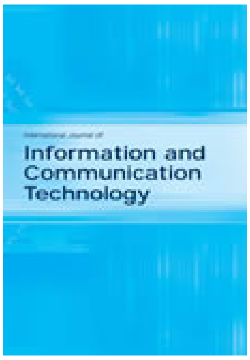

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

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DOI: 10.1504/IJICT.2025.10071988

Article History:

Received:	06 May 2025
Last revised:	23 May 2025
Accepted:	23 May 2025
Published online:	16 July 2025

Analysis of EFL learners' academic anxiety based on R language and graph neural network

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Abstract: The academic anxiety of English as a foreign language (EFL) learners has progressively become a major determinant of academic performance. Therefore, how best to forecast and evaluate the influence of these emotions on academic performance has become a hot issue of research in academia. This work suggests an academic anxiety emotion analysis based on graph neural network (GNN). This work uses the GNN model to investigate learners' anxiety feelings in depth by processing multimodal data on their emotional traits, therefore verifying the accuracy of the approach in forecasting academic anxiety emotions. According to the experimental results, the suggested approach has tremendous generalisation capacity and application possibilities and greatly beats conventional machine learning methods in many respects. This paper offers fresh perspectives on the academic anxiety and theoretical support for the design of emotional control techniques in education of EFL learners.

Keywords: graph neural network; GNN; academic anxiety; EFL learners; multimodal data; sentiment prediction; sentiment analysis.

Reference to this paper should be made as follows: Jin, R. (2025) 'Analysis of EFL learners' academic anxiety based on R language and graph neural network', *Int. J. Information and Communication Technology*, Vol. 26, No. 26, pp.1–16.

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1 Introduction

Many non-English speaking nations' educational systems now heavily rely on English as a foreign language (EFL) learning as globalisation develops. But EFL students sometimes experience different degrees of academic anxiety during the course of their education, which not only influences learning results but also has broad effects on academic performance and psychological well-being (Dewaele et al., 2023). Usually presenting itself as extreme concern, fear, and tension about academic activities, academic anxiety is an emotional condition that makes it difficult for students to realise their full potential and may even cause loss of motivation and learning difficulties. Thus, precisely spotting and evaluating EFL learners' academic worry has substantial theoretical relevance as well as practical worth for raising their learning results and standing (Ayub and Khaleel, 2024).

Although they can somewhat reflect learners' emotional state, traditional approaches for analysing academic anxiety mood mostly rely on self-report questionnaires and behavioural observations, which are limited by issues such high subjectivity, small data volume and low processing efficiency, so making it difficult to achieve comprehensive, dynamic and efficient mood analysis. Sentiment analysis techniques have opened fresh prospects in recent years as artificial intelligence technology develops rapidly and particularly in the effective application of GNN in several spheres (Khemani et al., 2024). GNN is a strong graph-structured data processing model that can efficiently capture the structural links in complicated data, therefore offering fresh concepts and technical methods for sentiment analysis. Together with the strong data analysis and visualisation tools of R language, it can effectively identify and anticipate academic anxiety, therefore offering EFL students tailored learning support.

This paper aims to investigate the academic anxiety of EFL learners depending on R language and graph neural network (GNN) model as well as investigate its affecting elements and modifying guidelines. Building a model for the analysis of academic anxiety will enable teachers to build more suitable teaching strategies and interventions, support their scientific decision-making, and thereby enhance the learning process and psychological health of EFL learners.

This study's innovations mostly in the following two respects:

On the one hand, this work suggests a GNN-based approach for analysing academic anxiety mood, which uses GNN to predict academic anxiety mood of EFL learners. By use of graph-structured data representation, the GNN is able to detect the underlying trends of mood variations, therefore enabling more accurate mood prediction. Conversely, this work integrates a multimodal data modelling method based on the GNN model for emotional aspects. Learning deep features on several emotional aspects helps the study to fully understand the academic anxiety emotions of EFL learners. This multilevel emotion feature modelling approach offers a theoretical framework for additional optimisation of the emotion detection job and increases the accuracy of emotional analysis.

This work creatively suggests a new method to academic anxiety sentiment analysis by merging GNN with sentiment feature modelling, therefore encouraging the use of sentiment analysis techniques in the assessment of academic performance of EFL learners.

2 Related work

2.1 Sentiment analysis methods

Studies on analysing the academic anxiety sentiment of EFL learners have concentrated on using several techniques to predict learners' emotions (Yu et al., 2018). Although most traditional sentiment analysis approaches rely on rules or manual feature extraction, as machine learning techniques have evolved more and more studies are adopting automated approaches for sentiment recognition and categorisation. Among the common algorithms are deep learning techniques, including support vector machine (SVM), decision tree (DT), and Naive Bayes.

