Leveraging Big Data Analytics To Map National-Level Student Engagement Patterns And Predict Success For Policy-Level Labour Course Planning

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Received: Jun. 03, 2026; Accepted: Jul. 29, 2026

The rapid growth of educational data has enabled big data analytics to improve engagement analysis and student success prediction. However, existing approaches primarily focus on prediction accuracy while overlooking engagement patterns and recommendation mechanisms. This research proposes an integrated big data framework to analyse engagement patterns, predict national-level student success and support policy-level labour-course planning. The framework uses OECD Education Global Positioning System (GPS) data and includes data preprocessing, feature extraction, K-means clustering, and an Adaptive Grey Wolf Optimizer (GWO)-based Hybrid Random Forest-Deep Neural Network (RF-DNN) model for feature selection, prediction, and hyperparameter optimization. A rules-based recommender system generates mathematics-focused labour-course recommendations based on predicted success and engagement patterns. Experimental results achieved $R^2 = 0.982$, $MSE = 0.0005$, $RMSE = 0.0225$, and $MAE = 0.0135$, demonstrating high prediction accuracy and low error. The proposed framework provides a scalable solution for engagement analysis, student success prediction, and policy-level course recommendations.

Keywords: Big Data Analytics, Student Engagement, Random Forest, Deep Neural Network, Adaptive Grey Wolf Optimizer, Course Recommendation

http://dx.doi.org/10.6180/jase.202612_35.016

1. Introduction

The rapid growth of educational data has created opportunities for us to learn more about student learning patterns and results in a more structured and scalable way [1]. Academic performance and engagement patterns are crucial factors contributing to student success in higher education, especially in labour courses [2]. Conventional assessment methods do not usually show the joint effects of behavioral and psychological variables like study habits and motivation [3]. As large educational datasets become available, Big Data Analytics helps identify meaningful patterns and improve understanding of student preparedness [4].

Existing methods use statistical techniques such as regression and correlation analysis to evaluate student performance and predict academic success [5]. DT, SVM, RF, and KNN improve prediction, while clustering and DL models identify engagement patterns and complex behaviors [6].

To overcome these issues, the proposed framework integrates preprocessing, feature extraction, clustering, and Adaptive GWO-optimized RF-DNN prediction with an Engagement Index and recommendation module, enabling accurate student success prediction and labour-course recommendations.

Develops an integrated big data analytics framework to investigate national-level engagement patterns and to predict course success in courses based on higher education labour courses.

- Utilize big educational data obtained from the OECD Education GPS to establish comprehensive, large-scale and trustworthy big data for analysis.
- Deploys clustering (K-Means) and feature extraction methods to identify and visualise patterns of national-level student engagement.
- Introduces hybrid predictive model which is a combination of RF, DNN and Adaptive GWO to predict the success of national-level performance analysis and educational recommendations.

The rest of the paper is organized as follows: Section 2 discusses the literature review of previous studies and methods that could be applied in predicting student performance and national-level student engagement. The proposed approach is detailed in Section 3 and includes data preparation, feature extraction, clustering and prediction techniques. The results of the experiment and the performance analysis are presented in Section 4, and Section 5 reveals the most important findings and future research directions.

Recent educational data mining studies have integrated [7] AI and machine learning models with institutional systems to improve student [8] success prediction and academic performance. CNN-SVM-RF-KNN ensemble achieved 93% accuracy but ignored motivation and behavioral student engagement factors. [9] KNN-SVM Hadoop-based framework achieved 87.32% accuracy but increased complexity and failed to capture latent behavioral patterns effectively. Existing studies focus on DL and hybrid methods to enhance the accuracy of prediction and feature representation. [10] proposed an NN-based framework with PCA optimization, achieving better precision and recall than RF/SVM, but limited by small datasets. GNN-TINet for multi-label student performance prediction, achieving 98.5% accuracy but with high complexity and computational cost.

