationships through an ensemble of boosted decision trees [38], whereas MLP learns hierarchical representations through interconnected neural network layers using backpropagation [39].

The predictive outputs were differentiated according to the objectives of the respective modelling tasks. For mental health risk classification, the models estimated the probability of students belonging to the specified risk category. In contrast, financial assistance estimation required regression-based predictions of monetary support amounts. Accordingly, the sigmoid activation function was applied to the output layer of the MLP classification model, while financial cost prediction required a separate regression configuration incorporating an appropriate continuous output layer and loss function. This distinction ensured that the model architectures were aligned with their respective classification and regression objectives.

The final hyperparameter configurations for both model families should be documented to ensure methodological transparency and reproducibility. The integration of predictive analysis with financial assistance estimation also depends on the availability and reliability of financial reference data. Where observed annual financial assistance amounts are available, regression models can be developed to estimate expenditure using historical financial records. Alternatively, a two-part modelling approach may be employed to estimate separately the probability of receiving financial assistance and the expected monetary amount conditional on receiving support [37]. Such an approach provides a methodological basis for distinguishing financial assistance eligibility from the estimated level of institutional expenditure.

To ensure reliable model evaluation, particular attention must be given to preventing information leakage throughout the data processing and model development stages. Predictor variables should include only information available before the intended assessment or financial assistance decision. Variables directly used to construct the target outcome should not simultaneously be treated as independent predictors of that outcome. For example, a mental health score used to define a mental health risk category should not be included as an independent predictor when evaluating the model's ability to classify that same category. Similarly, financial assistance types assigned after eligibility assessment should not be incorporated as predictors of the preceding eligibility decision.

Because the dataset includes augmented student records, additional validation safeguards are necessary to prevent artificially inflated predictive performance. Records derived from the same original student should remain within the same training or validation partition, and data augmentation procedures should be restricted to the training data. These measures are essential for maintaining independence between model development and evaluation datasets, reducing the risk of data leakage, and ensuring that reported predictive performance reflects the models' generalisation capabilities rather than similarities introduced through data augmentation.

The performance of the proposed AI-based framework was evaluated using regression metrics to assess the accuracy of annual student financial support cost predictions. Mathematical formulations were also developed to estimate institutional budget requirements and quantify differences between predicted and observed expenditure.

Let c_i denote the observed annual financial support cost for student i, $\hat{c}_i$ represent the corresponding predicted cost, and *n* denote the total number of students in the evaluation dataset. The mean observed annual cost is defined as:

$$\overline{c} = n^{-1} \sum_{i=1}^{n} c_i$$

Mean Absolute Error (MAE)

MAE measures the average absolute difference between observed and predicted financial support costs, providing an indication of the typical magnitude of prediction errors.

$$\overline{c} = n^{-1} \sum_{i=1}^{n} c_i$$

Root Mean Squared Error (RMSE)

RMSE measures the square root of the average squared prediction errors, assigning greater weight to larger deviations between predicted and observed costs.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(c_i - \hat{c}_i)^2}$$

Coefficient of Determination (R^2)

The coefficient of determination evaluates the proportion of variation in observed financial support costs explained by the predictive model relative to a baseline based on the mean observed cost.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(c_i - \hat{c}_i)^2}{\sum_{i=1}^{n}(c_i - \overline{c})^2}$$

This formulation requires variation in the observed financial support costs to ensure that the denominator is nonzero.

Residuals and Mean Prediction Bias

Residuals represent the differences between observed and predicted financial support costs. The mean residual provides an indication of systematic prediction bias.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(c_i - \hat{c}_i)^2}{\sum_{i=1}^{n}(c_i - \overline{c})^2}$$

Annual Institutional Expenditure

For a defined population of supported students, denoted by *S*, with $N_S = |S|$), the predicted and observed annual institutional expenditures are calculated as follows:

$$\hat{B} = \sum_{i \in S} \hat{c}_i\,, \qquad B = \sum_{i \in S} c_i$$

Here, $\hat{B}$ represents the predicted annual institutional budget, while *B* denotes the observed reference expenditure for the same student population and financial year.