Particularly in high-dimensional feature spaces, where SVMs can efficiently separate between anxious and non-anxious states by determining the maximum interval hyperplane, SVMs are extensively applied in emotion classification. From a training dataset D, one can represent D as:

$$D = \{(x_i, y_i)\}_{i=1}^{n} \tag{1}$$

SVM aims to identify a hyperplane to maximise the interval between the two categories where x_i is the input features and $y_i \in \{0, 1\}$ is the sentiment category. One can formulate its optimisation issue as:

$$L = \min_{w,b,\xi_i} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{2}$$

The normal vector of the hyperplane is w; b is the bias; ξ_i is a slack variable permitting a certain degree of misclassification; and C is a punishment coefficient regulating the tolerance of misclassification. SVM maximises the bounding intervals to increase the classification accuracy; its disadvantage is that it is highly sensitive to the choice of parameters and has great computing cost when handling large-scale data, which may result in protracted training time.

DT creates a tree structure by repeatedly separating the feature space into several categories each corresponding to a region. Usually, information gain or Gini index is employed in DT construction to choose the optimum partitioning features (Tangirala, 2020). The formula computing the information gain is:

$$IG(D, x_j) = H(D) - \sum_{v \in Values(x_j)} \frac{|D_v|}{|D|} H(D_v) \tag{3}$$

where D_v is a subset of characteristics x_j obtaining the value v; $|D_v|$ is the size of the subset; $H(D_v)$ is the entropy of the subset D_v. By quantifying data uncertainty both before and after feature splitting, the information gain chooses the best features. Although the model is straightforward to grasp and comprehend, DT has a drawback in that it is prone to overfitting, especially in cases of a limited training set or noisy data.

Based on Bayes' theorem and presuming conditional independence between features, the basic Bayesian method computes the conditional probability of every feature under a specified sentiment category, hence guiding classification. Park Bayes' posterior probability is computed specifically as:

$$P(y|x_1, x_2, \ldots, x_n) = \frac{P(y)\Pi_{i=1}^{n} P(x_i|y)}{P(x_1, x_2, \ldots, x_n)} \tag{4}$$

where $P(x_1, x_2, \ldots, x_n)$ is the total probability of the data; $P(x_i|y)$ is the conditional probability of feature x_i under emotion category y; $P(y)$ is the prior probability of an emotional category y. The basic Bayesian model can categorise the emotional condition of the learner by optimising the posterior probability (Yuzhong, 2021). Although the computational simplicity and efficiency of the model indicate that the features are independent of one another, in real applications this assumption usually does not hold totally and may result in restrictions on model performance.

Long-short-term memory networks (LSTMs) are especially fit for addressing temporal fluctuations in learners' emotions in the field of deep learning. By means of its special gating mechanism, LSTMs may effectively capture long-term relationships in the input sequences, hence generating dynamic predictions of learners' emotions (Al Chanti and Caplier, 2018). The state updating formulas for LSTMs follow this:

$$h_t = o_t * \tanh(c_t) \tag{5}$$

where o_t is the output gate; h_t is the hidden state at the point of current; c_t is the unit state. By use of information flow (forgetting gate, input gate, and output gate), LSTM either preserves or forgets prior information to precisely forecast the emotional state of the current instant. LSTM has a great computational overhead, requires a lot of labelled data for training, and its complicated structure causes the training process to be somewhat lengthy even if it can efficiently manage time-series data (Torres et al., 2021).

All things considered, present sentiment analysis techniques have not yet been able to completely satisfy the academic anxiety sentiment analysis needs of EFL learners. Thus, incorporating more advanced algorithms, including GNN, to overcome the drawbacks of conventional approaches has great research relevance and practical usefulness.

2.2 R language

Widely used in data science, machine learning, and other domains, R language is a programming language specifically designed for statistical computing and data analysis with strong statistical analysis and data visualising features (Sepulveda, 2020). Its main benefits come from the abundance of built-in statistical models and techniques as well as from the availability to a range of extension packages available via the CRAN library to satisfy various data processing requirements.

R language can effectively manage standard approaches like linear regression models in statistical analysis (Chong and Xia, 2018). For linear regression, the model representation is for instance:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \grave{o} \tag{6}$$

While the coefficient estimates of the model are obtained via least squares, which is quick and effective, in R linear regression can be fitted straight through the lm() function.

Algorithm 1 explains the training procedure of the regression model by means of pseudo-code for R-based regression analysis.

Regarding data processing, the R language offers effective tools, specifically, the dplyr package for handling data frame tasks (Shilane et al., 2024). Algorithm 2 exhibits the pseudo-code for data aggregation operations.

Particularly in plotting, the R language also has strong data visualising features; the ggplot2 package makes it simple to graph a range of graphs (Myint et al., 2020). Algorithm 3 shows, for instance, the pseudo-code for creating a scatterplot.

Another crucial aspect of the R language is its extensibility, which helps it to be compatible with other programming languages (e.g., C, C++, Python) hence improving its use and versatility. Users of the reticulate package can readily call Python libraries, hence expanding the toolkit for data analysis.