Recent studies integrate optimization algorithms and advanced neural frameworks to improve prediction performance. [11] proposed GRU with POA achieved 97.18% accuracy but relied on VLE data, while COA-WELM improved optimization but lacked behavioral analysis. Existing student performance prediction methods rely on scores and face limitations in engagement analysis, computation, interpretability, clustering, and generalization.

Current models of predicting student performance, like that suggested by [12], rely mainly on academic records and overlook behavioral and psychological factors. The proposed hybrid model improves prediction accuracy by integrating these factors while maintaining computational efficiency.

2. Materials and methods

The big data analytics framework follows the standard data analytics process to analyse country-level educational indicators and predict national-level mathematics performance for policy-level labour-course planning using the OECD Education GPS dataset. The first stage collects key educational indicators, while the second stage preprocesses the data. The third stage extracts features using statistical and correlation analysis. New variables are constructed by combining items, such as the Engagement Index (homework and motivation), Performance Spread (P90 - P10), and Total Low Performers, providing insights into national-level engagement, inequality, and academic performance. The fourth block does engagement pattern mapping with clustering analysis by applying the K-Means algorithm. The clusters are categorized as High, Moderate, and Low Engagement, representing national-level educational engagement patterns across participating countries. The final stages use Adaptive GWO-RF-DNN for prediction and rule-based learning recommendations. Fig. 1. Proposed Adaptive GWO-Optimized Hybrid RF-DNN Framework. The framework shows the workflow from OECD preprocessing to success prediction and course recommendation.

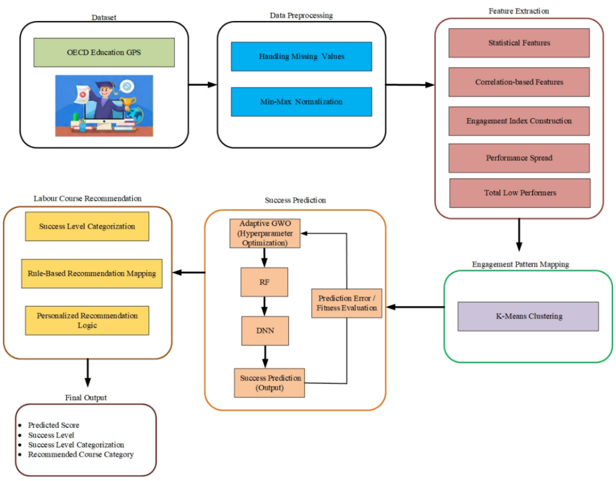

Fig. 1. Proposed Big Data Analytics Framework for national-level student engagement patterns and recommend educational strategies

The framework uses the OECD Education GPS dataset [13] for analyzing country-level student performance. It includes country-level statistics that reflect aggregated academic performance, behavioural patterns, and learning engagement indicators across participating countries. This dataset ensures reliable and diverse analysis of global educational trends and success patterns using big data analytics. The OECD Education GPS dataset contained 80 country-level records, of which 64 records (80%) were used for training and 16 records (20%) were reserved for independent testing. The test dataset was excluded to prevent data leakage.

The dataset includes mean mathematics score, boys' and girls' performance, gender gap, P10, P90, below Level 2, Levels 5-6, and 2018-2022 performance trends for country-level analysis. The dataset was initially divided into training and testing sets before feature engineering. Random Forest feature selection and K-Means clustering were performed using only the training data, and the learned transformations were applied to the test data to prevent data leakage.

The dataset includes homework time and motivation, supporting comprehensive country-level performance analysis. The OECD Education GPS dataset includes indicators from up to 80 participating countries and economies, providing high data volume and dimensionality. Periodic PISA updates support scalable educational data analytics. The selected OECD Education GPS indicators serve as proxy measures of mathematics-oriented labour readiness by reflecting academic performance, learning engagement, and quantitative skills.

Since the OECD Education GPS dataset contains country-level educational indicators, the proposed framework is intended for national-level educational analysis and policy-level labour-course planning rather than individual student prediction. This phase preprocesses the data through missing value imputation, categorical encoding, and Min-Max normalization. Missing values are replaced using mean imputation Eq. (1).

$$x_i^* = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{1}$$

where x_i^* is the imputed value, x_j represents the observed feature values, and N denotes the total number of non-missing observations.