Aggregate Expenditure Error

The aggregate expenditure error measures the difference between predicted and observed institutional expenditure. The absolute expenditure error represents the magnitude of this difference.

$$E_B = \hat{B} - B, \qquad \mathrm{AE}_B = \left|\hat{B} - B\right|$$

The absolute percentage expenditure error is calculated as:

$$\mathrm{APE}_B = \frac{|\hat{B} - B|}{B} \times 100\%, \qquad B > 0$$

A positive value of E_B indicates budget overestimation, whereas a negative value indicates budget underestimation.

Average Annual Financial Support Cost per Student

The predicted average annual financial support cost per supported student is determined by dividing the total predicted institutional expenditure by the number of students receiving assistance.

$$\hat{C}_{\mathrm{avg}} = \frac{\hat{B}}{N_S} = \frac{1}{N_S}\sum_{i \in S} \hat{c}_i\,, \qquad N_S > 0$$

For the scenario considered in this study, approximately 15% of the 5,000 students were identified as requiring financial assistance associated with mental health vulnerability. Accordingly, the estimated number of supported students was:

$$N_S = 0.15 \times 5{,}000 = 750$$

Based on an estimated average annual financial support allocation of USD 1,417 per student, the total projected institutional expenditure was calculated as:

$$\hat{B} = 750 \times 1{,}417 = \text{USD } 1{,}062{,}750 \text{ per year}$$

This corresponds to an estimated annual institutional financial assistance budget of approximately USD 1.06 million, with an average allocation of USD 1,417 per supported student.

The decision-support component integrates student-level risk predictions and estimated financial assistance requirements to facilitate institutional review and resource allocation planning. Explainable AI techniques, particularly SHapley Additive exPlanations (SHAP), may be incorporated to identify the relative contributions of individual predictor variables to model-generated predictions [44, 45]. Such explanations can improve model transparency and support institutional decision-making, although they do not establish causal relationships between predictor variables and student outcomes.

Overall, the proposed framework provides a systematic approach to integrating predictive analytics with institutional financial assistance planning. However, demonstrating optimised financial resource allocation would require the specification of an explicit optimisation objective, relevant budgetary constraints, and comparative evaluation against alternative allocation strategies.

4. Results and Discussion

The developed AI-based predictive framework demonstrated promising performance in identifying students at risk of mental health difficulties and estimating their associated financial assistance requirements. The framework was designed to integrate student-level risk classification with financial support cost estimation across different academic programmes within higher education institutions.

A comparative performance analysis was conducted using two machine learning models, namely Extreme Gradient Boosting (XGBoost) and Multilayer Perceptron (MLP). The results indicated that XGBoost achieved higher classification performance than MLP across the evaluated metrics. Specifically, XGBoost attained an accuracy of 94.8%, precision of 93.2%, recall of 92.7%, F1-score of 92.9%, and ROC-AUC of 0.96. In comparison, the MLP model achieved an accuracy of 92.6%, precision of 90.7%, recall of 89.8%, F1-score of 90.2%, and ROC-AUC of 0.94.

These findings suggest that XGBoost was more effective than MLP for the evaluated student-risk classification task. The comparatively strong performance of XGBoost may be associated with its ability to capture complex interactions among structured socioeconomic, academic, and mental health-related variables through ensemble decision trees. Meanwhile, the MLP architecture provided a flexible mechanism for representing nonlinear relationships through interconnected hidden layers. Nevertheless, the comparative results indicate that this architectural flexibility did not translate into superior predictive accuracy for the dataset examined.