Algorithm 1 Pseudo-code for performing linear regression in R

Input: Input features x, target variable y, regularisation parameter λ
Output: Estimated coefficients β

Begin
  Initialise $\beta = [0, 0, \ldots, 0]$
  for each iteration **do**
    Calculate the predicted output y_pred = $X * \beta$
    Compute the residuals: residuals = $y - y$_pred
    Calculate the cost function: cost = $(1/N) * \Sigma\ (residuals^2) + \lambda * \Sigma\ (\beta^2)$
    Compute the gradient of the cost function with respect to β
    Update β using gradient descent: $\beta = \beta - \alpha$ * gradient
  end for
  Return β
End

Algorithm 2 Pseudo-code for aggregating data in R

Input: Dataset, Grouping variables, aggregation function (mean, sum, etc.)
Output: Aggregated results

Begin
  Group data by grouping variables
  Apply aggregation function (mean, sum, etc.) to each group
  Return the aggregated results
End

Algorithm 3 Pseudo-code for plotting a scatter plot in R using ggplot2

Input: Dataset, variables to plot (x, y)
Output: Scatter plot

Begin
  Create ggplot object: ggplot(data, aes(x = variable1, y = variable2))
  Add scatter plot layer: + geom_point()
  Display the plot
End

2.3 Graph neural network

Widely applied to handle nodes, edges, and their interactions in graph data, GNN is a class of data models grounded on graph topologies. GNN is fundamentally based on learning the embedded representation of a node by means of information propagation among the interrelationships of the graph structure (Wu et al., 2020).

GNN operates essentially layer by layer updating the representation of every node with information from its neighbours. The representation of a node changes layer by layer via the message passing mechanism given a graph G; the equation below updates node v_i at the k^{th} layer:

$$G = (V, E) \tag{7}$$

$$h_i^{(k+1)} = \sigma\left(W^{(k)} h_i^{(k)} + \sum_{j \in N(i)} \frac{1}{|N(i)|} W^{(k)} h_j^{(k)}\right) \tag{8}$$

where $h_i^{(k)}$ is the representation of node v_i at layer k; $W(k)$ is the weight matrix at layer k; $N(i)$ is the collection of surrounding nodes of node v_i; σ is the activation function, that is ReLU. The information of surrounding nodes progressively incorporates in the representation of a node through this information transfer process.

Graph convolution operation is widely utilised in GNN to accomplish information aggregation (Ding et al., 2022). Graph convolution's basic concept is weighted summing of the data of the surrounding nodes updating the target node's representation. The updating formula for the graph convolution layer is particularly:

$$H^{(k+1)} = \sigma\left(\hat{A} H^{(k)} W^{(k)}\right) \tag{9}$$

$$\hat{A} = D^{-1/2} A D^{-1/2} \tag{10}$$

where $\hat{A}$ is the normalised adjacency matrix; $H^{(k)}$ is the k^{th} layer node representation matrix; $W^{(k)}$ is the weight matrix of that layer.

Many GNN models include jump connections to improve the expressive capability of the model and better capture the links across nodes. The graph sample and aggregation model, for instance, aggregates the neighbourhood information of nodes using this formula:

$$h_i^{(k+1)} = \sigma\left(W^{(k)} \cdot AGGREGATE\left(\left\{h_j^{(k)} : j \in N(i) \cup \{i\}\right\}\right)\right) \tag{11}$$

Under this design, *AGGGREATE* is an aggregation mechanism available for averaging, summing, or maximal pooling to gather the data of surrounding nodes (Lu et al., 2022). Jump connections enable the GNN to capture local and global information of the nodes, hence improving the expressiveness of the model.

Furthermore, graph attention network (GAT) allow GNNs to dynamically allocate varying weights to neighbour nodes. GAT's key goal is to teach the relationship between nodes using self-attention's technique. GAT uses a formula for updates:

$$h_i' = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W h_j\right) \tag{12}$$

where the self-attention mechanism determines α_{ij}, the attention coefficient between node i and node j. By constantly adjusting the weight of the information of surrounding nodes depending on the relative importance between the nodes, the attention coefficient helps to improve the GNN's graph data representation (Zhou et al., 2021).

Ultimately, the GNN is able to capture the intricate linkages and interactions between nodes in graph data by pooling the information of node neighbours, adding jump connections and the attention mechanism, so considerably improving the learning capacity on graph data.

3 Research methodology

3.1 Data collection and pre-processing

Appropriate for analysis of academic anxiety, the dataset used in this study is 'Data: facilitating anxiety, learning motivation and EFL academic performance', which comprises numerous characteristics of EFL learners' anxiety, learning motivation and academic success. The dataset comprises various factors, mostly related to ratings on academic achievement, motivation, and anxiety.

First done to guarantee data quality and usability following data collecting was data preparation. Data normalisation, outlier identification, and missing value handling constituted part of the preparation chores.

First, mean interpolation was applied to handle missing values. Box-and-line graphs were used to identify and eliminate data points obviously outside of reasonable range in cases of outliers. Second, all variables were normalised in order to remove the impact of several scales and data ranges on the analytical outcomes. The normalisation formula followed this:

$$\hat{X} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{13}$$

where X is the original data; $\hat{X}$ is the normalised variable value; min(X) and max(X) are respectively the minimum and maximum values of the variable.