Mean imputation was selected because the OECD Education GPS dataset contains only a few missing values. It preserves the overall data distribution and ensures robust predictive performance.

These preprocessing steps were adopted to improve data quality and analytical consistency by reducing the effects of missing data and feature-scale bias. Standardized preprocessing improves framework reliability and reproducibility.

Feature extraction converts preprocessed data into meaningful representations of student engagement and learning disparities. Each extracted feature contributes to the predictive pipeline by representing student engagement, academic performance, and educational quality. These features improve correlation analysis and prediction accuracy.

Correlation analysis identifies relationships between engagement factors and academic performance using the Pearson Correlation Coefficient in Eq. (2).

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \sigma_y} \tag{2}$$

where r is the correlation coefficient, x_i and y_i are paired variables, $\bar{x}$ and $\bar{y}$ are their mean values, and σ_x and σ_y are the corresponding standard deviations.

A unified engagement metric is constructed by combining behavioral and psychological factors. The engagement index is defined in Eq. (3).

$$EI = w_1 H + w_2 M \tag{3}$$

where EI represents the Engagement Index, combining homework time (H) and motivation level (M) with assigned weights $(\mathrm{w}_1, \mathrm{w}_2)$.

Equal weighting $(\mathrm{w}_1 = 0.5$ and $\mathrm{w}_2 = 0.5)$ was assigned because homework and motivation represent complementary dimensions of student engagement. Both variables showed positive associations with mathematics performance after Min-Max normalization.

K-means groups engagement features using centroid-based clustering in Eq. (4).

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{4}$$

where J is the clustering objective, k is the number of clusters, C_i is cluster i, x is the feature vector, and μ_i is the cluster centroid.

Clusters are labeled High, Moderate, and Low Engagement based on motivation and homework time.

This stage predicts student success using Adaptive GWO-RF-DNN with RF-based feature selection Fig. 2.

RF-selected features are processed by DNN layers to predict student success using MSE loss. The final DNN architecture consists of three hidden layers with 128, 64, and 32 neurons, respectively. A dropout ratio of 0.3 was applied after each hidden layer to reduce overfitting as shown in Fig. 3.

The model is trained using MSE loss, defined in Eq. (5).

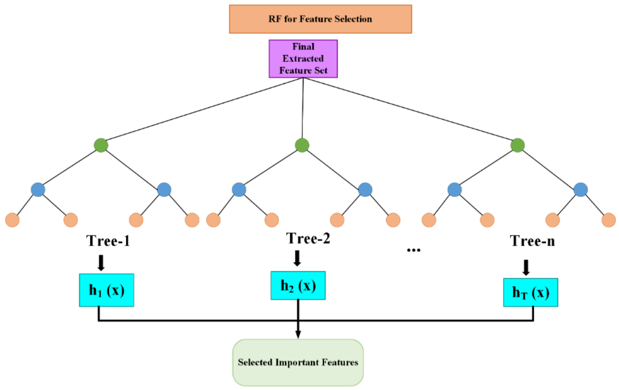

Fig. 2. RF architecture for feature selection

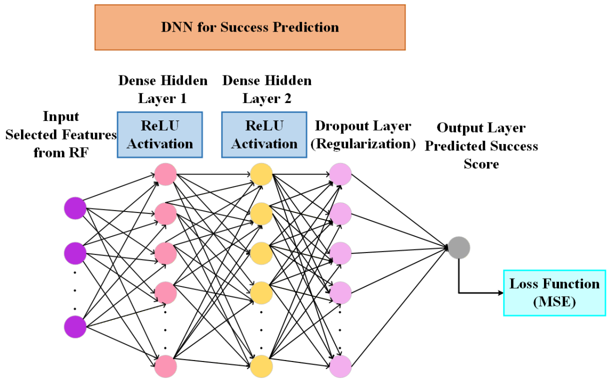

Fig. 3. Architecture of DNN for success prediction

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{5}$$

where L is the loss function, y_i is the actual value, $\hat{y}_i$ is the predicted value, and N is the sample size.