The regression-based financial assistance cost estimation results further demonstrated differences in predictive performance between the two models. XGBoost achieved an MAE of USD 162.45, RMSE of USD 215.30, and R^2 of 0.92. In comparison, MLP recorded an MAE of USD 186.75, RMSE of USD 245.80, and R^2 of 0.88. The lower MAE and RMSE values obtained by XGBoost indicate smaller prediction errors, while its higher R^2 value suggests better explanatory performance relative to the mean-cost baseline. The comparative classification and regression results are presented in Table 2, while the mathematical formulation and financial allocation workflow are illustrated in Figure 6.

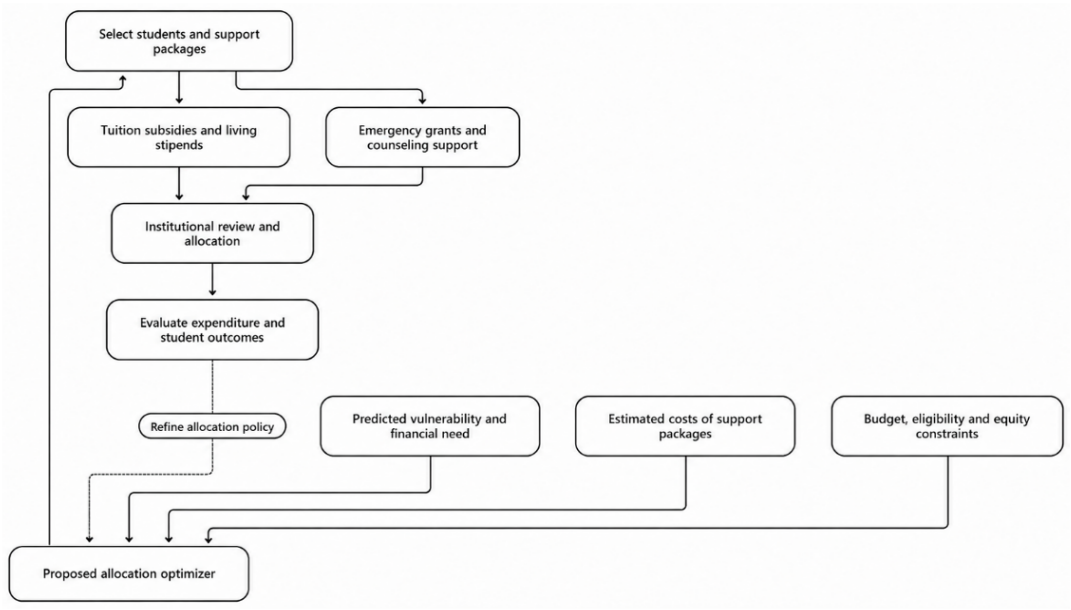
Table 2
Comparative Performance of XGBoost and MLP Models for Student Risk Classification and Financial Support Cost Prediction

Performance metric	XGBoost	MLP
Accuracy	94.80%	92.60%
Precision	93.20%	90.70%
Recall	92.70%	89.80%
F1-score	92.90%	90.20%
ROC-AUC	0.96	0.94
MAE (cost prediction)	USD 162.45	USD 186.75
RMSE (cost prediction)	USD 215.30	USD 245.80
R^2 (cost prediction)	0.92	0.88

The financial assistance cost analysis estimated that approximately 15% of the student population, corresponding to 750 students out of 5,000, required financial support associated with mental health vulnerability. Based on the estimated average annual allocation of USD 1,417 per supported student, the projected annual institutional expenditure was approximately USD 1.06 million. This estimate provides a quantitative basis for institutional budget planning and the assessment of potential financial assistance requirements.

Further analysis of variations across academic programmes indicated that students enrolled in Engineering and Health Sciences exhibited comparatively higher levels of financial stress and mental health risk. The estimated annual financial assistance requirements for students in these programmes ranged from approximately USD 1,495 to USD 1,555 per student, with reported percentage variations of 11–14% relative to other academic programmes. These findings suggest that financial assistance requirements may differ across academic disciplines, highlighting the potential importance of considering programme-specific characteristics when developing institutional support strategies.

