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PAPER

Evaluation of Vocational Education and Training Outcomes Based on Mobile Learning

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ABSTRACT

With the rapid advancement of information technology (IT), mobile learning has gradually become a significant approach in vocational education and training. University students utilize mobile applications for learning, which not only enhances the flexibility and efficiency of their studies but also promotes the equitable distribution of educational resources. However, effectively evaluating the impact of these applications in vocational education and training remains an urgent issue to be addressed. Current study methods predominantly focus on the analysis of static data, which inadequately captures the dynamic changes in students' learning behaviors. Additionally, traditional predictive models exhibit low accuracy and poor generalization capabilities when handling high-dimensional, nonlinear time-series data. This study proposes an evaluation method for vocational education and training outcomes based on an improved gated recurrent unit (GRU) model, which comprises three main components: decomposition of university students' mobile application time-series data based on the variable dependence model (VDM), preprocessing of the mobile application data, and outcome evaluation using the improved GRU model. Incorporation of an attention mechanism enhances the predictive performance of the model, providing data support and a decision-making basis for educators and developers.

KEYWORDS

mobile learning, vocational education, time series, gated recurrent unit model (GRU), outcome evaluation, attention mechanism

1 INTRODUCTION

As the rapid advancement of information technology (IT) unfolds, mobile learning has emerged as a pivotal mode of vocational education and training [1–4]. The widespread adoption of mobile applications enables students to learn anytime and anywhere, significantly enhancing the flexibility and efficiency of learning [5–9]. Particularly among university students, the frequency of use of mobile learning applications has been increasing. Consequently, effectively assessing the impact of

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these applications in vocational education and training has become a significant topic in current educational study.

Studies have demonstrated that vocational education and training based on mobile learning not only enhance students' autonomous learning abilities and practical skills but also promote the equitable distribution and utilization of educational resources [10, 11]. Therefore, accurately assessing the effectiveness of mobile learning is crucial for optimizing teaching strategies and enhancing educational quality [12–16]. However, study in this area still faces numerous shortcomings, especially in terms of handling and analyzing complex time series data, where a unified and effective methodology has yet to be established.

Existing study methodologies primarily focus on the analysis of static data, which inadequately captures the dynamic changes in student learning behaviors [17, 18]. Additionally, traditional predictive models often struggle with low accuracy and poor generalization capabilities when dealing with high-dimensional, nonlinear time series data [19–22]. These deficiencies limit the application and dissemination of current study in assessing the effectiveness of vocational education and training.

This study introduces a method to assess the effectiveness of vocational education and training using an enhanced gated recurrent unit (GRU) model. The study involves three main steps: first, decomposing university students' mobile app usage data with the variable dependence model (VDM) to capture more relevant and interpretable information; second, preprocessing the decomposed data to improve data quality and model input effectiveness; and third, applying the improved GRU model with an attention mechanism to enhance prediction accuracy. This method provides a valuable tool for educators and developers, offering both theoretical and practical benefits.

2 DECOMPOSITION OF UNIVERSITY STUDENTS' MOBILE APPLICATION TIME SERIES DATA BASED ON THE VARIABLE DEPENDENCE MODEL

The proposed assessment of the effectiveness of vocational education and training, which is based on the prediction of time series data from mobile applications used by university students, involves modeling and analyzing the usage patterns of these applications. The effectiveness of vocational education and training programs is evaluated by collecting and processing data such as downloads, frequency of use, and user activity levels from these mobile applications. A time series model was constructed to forecast the future usage trends and changes of these applications. Through the analysis of this data, changes in students' interests and needs regarding different vocational education and training content were discerned, and the actual impact of these programs on enhancing students' vocational skills and knowledge was assessed. This method facilitates the identification by educational institutions of which training programs are more popular among students and which require improvement, thereby optimizing the allocation of educational resources and enhancing the quality of education.

Figure 1 illustrates the framework for the proposed time series prediction model, which comprises three main stages:

a) First stage: time series data decomposition based on VDM-Particle Swarm Optimization (PSO). In this stage, time series data derived from the use of mobile applications for vocational education and training by university students were decomposed into multiple modal variables. The main parameters of the variational mode decomposition (VMD) were optimized using the proposed adaptive PSO algorithm, thereby achieving more precise results in time series decomposition.

b) Second stage: data preprocessing. During this stage, the decomposed multimodal variables were standardized or normalized to eliminate noise and fluctuations in the data. Concurrently, combining students' emotional scores and the number of functions of the applications, the information was vectorized, structuring the data for more efficient processing.

c) Third stage: prediction of the effectiveness of vocational education and training using the attention-based GRU (Att-GRU) model. In this final stage, the preprocessed data was predicted using the Att-GRU model, which captures complex patterns and long- and short-term dependencies within the time series data. This model predicts how university students will use vocational education and training applications over an upcoming period. The predictions were then transformed back into data in an intuitively understandable form through the inverse VDM process, providing a quantifiable assessment of the effectiveness of vocational education and training.