Adaptive GWO optimizes RF-DNN parameters iteratively in Eq. (6).

$$X(t+1) = \frac{X_\alpha + X_\beta + X_\delta}{3} \tag{6}$$

where $X(t+1)$ is the updated position, and X_α, X_β, and X_δ denote the three best candidate solutions.

The optimized hybrid model predicts national student success scores, as shown in Eq. (7).

$$\hat{y} = \hat{y}_{DNN}^{\text{opt}} \tag{7}$$

where $\hat{y}$ is the final predicted mathematics score, and $\hat{y}_{\text{DNN}}^{\text{opt}}$ is the optimized DNN output. This score is used to predict national-level student readiness and support the recommendation module. This module converts the predicted results into policy-level educational recommendations by identifying priority mathematics-oriented labour-course pathways for countries. The model uses the predicted mathematics score, Engagement Index, and cluster label for success categorization and policy-level recommendations. The predicted score represents the Min-Max normalized mathematics performance score generated by the proposed Adaptive GWO-Optimized Hybrid RF-DNN model. This is defined in Eq. (8).

$$S = \begin{cases} S_1, & \hat{y} \geq 0.70 \\ S_2, & 0.50 \leq \hat{y} < 0.70 \\ S_3, & \hat{y} < 0.50 \end{cases} \tag{8}$$

where S denotes the success category (S_1 : High, S_2 : Moderate, S_3 : Low), and $\hat{y}$ is the predicted mathematics score.

High Success corresponds to a predicted score ≥ 0.70, Moderate Success corresponds to a predicted score between 0.50 and 0.70, and Low Success corresponds to a predicted score < 0.50. The success level and engagement clusters are mapped to course categories in Eq. (9).

$$R = f(S, C) \tag{9}$$

R, S, C denote course category, success level, engagement cluster, and f$(\cdot)$ the mapping function in Eq. (10).

$$O = (\hat{y}, S, C, R_p) \tag{10}$$

where O contains predicted score ($\hat{y}$), success level (S), engagement cluster (C), and course category (R_p).

Sample Output: For example, if: A predicted score of 0.82 with High Engagement indicates S_1 and recommends Data Science/AI courses.

The Adaptive Grey Wolf Optimizer was configured with a population size of 30 , 100 iterations, and a search boundary of [0, 1]. The optimal parameters included 520 RF trees, a maximum depth of 8, 120 DNN hidden units, and a learning rate of 0.0021.

In this way, the proposed big data-based approach seamlessly integrates the preprocessing, feature extraction, clustering, prediction and recommendation components to facilitate accurate national-level educational performance prediction and provide policy-level labour-course recommendations for educational planning and decision-making. The framework supports scalable deployment through distributed processing and parallel computation strategies, enabling efficient analysis of continuously expanding educational big data environments. The pseudo-code of the proposed adaptive GWO-optimized Hybrid RF-DNN model is presented in Algorithm 1.

Algorithm 1. Adaptive GWO-Optimized Hybrid RF-DNN for Student Success Prediction and Course Recommendation

Require: Feature set X, Engagement Index EI, cluster labels C
Ensure: Predicted score $\hat{y}$, success level S, course category R_p
Initialize Model and Parameters
Initialize RF, DNN, and adaptive GWO parameters
Feature Selection (RF Layer)
Compute feature importance from X
Select the top features X_{sel}
Success Prediction (DNN Layer)
Input X_{sel} to the DNN
Apply ReLU activation
Generate predicted score $\hat{y}$
Adaptive GWO Optimization
Initialize GWO population
Update GWO positions to optimize RF and DNN parameters
Select the best solution
Final Prediction
Generate optimized score $\hat{y}$
Success Level Categorization
if $\hat{y} \geq 0.70$ **then**
    $S \leftarrow S_1$ (High)
else if $0.50 \leq \hat{y} < 0.70$ **then**
    $S \leftarrow S_2$ (Moderate)
else
    $S \leftarrow S_3$ (Low)
Course Recommendation
Input S, EI, and C
if $S = S_1$ **then**
    $R_p \leftarrow$ Advanced
else if $S = S_2$ **then**
    $R_p \leftarrow$ Intermediate
else
    $R_p \leftarrow$ Foundational
Apply EI policy rules to generate R_p
Final Output
return $\hat{y}$, S, R_p