Stratified sampling was applied to equally choose samples for analysis in every level of anxiety therefore guaranteeing balanced findings (Mweshi and Sakyi, 2020). All variables were also standardised so that various factors could be matched on a common scale. The standardising formula followed this:

$$Z = \frac{X - \mu}{\sigma} \tag{14}$$

where Z is the standardised data; X is the original data; μ is the data's mean; σ is the data's standard deviation. Standardisation removes the effect of unit variations on the analysis outcomes since it makes the mean of every variable 0 and the standard deviation 1 (Weir et al., 2018).

The interquartile range (IQR) approach applied with the following formula for outlier detection:

$$IQR = Q_3 - Q_1 \tag{15}$$

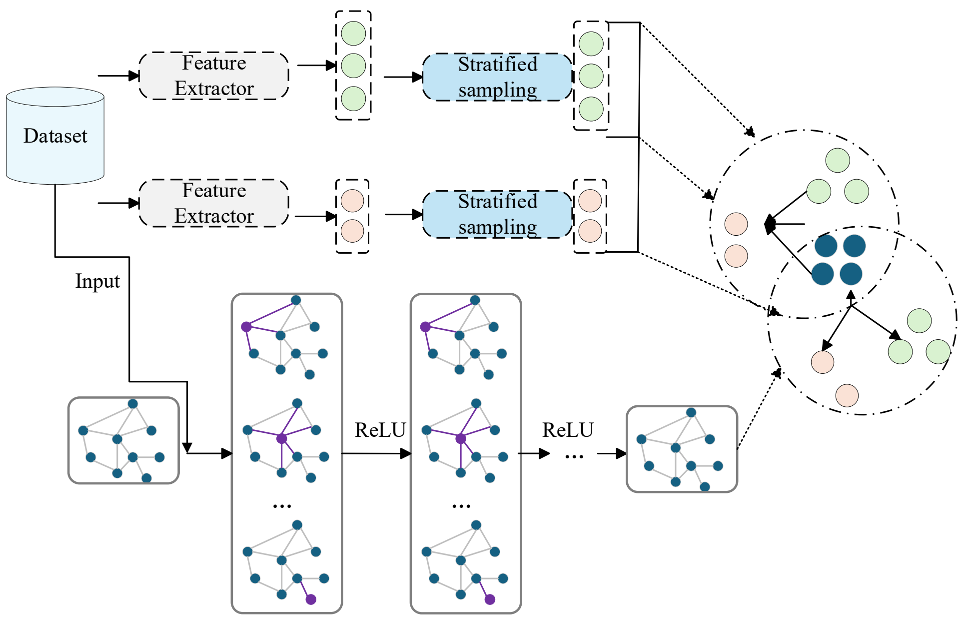
where IQR is used to identify data outliers; Q_1 and Q_3 are respectively the 25th and 75th percentile of the data. Any data point less Q_1 – 1.5 × IQR or more than Q_3 – 1.5 × IQR will be regarded as an outlier and eliminated.

By means of these data collecting and pre-processing phases, the quality of the data is guaranteed, noise that can influence the analysis outcomes is removed, and trustworthy fundamental data are supplied for next GNN modelling.

3.2 GNN modelling

As shown in the model in Figure 1, it is assumed that each node in building the emotional-achievement relationship graph between learners represents a learner, the features of the nodes include academic achievement, emotional scores, etc. while the edges reflect the emotional and academic influence between learners.

Figure 1 Model for analysing EFL learners' academic anxiety emotions (see online version for colours)



Defining a node feature propagation model will thus be the initial stage, considering learners' emotional similarity and mutual emotional feedback in addition to assuming that the link between nodes depends not simply on direct connections. The update equation for node features follows for every node v_i:

$$h_i^{(k+1)} = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W^{(k)} h_j^{(k)} + b^{(k)}\right) \tag{16}$$

where α_{ij} is the weighted emotional similarity between nodes v_i and v_j; $W^{(k)}$ is the weight matrix at layer k; $b^{(k)}$ is the bias term; $h_i^{(k)}$ indicates the feature vector of node v_i at layer k; $N(v_i)$ denotes the set of surrounding nodes of node v_i; σ is the activation function. This formula considers the need of affective similarity in node messaging so that it can reflect the emotive linkages among learners.

Following every layer of graph convolution, the node features undergo a pooling process to compile the learners' whole emotional state. This work makes advantage of maximum pooling operation:

$$h_i^{(pool)} = \max\left(h_i^{(k)}\right) \tag{17}$$

By choosing the largest value of every attribute in surrounding nodes, this process extracts the most important ones for the prediction of academic anxiety feelings.

The self-attention method is applied to improve the propagation and aggregation of node attributes so increasing the capacity of the model to replicate intricate emotional interactions amongst learners (Zhao et al., 2021). The self-attention mechanism enables the network to concentrate on the most pertinent surrounding nodes thereby extracting the data on academic performance and emotional state more efficiently. One may write a node's self-attention weight as:

$$\alpha_{ij} = \frac{\exp\left(h_i^{(k)} h_j^{(k)}\right)}{\sum_{j \in N(v_i)} \exp\left(h_i^{(k)} h_j^{(k)}\right)} \tag{18}$$

By computing the similarity of node characteristics, this formula finds the significance of surrounding nodes and thereby guides the influence of each neighbour on the update of node v_i features.