The predicted distribution of financial assistance costs across different support categories for the identified 15% of students is illustrated in Figure 7. This analysis provides additional information on the potential allocation of institutional financial resources across different forms of student assistance. By integrating student-risk classification, financial support cost prediction, and programme-level expenditure analysis, the proposed framework offers a data-driven foundation for supporting institutional financial planning and identifying students who may require targeted assistance.



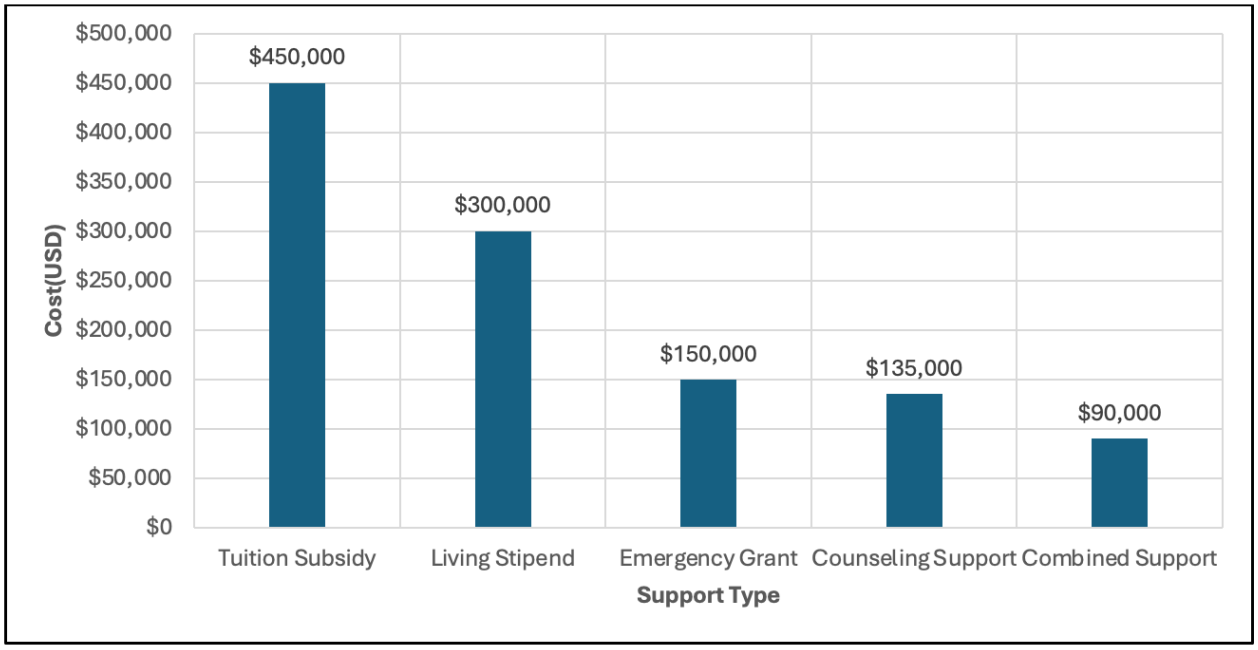
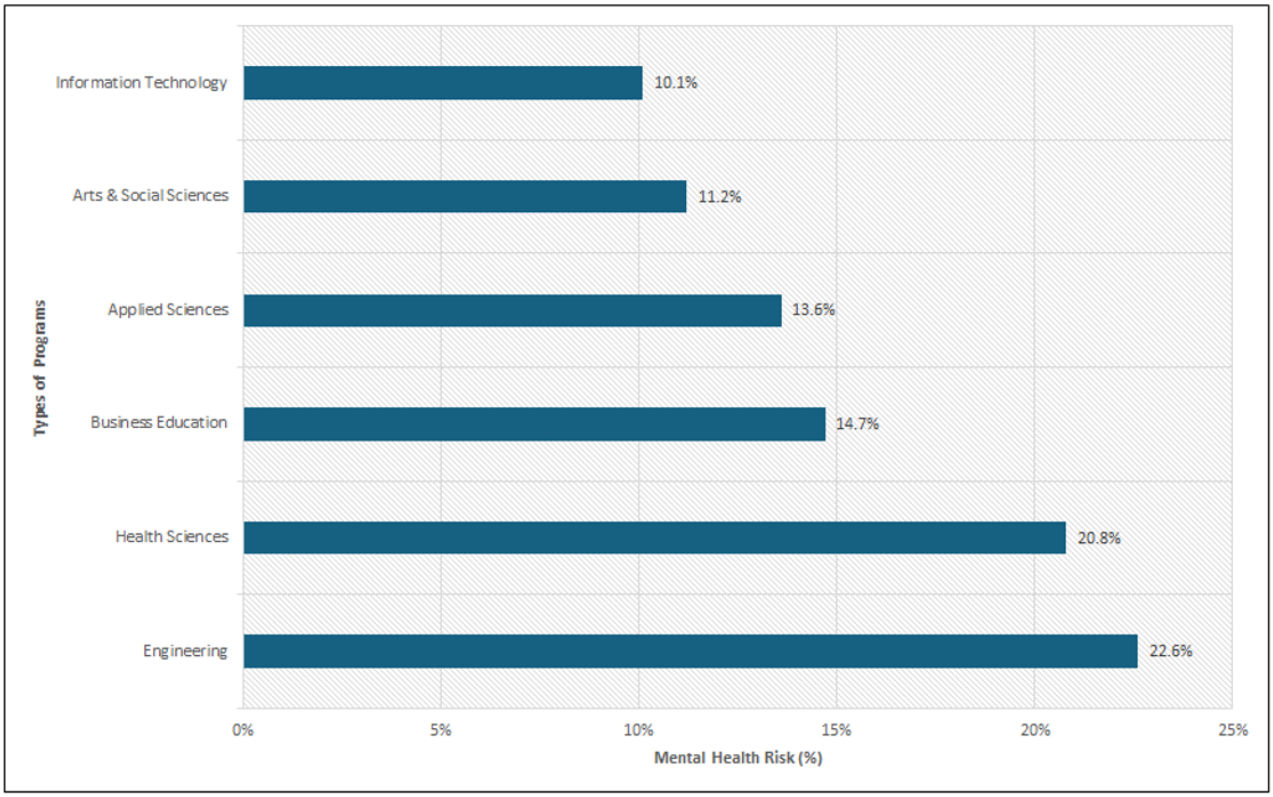