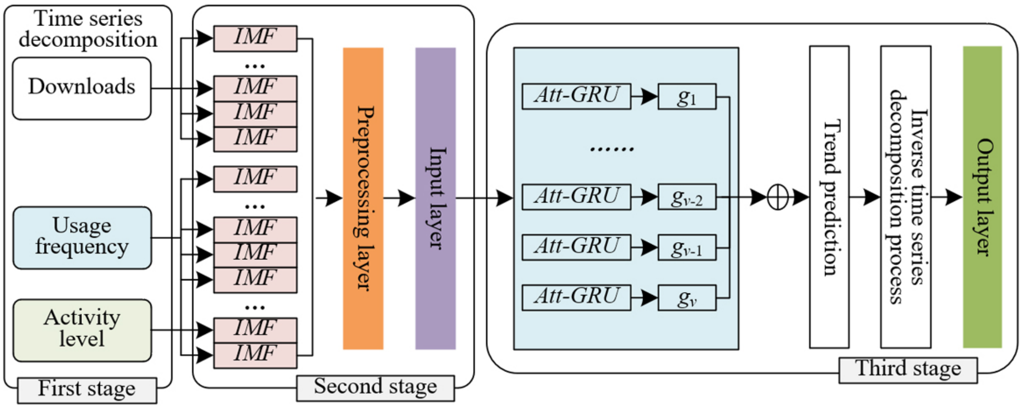

Fig. 1. Framework for the proposed time series prediction model

In the first stage, the VMD algorithm transfers the process of signal decomposition into a variational method, wherein the optimal solution of the constrained variational model is sought to achieve adaptive sequence decomposition. Specifically, time series data from mobile applications used by university students for vocational education and training typically contain complex nonlinear and non-stationary characteristics. Throughout the iterative process, the VMD algorithm continuously updates the frequency center and bandwidth of each modal component, ensuring the adaptiveness and accuracy of the decomposition. It is assumed that the signal is decomposed into J modal components; the original time series is represented by $d(s)$, the J-th modal and its corresponding center frequency are represented by $i_j(s)$ and μ_j, respectively. The squared $L2$ norm is denoted by $\| \|_2^2$, the convolution operation by $*$, and the unit impulse function by $\sigma(s)$. The corresponding constrained variational model is formulated as follows:

$$\begin{cases} \underset{\{i_j(s)\},\{\mu_j\}}{MIN} \left\{ \sum_{j=1}^{J} \left\| \partial_s \left[\left(\delta(s) + \frac{k}{\pi s} \right) * i_j \right] * e^{-k\mu_j s} \right\|_2^2 \right\} \\ s.t.\ \ d(s) = \sum_{j=1}^{J} i_j(s) \end{cases} \tag{1}$$

To effectively handle complex time series data and decompose it into multiple modal components with meaningful physical and statistical properties, this study introduces the augmented Lagrangian function and employs the alternating direction method of multipliers (ADMM) to find the optimal solution to this constrained variational problem. The quadratic penalty term, represented by β, ensures the accuracy of signal reconstruction, while the Lagrange multipliers, denoted by $\sigma(s)$, maintain the strictness of the constraints. The computation formula for the solution is as follows:

$$M\left(\left\{i_j\right\},\left\{\mu_j\right\},\eta(s)\right)=\beta\sum_{j=1}^{J}\left\|\partial_s\left[\left(\sigma(s)+\frac{k}{\pi s}\right)*i_j(s)\right]*e^{-k\mu_j s}\right\|_2^2 + \left\|d(s)-\sum_j i_j(s)\right\|_2^2+\left(\eta(s),d(s)-\sum_j i_j(s)\right) \tag{2}$$

When the VMD algorithm is utilized to decompose time series data from mobile applications used by university students, the selection of the modal number (J) and the quadratic penalty term (β) significantly influences the decomposition outcomes. These parameters are directly related to the effectiveness and precision of the decomposition, thereby impacting the accuracy of the vocational education and training effectiveness assessment. If the value of J is too low, key information might be lost, as a smaller number of modes cannot fully capture all critical features in the mobile application data series, particularly where low-frequency components may include noise due to insufficient smoothness. This limitation can prevent the assessment model from accurately reflecting the true learning behaviors and outcomes of students using vocational education and training applications. Conversely, if the value of J is too high, it may lead to over-decomposition, generating redundant modal components, which not only increases computational complexity and time costs but may also introduce unnecessary noise and interference, obscuring important features and complicating the extraction of useful information by the assessment model. The magnitude of β directly affects noise suppression and signal retention during the decomposition process. When β is low, the decomposition results may include more noise components, which can interfere with the accurate analysis of student learning behaviors and affect the reliability of the assessment outcomes. Conversely, while a high value of β can effectively suppress noise, it may also cause important parts of the signal or spectrum to be distributed across multiple modal components, leading to information dispersion and modal crossover, which in turn affects the assessment model's ability to extract and interpret key features.