At last, this work provides a regression loss function based on node attributes so enabling the GNN to efficiently learn the association between academic anxiety mood and academic performance. The loss function, assuming y_i as the intended output, can be stated as:

$$L = \sum_{i=1}^{N} \left(y_i - f\left(h_i^{(final)}\right)\right)^2 \tag{19}$$

where N is the total number of nodes; $f(h_i^{(final)})$ is the expected value outputted by the last layer of the GNN, so indicating the academic performance or anxiety score of node vi.

Gradient descent ultimately optimises the model by changing the GNN's parameter W(k):

$$W^{(k)} = W^{(k)} - \eta \frac{\partial L}{\partial W^{(k)}} \tag{20}$$

where $\frac{\partial L}{\partial W^{(k)}}$ is the gradient of the loss function concerning the parameter and η is the learning rate.

By means of the foregoing procedures, the GNN is able to efficiently capture the intricate interaction between emotion and academic performance among EFL learners, therefore offering a useful tool for academic performance prediction and a means of academic anxiety sentiment analysis.

3.3 Modelling the characteristics of academic anxiety

Further in-depth modelling of EFL learners' academic anxiety is needed following data cleaning, feature screening and standardisation. This study generates feature constructions around four central variables based on pre-processed data. First, the numerical expression of anxiety can be defined with this formula:

$$A_i = \frac{1}{n}\sum_{j=1}^{n}\left(s_{ij} \times w_j\right) \tag{21}$$

where A_i is the general anxiety score of the i^{th} student; s_{ij} is the score of the i^{th} learner on the j^{th} scale question; w_j is the importance weight of the j^{th} question. Through weighted summation, the several contributions of various scale questions to the total anxiety level are taken into account holistically to avoid the homogeneous impact of the scores of each question on the total evaluation, so ensuring more in line with the actual distribution of mental states the quantitative results of the anxiety characteristics.

Potential variables like learning motivation and self-efficacy have to be fused and modelled throughout the process of node feature representation (Xia and Qi, 2023). The feature similarity matrix is built with this formula for this aim:

$$S_{ij} = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right) \tag{22}$$

where σ is a parameter to change the distance scale; x_i and x_j correspondingly indicate the characteristics of learners i and j. Defining the neighbourhood relationship in the next graph building will depend much on this matrix.

A self-encoder-assisted feature reconstruction technique is proposed to further extract the deep structural correlations in the anxiety features by defining the reconstruction loss function as follows:

$$L_{rec} = \sum_{i=1}^{n}\left\|x_i - \hat{x}_i\right\|_2^2 \tag{23}$$

where $\hat{x}_i$ is the reconstructed feature output from the self-encoder and x_i is the original feature. Reducing the reconstruction loss helps to reduce the high dimensional input without sacrificing any significant emotional content.

Feature fusion is necessary to underline significant features following feature extraction from several sources (Ma et al., 2021). Defined as follows is the weighted feature fusion approach:

$$z_i = \sum_{k=1}^{m}\alpha_k \cdot f_i^{(k)} \tag{24}$$

where $f_i^{(k)}$ is the k^{th} characteristic; α_k is the appropriate weight coefficient; the total weight is 1. Weighted fusion of data from many feature sources improves the ability of the node description.

At last, normalisation of the feature matrix is necessary to adjust the GNN input. There is a normalisation formula as follows:

$$X' = \frac{X - \mu}{\sigma} \tag{25}$$

where accordingly the feature mean and standard deviation are μ and σ. Better suited to the propagation mechanism of GNN, the normalised feature matrix will help to prevent the gradient explosion or disappearance issue.

4 Experiment and analysis of results

4.1 Experimental design

In the experiment, linear regression was used to investigate the underlying link between academic achievement and anxiety after first data analysis conducted in R language. This stage allowed it to offer a first statistical basis for later sophisticated modelling.

First standardised and processed for missing values, the raw data were then displayed using R language to investigate feature relationships in the data preparation stage. The preliminary correlation study led one to build a relationship model between academic achievement and anxiety using a linear regression model. The linear regression model has this fundamental form:

$$Academic\ performance = \beta_0 + \beta_1 \times anxiety\ level + \epsilon \tag{26}$$

where ϵ is the error term; β_1 is the anxiety regression coefficient; β_0 is the intercept. The approach lets one make a first assessment of the degree of anxiety influencing academic performance. To confirm the relationship even more, the pertinent model indicators were computed to evaluate their fitting impact:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2}{\sum_{i=1}^{n} \left(y_i - \overline{y} \right)^2} \tag{27}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2 \tag{28}$$

where $\hat{y}_i$ is the i^{th} projected value; n is the sample count; y_i is the i^{th} observation, that is, the true value. The model better explains the variability of the data the closer the R^2 value is to 1 (Plonsky and Ghanbar, 2018). The MSE of the model represents its average prediction error; so, the model fits better the less the value is (Karunasingha, 2022).