Fig. 6. Mathematical formulation and financial allocation workflow



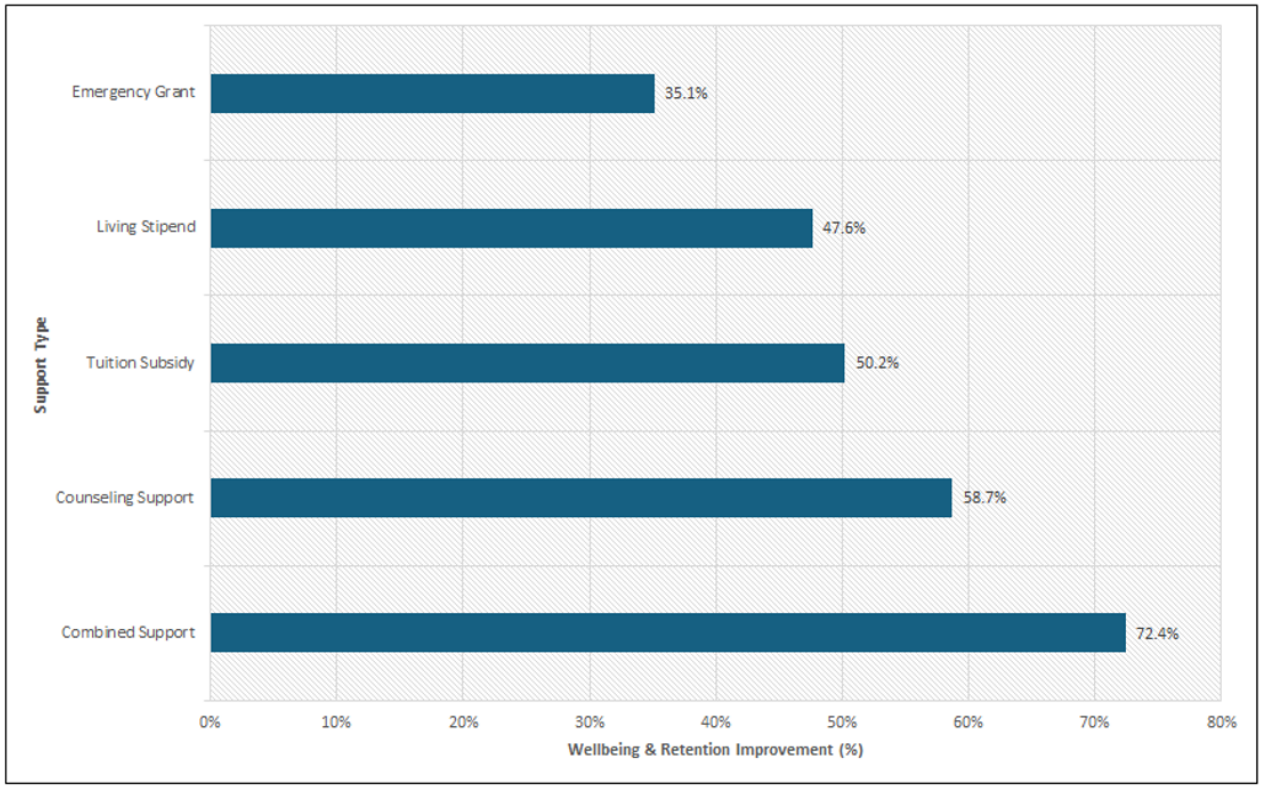


Fig. 7. Percentage of variation with respect to program-wise and support-type

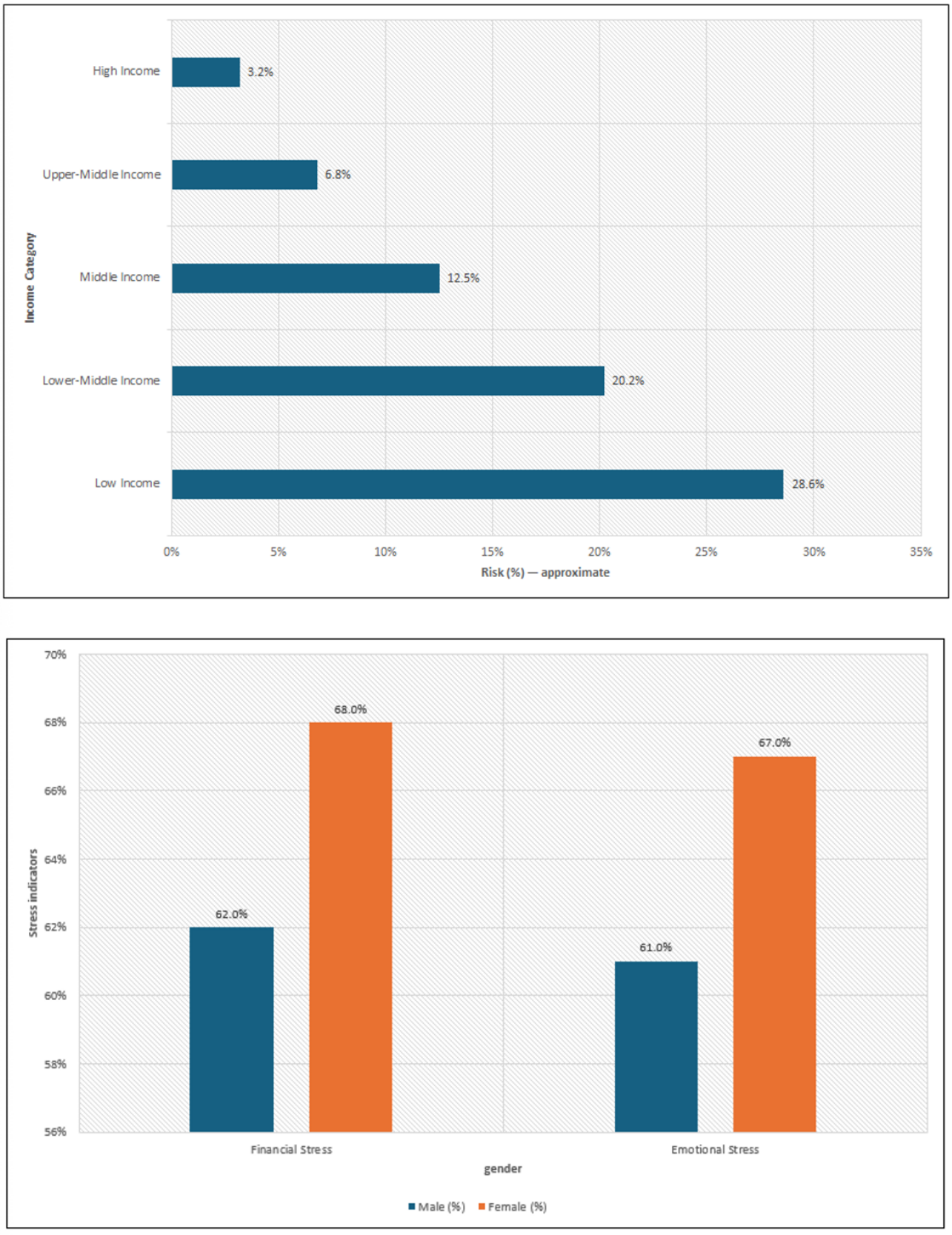


Fig. 8. Percentage of variation with income classification and gender-based variation

In contrast, students enrolled in Arts and Social Sciences exhibited moderate financial assistance requirements, with estimated annual support costs ranging from USD 1,180 to USD 1,205 per

student. These findings indicate variations in financial assistance requirements across academic programmes, suggesting that institutional support strategies may need to account for differences in students' socioeconomic circumstances, academic demands, and financial vulnerability.

The analysis of financial assistance categories revealed substantial differences in the estimated costs associated with various support mechanisms. Combined assistance packages comprising tuition fee subsidies, counselling services, and living stipends were associated with the highest estimated annual expenditure, ranging from USD 2,450 to USD 2,525 per student. These integrated support mechanisms may provide more comprehensive assistance by addressing both financial difficulties and mental health-related needs. Tuition fee subsidy programmes required approximately USD 2,100–2,185 per student annually, whereas emergency grants involved comparatively lower estimated expenditure, averaging USD 980–1,025 per student. The findings highlight the importance of considering the financial implications of different assistance mechanisms when developing institutional support policies.

Income-based analysis further indicated that students from low-income and lower-middle-income households exhibited higher levels of psychological distress and greater dependence on institutional financial assistance. Collectively, these groups accounted for approximately 62% of the total estimated financial support allocation. This finding suggests that socioeconomic vulnerability is an important consideration in identifying students who may require targeted institutional assistance. The distribution of financial support requirements across academic programmes, assistance categories, income classifications, and gender groups is illustrated in Figures 7 and 8.

Gender-based analysis revealed slightly higher emotional stress indicators among female students compared with their male counterparts. The estimated financial assistance requirements for female students were approximately 3–4% higher than those for male students. These differences may reflect variations in reported psychological distress, socioeconomic circumstances, or other factors influencing financial vulnerability. However, further investigation is necessary to determine the underlying factors contributing to these differences and assess their statistical significance.