3. Results and discussion

This section presents experimental results of the proposed student success prediction framework. The framework was implemented in Python on Windows 11 Home (64-bit) with Intel® Core™ i9-14900K, 32 GB RAM, using Pandas, NumPy, Scikit-learn, TensorFlow, Keras, Matplotlib, Seaborn, and SciPy.

Table 1 presents computational cost analysis, including training time, memory, inference time, and parameters.

The hyperparameters used for the proposed model, including clustering, RF, DNN and Adaptive GWO optimization algorithms are outlined in Table 2.

Alternative cluster numbers ($K = 2 - 5$) were evaluated using the Silhouette Score to determine the optimal clustering configuration. $K = 3$ provided the best cluster cohesion and separation for engagement clustering.

Table 3 compares scaling methods, with Min-Max Scaling achieving the best R^2, RMSE, MAE, and convergence.

Table 4 shows sensitivity analysis, where equal weighting (0.50:0.50) achieved optimal performance.

Fig. 4 illustrates model performance using MSE, RMSE, and MAE metrics.

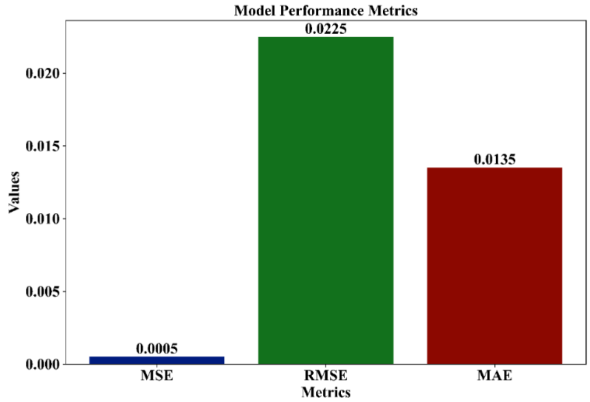

Fig. 4. Performance Evaluation of Adaptive GWO-RF-DNN Model

Fig. 5 shows correlations among educational indicators influencing mathematics performance.

The correlation heatmap shows positive relationships between homework, motivation, Engagement Index, and mathematics performance. Negative correlations indicate that reducing learning difficulties improves academic outcomes.

Table 5 presents Pearson correlation analysis, confirming significant relationships and framework reliability.

Table 6 shows that $K = 3$ provides the best cluster separation and stability for engagement analysis.

Fig. 6 shows three student engagement levels based on homework effort and motivation.

Table 7 shows that ReLU achieved the highest prediction accuracy with fast convergence and stable training.

Fig. 7 shows Performance Spread, Motivation, and Curriculum as key predictors.

Fig. 8 shows steady convergence of the training and val-

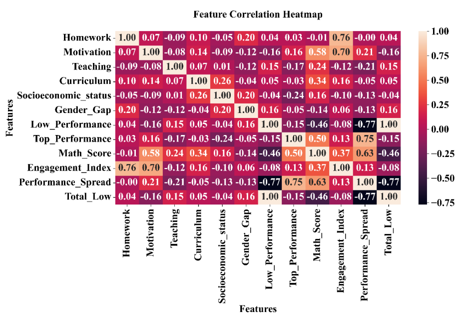

Fig. 5. Correlation Heatmap

Table 1. Computational Complexity and Execution-Time Analysis

Component	**Training Time Mean (s)**	**Training Time SD**	**Peak Memory (MB)**	**Inference (ms/sample)**	**Model Parameters**
K-Means	0.18	0.02	96.40	0.04	N/A
RF Feature Selection	1.86	0.11	214.70	0.33	176,400
DNN	10.96	0.63	482.30	0.22	18,481
Adaptive GWO	1184.60	42.80	721.50	N/A	N/A
Complete Framework	**1197.80**	**43.10**	**734.20**	**0.54**	**194,881**