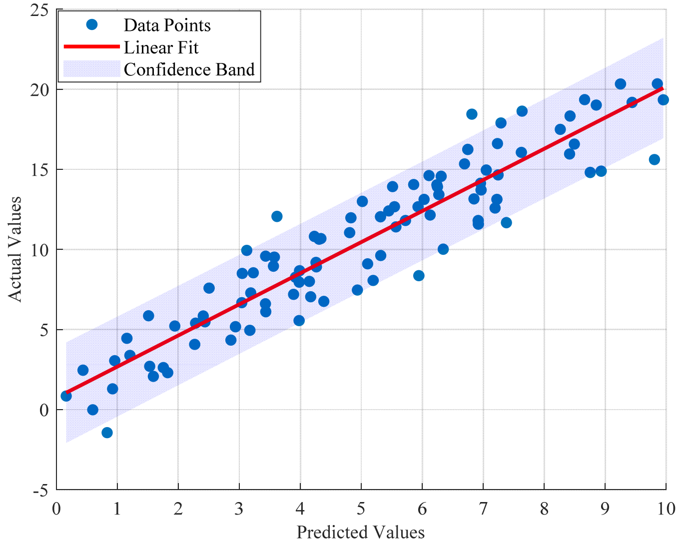
The dataset was split in the model training process in an 8:2 ratio between training set and test set. Five separate trials were also carried out in order to raise the experiment's dependability; the average value was then obtained as the outcome. The hyperparameters of the GNN are set as follows during the training process: the number of nodes in the hidden layer is 64, the activation function is ReLU, the optimiser is Adam, the initial learning rate is 0.001, the number of training rounds is 300 (Fofana et al., 2021), and the early stopping mechanism is used to prevent overfitting.

4.2 Results and discussion

Two related experiments were planned in this work to validate the effectiveness of the proposed model in this paper in the prediction of academic anxiety mood: experiment 1 was a benchmark validation experiment of the model and experiment 2 was a comparison experiment with other main algorithms.

Experiment 1 confirms in this research the appropriate ability of the proposed model to evaluate its capacity to forecast academic anxiety. Figure 2 shows the experimentally obtained data shown in *R*.

Figure 2 Model performance evaluation (proposed model fitting ability) (see online version for colours)



The picture shows the link between the expected and actual values of the model; the linear fit and confidence bands help to visually depict the model's prediction ability. The graphic shows that the data points (blue dots) are rather aligned along the red linear fit line, suggesting a strong linear relationship between the model's forecasts and the real values. With a linear fit line's about two slope, the actual value rises by roughly two units on average for every unit increase in the projected value.

Spread around the linear fit line, the confidence bands – light blue areas – offer a clear estimate of the uncertainty in the predictions of the model. With bigger confidence bands implying more model prediction uncertainty over some range of expected values, the width of the confidence bands reflects the confidence intervals of the model predictions. Overall, nevertheless, the rather limited confidence bands indicate that the model can usually generate more accurate forecasts.

The somewhat equal distribution of data points inside the confidence ranges confirms the dependability of the model forecasts even further. The model performs satisfactorily generally despite certain outliers, which could be the result of random fluctuations in the data or intricate correlations the model misses.

All things considered, the figures show that the suggested model captures the link between emotions and academic achievement and shows good performance in estimating the academic anxiety of EFL learners. These findings offer insightful references for further mood studies and instructional programs.

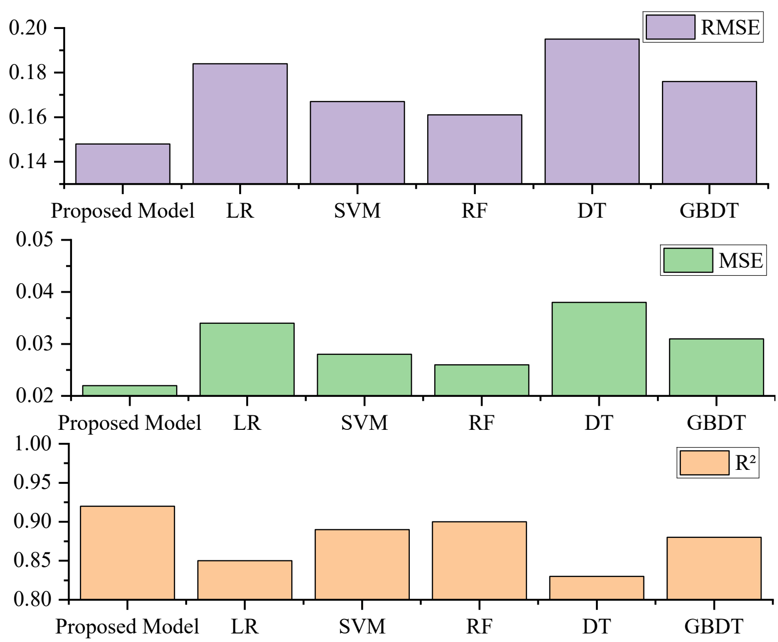
The next experiment intends to evaluate the performance of the proposed model with other typical classical machine learning techniques after benchmarking. The same evaluation criteria for model comparison apply in this experiment. Table 1 summarises the outcomes:

Plotting the performance of every model against one another using the R language helps one to observe the variations in the experimental findings even more. Figure 3 shows this.