Overall, the findings demonstrate the potential of integrating AI-based mental health risk prediction with financial assistance estimation to support early identification of vulnerable students and institutional resource planning. Targeted financial assistance may contribute to reducing financial pressures that adversely affect academic continuity, psychological well-being, and student retention. Nevertheless, the extent to which these interventions directly reduce dropout rates or improve mental health outcomes requires further empirical evaluation.

From an economic perspective, preventive financial assistance strategies may help institutions address potential long-term costs associated with student dropout, delayed graduation, and reduced educational attainment. However, quantifying these benefits would require longitudinal evidence and formal cost-effectiveness analysis. The proposed framework provides a structured mechanism for estimating financial assistance requirements and identifying potential differences in resource needs across student populations.

The findings also have implications for institutional policy development. Universities and relevant government agencies may consider integrating AI-based predictive analytics with financial assistance planning to strengthen evidence-informed decision-making. Such integration could facilitate the early identification of students experiencing financial vulnerability, support more transparent assessment of assistance requirements, and improve institutional budget planning. Appropriate governance arrangements, data protection safeguards, and fairness assessments are essential to ensure that AI-assisted decisions remain accountable and equitable.

5. Conclusion and Future Scope

This study investigated the application of an artificial intelligence (AI)-based decision-support framework for integrating student mental health risk prediction with financial assistance estimation in higher education institutions. The findings highlight the relevance of financial vulnerability in understanding student mental health risks, academic challenges, and potential difficulties in maintaining educational continuity.

The proposed framework incorporated two machine learning models, Extreme Gradient Boosting (XGBoost) and Multilayer Perceptron (MLP), to identify students classified as being at risk of mental health difficulties and estimate their financial assistance requirements. The comparative analysis demonstrated that XGBoost achieved superior predictive performance, with an accuracy of 94.8% and an ROC-AUC of 0.96, compared with the MLP model, which achieved an accuracy of 92.6% and an ROC-AUC of 0.94. XGBoost also demonstrated lower financial cost prediction errors, indicating its potential suitability for structured student data analysis and institutional expenditure estimation.

Based on the dataset comprising 5,000 students, approximately 15% were identified as requiring financial assistance associated with mental health vulnerability. The estimated annual institutional expenditure was approximately USD 1.06 million, corresponding to an average financial assistance allocation of USD 1,417 per supported student. Further analysis revealed variations in estimated support requirements across academic programmes, income categories, gender groups, and financial assistance mechanisms. These findings provide a quantitative basis for understanding potential institutional financial commitments and identifying student groups requiring additional support.

The study also highlights the potential relevance of integrated financial assistance mechanisms, including tuition fee subsidies, living stipends, emergency grants, and counselling services, in addressing the interconnected challenges of financial stress and student mental health. Although these interventions may contribute to improved student well-being, academic continuity, and retention, their effectiveness requires further investigation using appropriate longitudinal or intervention-based research designs.

Overall, the proposed AI-based framework provides a systematic, data-driven approach to integrating mental health risk assessment with financial assistance planning in higher education institutions. Its principal contribution lies in combining predictive modelling, financial support cost estimation, and institutional decision-support mechanisms within a unified analytical structure. The framework may assist university administrators and policymakers in identifying financially vulnerable students, estimating potential assistance requirements, and developing more transparent and evidence-informed resource allocation strategies.

Future research should focus on validating the proposed framework using real-world, longitudinal student datasets and assessing its predictive performance across different institutional and socioeconomic contexts. Further development may involve integration with real-time smart campus information systems, incorporating continuously updated academic, financial, and student well-being indicators. Comparative investigations across Gulf Cooperation Council (GCC) countries and other international higher education systems could provide additional insights into the framework's generalisability and institutional applicability.

Future studies should also examine the effectiveness and cost-effectiveness of different financial assistance interventions, incorporate fairness and explainability assessments, and develop explicit optimisation models that account for institutional budget constraints and student support priorities. These developments could contribute to more adaptive, transparent, and equitable AI-assisted financial assistance systems that support sustainable student well-being management across diverse higher education environments.

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