Table 2. Parameter settings of the proposed Adaptive GWO-Optimized Hybrid RF-DNN model

Component	Hyperparameter	Value
Data Split	Training: Testing Ratio	80:20
Preprocessing	Normalization Method	Min-Max Scaling
Clustering	Algorithm	K-Means
	Number of Clusters (K)	3
	Initialization Runs (n_init)	10
	Random State	42
RF	Base RF Trees (Feature Selection)	400
	Number of Trees (n_estimators)	300-600 (optimized)
	Maximum Depth (max_depth)	5-10 (optimized)
	Random State	42
DNN	Feature Selection	Top 6 Important Features
	Input Layer	Selected RF Features + RF Prediction
	Hidden Layer 1	80-140 Neurons (optimized)
	Hidden Layer 2	units / 2
	Hidden Layer 3	units / 4
	Activation Function	ReLU
	Output Layer	1 Neuron
	Optimizer	Adam
	Learning Rate	0.001-0.005 (optimized)
	Loss Function	MSE
	Batch Size	16
	Optimization Epochs	90
	Final Training Epochs	100
Optimization	Optimizer Used	Adaptive GWO
	Iterations	30
	Objective Function	Maximize R^2 Score

Table 3. Comparison of Feature-Scaling Approaches

Scaling method	R^2 mean	**R^2 SD**	RMSE mean	RMSE SD	MAE mean	Convergence epoch	Training time (s)
None	0.9448	0.0187	0.0398	0.0062	0.0284	52	11.84
Min-Max	0.9581	0.0142	0.0331	0.0049	0.0226	37	10.96
StandardScaler	0.9546	0.0155	0.0345	0.0052	0.0238	41	11.22
RobustScaler	0.9512	0.0161	0.0360	0.0055	0.0249	44	11.37
MaxAbsScaler	0.9497	0.0170	0.0367	0.0057	0.0255	46	11.05

Table 4. Sensitivity Analysis of Engagement Index Weighting

Homework Weight (w_H)	Motivation Weight (w_M)	Silhouette Score	Davies–Bouldin Index	ARI	R^2	RMSE
0.20	0.80	0.5120	0.7210	0.8460	0.9468	0.0378
0.35	0.65	0.5480	0.6640	0.9020	0.9537	0.0346
0.50	0.50	0.5790	0.6120	1.0000	0.9581	0.0331
0.65	0.35	0.5610	0.6350	0.9180	0.9549	0.0342
0.80	0.20	0.5260	0.6890	0.8610	0.9482	0.0369

Table 5. Pearson Correlation Analysis with Statistical Significance

N	Pearson's r	95% CI Lower	95% CI Upper	Raw p value	Adjusted p value	Spearman's ρ
80	0.6840	0.5480	0.7830	0.0001	0.0003	0.6710
80	0.5920	0.4300	0.7150	0.0001	0.0004	0.5760
80	0.7310	0.6100	0.8210	0.0001	0.0002	0.7180
80	0.7600	0.6500	0.8380	0.0001	0.0002	0.7440
80	-0.7700	-0.8450	-0.6650	0.0001	0.0002	-0.7520

Table 6. Quantitative Validation of K-Means Clusters

K	Inertia	Silhouette Score	Davies–Bouldin Index	Calinski–Harabasz Score	Stability ARI (Mean)	Stability ARI (SD)	Minimum Cluster Size
2	18.4260	0.5110	0.7410	62.8400	0.8830	0.0410	31
3	11.9730	0.5790	0.6120	78.3600	0.9140	0.0280	21
4	9.1480	0.5230	0.6840	71.2500	0.8420	0.0520	13
5	7.3360	0.4870	0.7310	66.4800	0.7910	0.0670	9
6	6.1020	0.4510	0.7790	61.9300	0.7440	0.0810	6