Table 1 Comparison with traditional machine learning models

Model	R^2	*MSE*	*RMSE*
Proposed model	0.92	0.022	0.148
LR	0.85	0.034	0.184
SVM	0.89	0.028	0.167
RF	0.90	0.026	0.161
DT	0.83	0.038	0.195
GBDT	0.88	0.031	0.176

Figure 3 Results of the multiple model academic anxiety comparison experiment (see online version for colours)



In all evaluation criteria, the model of this work beats other popular conventional machine learning models, according the comparison. This paper's model performs considerably better than LR (R^2: 0.85, MSE: 0.034) and SVM (R^2: 0.89, MSE: 0.28 especially in the metrics of R^2 (0.92), MSE (0.222) and RMSE (0.148). Although these models performed well in handling feature relationships, this paper's model demonstrated stronger fitting ability and accuracy on the challenging task of predicting academic anxiety. This paper's model also had better performance than RF (R^2: 0.90, MSE: 0.026) and GBDT (R^2: 0.88, MSE: 0.031).

With a R^2 of just 0.83 and greater MSE and RMSE than the other models, the DT model performs the lowest in terms of capturing intricate feature interactions and cannot sufficiently address the issue of estimating academic anxiety.

The suggested approach clearly displays better prediction capability than several conventional machine learning models based on the experimental data. Particularly in the prediction of academic anxiety, the GNN model can efficiently learn intricate feature correlations and hence produce better outcomes.

5 Summary and prospects

5.1 Summary of research

In this work, we present a GNN-based method for academic anxiety sentiment analysis and validate the efficacy of the proposed model in this domain by modelling the anxiety of EFL students. Especially in the assessment metrics of R^2, MSE, and RMSE, the GNN model shows better prediction performance than conventional machine learning algorithms by means of experimental validation. This implies that GNNs can efficiently capture the interactions among intricate features in the sentiment analysis task, hence enhancing the prediction accuracy.

Still, this study has several limits. First of all, especially in cases of non-balanced data, which would influence the performance of the model, the small sample size of the given dataset could have affected the generalisation capacity and stability of the model. Second, the great computational complexity of the GNN model – especially when trained on big-scale datasets – may run into significant computational overheads and memory usage, therefore restricting its efficiency in practical uses. Finally, although the GNN model performs well in this study, its structure is more complicated, which results in a poorer interpretability of the model, thereby influencing the interpretability and tunability of the model in some circumstances and complicating the process of decision-making of the model.

5.2 Directions for future research

Future studies can be enhanced and broad in the following directions in response to the limits in current one:

First, there could be some data imbalance issues given the somewhat small sample size of the dataset employed in the present investigation. In order to increase the generalisation capacity of the model, future studies can aim to include more varied datasets – especially multi-source datasets. Concurrently, migration learning approaches or data improvement strategies might be investigated to enable the model to more effectively handle the difficulties of many data sources.

Second, although the GNN model in our work obtained better results in academic anxiety sentiment analysis, its great computational complexity may cause computational bottlenecks particularly on large-scale datasets. Future studies should take into account improving the GNN model's architecture, including sparse matrix approaches to lower the computational overhead or a more effective variation of graph convolutional networks (GCNs), hence lowering the computational overhead (Min et al., 2020).

At last, the more complicated GNN model suggested in this work results in poor interpretability. Future studies should concentrate on investigating GNN interpretability and aim to build model structures that might offer a better foundation for decision making. Interpretable machine learning techniques, for instance, can be used to clarify the decision-making process of GNN models and enhance their operability in useful applications as well as their transparency.

Declarations

All authors declare that they have no conflicts of interest.

References

Al Chanti, D. and Caplier, A. (2018) 'Deep learning for spatio-temporal modeling of dynamic spontaneous emotions', *IEEE Transactions on Affective Computing*, Vol. 12, No. 2, pp.363–376.

Ayub, S. and Khaleel, B. (2024) 'The needs of graduates required by the employment industries: analysis of English language speaking course outlines at Pakistani universities', *Journal of Language and Pragmatics Studies*, Vol. 3, No. 1, pp.9–21.

Chong, J. and Xia, J. (2018) 'MetaboAnalystR: an R package for flexible and reproducible analysis of metabolomics data', *Bioinformatics*, Vol. 34, No. 24, pp.4313–4314.

Dewaele, J-M., Botes, E. and Meftah, R. (2023) 'A three-body problem: the effects of foreign language anxiety, enjoyment, and boredom on academic achievement', *Annual Review of Applied Linguistics*, Vol. 43, pp.7–22.

Ding, Y., Zhang, Z., Zhao, X., Hong, D., Li, W., Cai, W. and Zhan, Y. (2022) 'AF2GNN: graph convolution with adaptive filters and aggregator fusion for hyperspectral image classification', *Information Sciences*, Vol. 602, pp.201–219.

Fofana, T., Ouattara, S. and Clement, A. (2021) 'Optimal flame detection of fires in videos based on deep learning and the use of various optimizers', *Open Journal of Applied Sciences*, Vol. 11, No. 11, pp.1240–1255.

Karunasingha, D.S.K. (2022) 'Root mean square error or mean absolute error? Use their ratio as well', *Information Sciences*, Vol. 585, pp.609–629.

Khemani, B., Malave, S., Patil, S., Shilotri, N., Varma, S., Vishwakarma, V. and Sharma, P. (2024) 'Sentimatrix: sentiment analysis using GNN in healthcare', *International Journal of Information Technology*, Vol. 16, No. 8, pp.5213–5219.

Lu, B., Gan, X., Jin, H., Fu, L., Wang, X. and Zhang, H. (2022) 'Make more connections: urban traffic flow forecasting with spatiotemporal adaptive gated graph convolution network', *ACM Transactions on Intelligent Systems and Technology (TIST)*, Vol. 13, No. 2, pp.1–25.

Ma, J., Tang, L., Xu, M., Zhang, H. and Xiao, G. (2021) 'STDFusionNet: an infrared and visible image fusion network based on salient target detection', *IEEE Transactions on Instrumentation and Measurement*, Vol. 70, pp.1–13.

Min, Y., Wenkel, F. and Wolf, G. (2020) 'Scattering GCN: Overcoming oversmoothness in graph convolutional networks', *Advances in Neural Information Processing Systems*, Vol. 33, pp.14498–14508.

Mweshi, G.K. and Sakyi, K. (2020) 'Application of sampling methods for the research design', *Archives of Business Review*, Vol. 8, No. 11, pp.180–193.

Myint, L., Hadavand, A., Jager, L. and Leek, J. (2020) 'Comparison of beginning R students' perceptions of peer-made plots created in two plotting systems: a randomized experiment', *Journal of Statistics Education*, Vol. 28, No. 1, pp.98–108.

Plonsky, L. and Ghanbar, H. (2018) 'Multiple regression in L2 research: a methodological synthesis and guide to interpreting R2 values', *The Modern Language Journal*, Vol. 102, No. 4, pp.713–731.

Sepulveda, J.L. (2020) 'Using R and bioconductor in clinical genomics and transcriptomics', *The Journal of Molecular Diagnostics*, Vol. 22, No. 1, pp.3–20.

Shilane, D., Di Crecchio, N. and Lorenzetti, N.L. (2024) 'Some pedagogical elements of computer programming for data science: a comparison of three approaches to teaching the R language', *Teaching Statistics*, Vol. 46, No. 1, pp.24–37.

Tangirala, S. (2020) 'Evaluating the impact of GINI index and information gain on classification using decision tree classifier algorithm', *International Journal of Advanced Computer Science and Applications*, Vol. 11, No. 2, pp.612–619.

Torres, J.F., Hadjout, D., Sebaa, A., Martínez-Álvarez, F. and Troncoso, A. (2021) 'Deep learning for time series forecasting: a survey', *Big Data*, Vol. 9, No. 1, pp.3–21.

Weir, C.J., Butcher, I., Assi, V., Lewis, S.C., Murray, G.D., Langhorne, P. and Brady, M.C. (2018) 'Dealing with missing standard deviation and mean values in meta-analysis of continuous outcomes: a systematic review', *BMC Medical Research Methodology*, Vol. 18, pp.1–14.

Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C. and Yu, P.S. (2020) 'A comprehensive survey on graph neural networks', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 32, No. 1, pp.4–24.

Xia, X. and Qi, W. (2023) 'Learning behavior interest propagation strategy of MOOCs based on multi entity knowledge graph', *Education and Information Technologies*, Vol. 28, No. 10, pp.13349–13377.

Yu, L-C., Lee, C-W., Pan, H., Chou, C-Y., Chao, P-Y., Chen, Z., Tseng, S., Chan, C-L. and Lai, K.R. (2018) 'Improving early prediction of academic failure using sentiment analysis on self-evaluated comments', *Journal of Computer Assisted Learning*, Vol. 34, No. 4, pp.358–365.

Yuzhong, H. (2021) 'Students' emotional analysis on ideological and political teaching classes based on artificial intelligence and data mining', *Journal of Intelligent & Fuzzy Systems*, Vol. 40, No. 2, pp.3801–3809.

Zhao, Z., Wang, K., Bao, Z., Zhang, Z., Cummins, N., Sun, S., Wang, H., Tao, J. and Schuller, B.W. (2021) 'Self-attention transfer networks for speech emotion recognition', *Virtual Reality & Intelligent Hardware*, Vol. 3, No. 1, pp.43–54.

Zhou, H., Ren, D., Xia, H., Fan, M., Yang, X. and Huang, H. (2021) 'AST-GNN: an attention-based spatio-temporal graph neural network for interaction-aware pedestrian trajectory prediction', *Neurocomputing*, Vol. 445, pp.298–308.