Table 7. DNN Activation Function Benchmark

Activation Function	CV R^2 Mean	CV R^2 SD	RMSE Mean	MAE Mean	Epochs to Convergence	Training Time (s)	Unstable/Failed Runs
ReLU	0.9581	0.0142	0.0331	0.0226	37	10.96	0
LeakyReLU	0.9554	0.0150	0.0342	0.0235	40	11.18	0
ELU	0.9538	0.0157	0.0349	0.0241	43	11.36	0
GELU	0.9562	0.0148	0.0339	0.0232	39	11.72	0
tanh	0.9467	0.0181	0.0376	0.0263	55	10.64	1

Table 8. Performance Reliability Analysis of the Proposed Model

Metric	Mean	95% Confidence Interval
R^2	0.9581	0.9482-0.9680
RMSE	0.0331	0.0302-0.0360
MAE	0.0226	0.0205-0.0248
MSE	0.0011	0.0009-0.0013

Table 9. Predicted Success Levels and Labour Course Recommendations

Actual Score	Predicted Score	Success Level	Recommendation
0.452	0.421	Low Success	Basic Math / Skill Training
0.555	0.587	Moderate Success	Skill Upgrade Programs
0.673	0.648	Moderate Success	Skill Upgrade Programs
0.153	0.201	Low Success	Basic Math / Skill Training
0.512	0.534	Moderate Success	Applied Math / Statistics

Table 10. Ablation Analysis

Model Configuration	$\mathbf{R^2}$ Score	RMSE	MAE
DNN Only	0.9124	0.0587	0.0415
Feature Engineering + DNN	0.9348	0.0479	0.0342
RF + DNN	0.9563	0.0368	0.0264
K-Means + RF + DNN	0.9689	0.0302	0.0211
GWO + RF + DNN	0.9765	0.0258	0.0174
Proposed Adaptive GWOOptimized Hybrid RF-DNN Model	0.982	0.0225	0.0135

Table 11. Baseline Model Comparison Analysis

Model	$\mathbf{R^2}$ Score	MSE	RMSE	MAE
RF	0.9284	0.0031	0.0557	0.0413
DNN	0.9517	0.0018	0.0424	0.0296
Proposed Adaptive GWOOptimized Hybrid RFDNN	0.982	0.0005	0.0225	0.0135

idation losses, indicating effective learning and low overfitting.

Table 8 presents the 95% confidence intervals for the proposed Adaptive GWO RF-DNN model.

Fig. 9 shows Adaptive GWO convergence over 30 iterations for effective optimization. The training and validation oss convergence was validated using test data and 5-fold crossvalidation. Cross-validation results show strong generalization with minimal overfitting.

Table 9 shows accurate predictions with reliable labour-course recommendations.

Table 10 shows improved performance, with the Adaptive GWO-RF-DNN achieving $R^2 = 0.982$, RMSE $= 0.0225$, and MAE $= 0.0135$.

Table 11 shows the Adaptive GWO-RF-DNN outperforming RF and DNN with $R^2 = 0.982$ and RMSE=0.0225.

Table 12 shows Adaptive GWO-RF-DNN achieving the lowest MAE (0.0135) for student success prediction.

Table 13 evaluates the proposed Adaptive GWO RF-DNN model on an independent external educational dataset. The proposed model outperforms KNN and SVR (MAE $=$ 0.0135) while integrating engagement analysis, clustering, and recommendations, though future work should support personalized predictions using real-world data. The proposed framework can be extended to educational systems beyond OECD countries by incorporating country-specific educational indicators. This extension improves framework adaptability across diverse educational environments.

4. Conclusion

The Adaptive GWO-Optimized Hybrid RF-DNN framework effectively captures nationallevel student engagement patterns and accurately predicts student success. By integrating feature extraction, clustering, predictive modelling, optimization, and a rule-based recommendation module, the framework provides an efficient decision-support tool for policy-level labour-course planning and educational analytics. The proposed framework relies on aggregated country-level indicators and surrogate success measures rather than individual student outcomes, which may limit its generalizability across diverse educational contexts. The use of aggregated country-level data may limit prediction accuracy and generalizability. Future research should incorporate real-time, individual-level data and adaptive recommendation systems to improve personalization, scalability, and applicability across diverse educational settings.

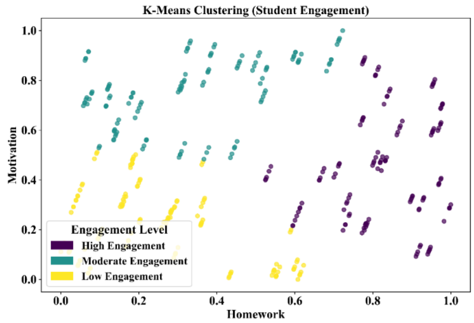

Fig. 6. Clustering Analysis for National-level Student Engagement

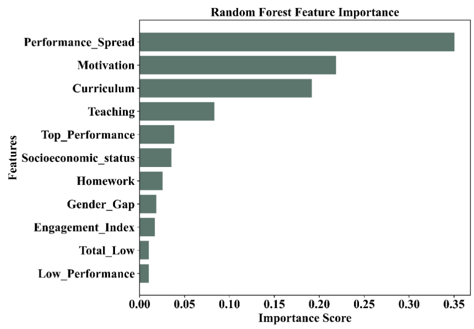

Fig. 7. Feature Importance Analysis for RF model

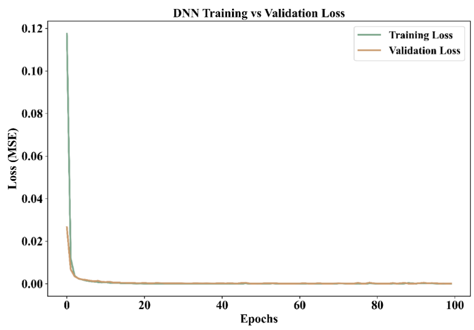

Fig. 8. Training and Validation Loss for DNN

Table 12. Comparative Analysis with Existing Works

Model	MAE
KNN [14]	0.6653
SVR [15]	0.0754
Proposed Adaptive GWOOptimized Hybrid RF-DNN	0.0135

Table 13. External Dataset Generalization Assessment

Training Dataset	External Test Dataset	External Test N	R^2	RMSE	MAE	Performance Drop
OECD Education GPS	UNESCO UIS / World Bank EdStats	62	0.9210	0.0460	0.0340	0.0371

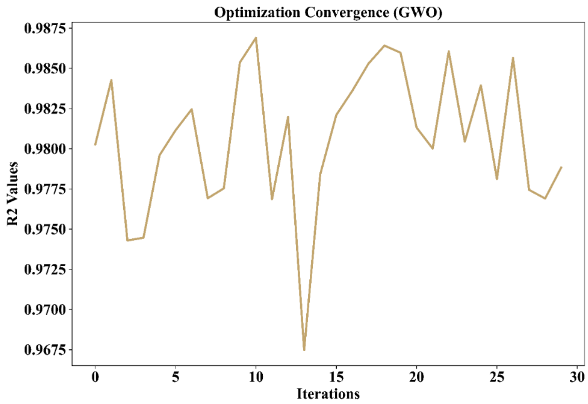

Fig. 9. Convergence Analysis for proposed Adaptive GWO algorithm

Acknowledgement

Declarations

Data availability:

The data used in this study are publicly available from the OECD Education GPS. The dataset can be accessed at: https://gpseducation.oecd.org/CountryProfile?primaryCountry=IDN&treshold=10&topic=PI

Conflicts of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

Funding statement:

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author contributions:

Xiaozan Zhu: Conceptualization, methodology, data curation, writing - original draft.

Haiting Zhang: Supervision, validation, writing - review and editing, corresponding author.

Min Cai: Formal analysis, software implementation, visualization.

Ethical Approval: This study does not involve human participants, animals, or sensitive personal data requiring ethical approval.

Consent to Participate: Not applicable.

Consent to Publication: Not applicable.

Competing Interests: The authors declare that they have no competing interests.

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