In the assessment of vocational education and training effectiveness, the mobile application data series contains a wealth of complex, nonlinear feature information. If the decomposition parameters are improperly selected, key behavioral patterns and learning outcomes of students using vocational education and training applications may not be effectively extracted. Traditional VMD methods require the modal number (J) and the quadratic penalty term (β) to be set based on experience, but such empirical parameter settings often lack a scientific basis and can lead to insufficient parameter selection, thereby impacting the rationality and effectiveness of the decomposition results. To address this, this study introduces the VDM-PSO method to optimize key parameters K and α in VMD, thereby enhancing the accuracy of the decomposition and the precision of the predictions.

Mobile application data from university students may contain various learning behaviors and patterns. Only through precise decomposition and prediction can the learning outcomes in vocational education and training be effectively assessed. In the traditional PSO method, the inertia weight is fixed, which may not achieve a good balance between global and local searches, leading to difficulty in rapidly converging to the global optimum in complex search spaces. Therefore, this chapter proposes an adaptive parameter adjustment method. By dynamically adjusting the inertia weight, it is made larger at the beginning of the search to enhance global search capabilities and gradually reduced later in the search to strengthen local search capabilities, thereby improving the overall optimization performance of the algorithm. It is assumed that the particle's position vector is represented by $a = (a_J, a_\beta)$, the velocity vector by $n = (n_J, n_\beta)$, the inertia weight by μ, cognitive and social coefficients by z_1 and z_2, uniform random numbers within the range by e_1 and e_2, the best position of a specific particle at the s-th iteration by o_J and o_β, and the best position in the search space by the swarm by h_J and h_β. The position update formula for each particle is as follows:

$$\begin{bmatrix} a_J(s+1) \\ a_\beta(s+1) \end{bmatrix} = \mu \begin{bmatrix} a_J(s) \\ a_\alpha(s) \end{bmatrix} + z_1 e_1 * \left(\begin{bmatrix} o_J \\ o_\beta \end{bmatrix} - \begin{bmatrix} a_J(s) \\ a_\beta(s) \end{bmatrix} \right) + z_2 e_2 * \left(\begin{bmatrix} h_J \\ h_\beta \end{bmatrix} - \begin{bmatrix} a_J(s) \\ a_\beta(s) \end{bmatrix} \right) \tag{3}$$

$$\begin{bmatrix} a_J(s+1) \\ a_\beta(s+1) \end{bmatrix} = \begin{bmatrix} a_J(s) \\ a_\beta(s) \end{bmatrix} + \begin{bmatrix} n_J(s+1) \\ n_\beta(s+1) \end{bmatrix} \tag{4}$$

Assuming the fitness value of the current particle is represented by d, the average fitness value of all particles during the current iteration stage by d_{AVG}, and the maximum fitness value among all particles during the current iteration stage by d_{MAX}, the adaptive adjustment of the inertia weight (μ) is defined as follows:

$$\mu = \begin{cases} j_1, d \le d_{AVG} \\ j_1 \dfrac{d_{MAX} - d}{d_{MAX} - d_{AVG}}, d > d_{AVG} \end{cases} \tag{5}$$

Mobile learning data series often contain vast amounts of complex information and noise, reflecting students' learning behaviors and patterns over various time periods. To effectively extract valuable information from these data, a technique capable of fine decomposition and optimization is required. VDM-PSO achieves efficient processing of university students' mobile application data by combining VMD and PSO. The core of VDM-PSO lies in optimizing the parameters of VMD using the PSO algorithm, allowing the decomposition process to better adapt to data characteristics. Specifically, the design of the fitness function is crucial. This study introduces maximum entropy as the fitness function to evaluate the decomposition results. Entropy, a measure of signal uncertainty or the amount of information, is maximized between modal components in VDM-PSO, enabling the selection of modal components that contain more information and are more representative. This means that the decomposed sub-signals not only possess higher information content but also reduce insignificant or redundant components, thus enhancing the effectiveness of data decomposition. Specifically, suppose there is a time series data sequence $a(s)$, decomposed into J modal components, each represented as $i_j(s)(j = 1, 2, \ldots, J)$, where the amplitude of the sub-modal in time domain s is represented by M_j, the length of the sub-modal by V, and the probability density function of i_j by $Oe(\cdot)$. The entropy of a modal component, denoted by $G(i_j(s))$, is defined as follows:

$$G\left(i_j(s)\right) = -\sum Oe\left(i_j(s)\right)\log\left(Oe\left(i_j(s)\right)\right) \tag{6}$$

$$Oe\left(i_j(s)\right) = \frac{M_j}{\sum_{j=1}^{V} M_j} \tag{7}$$

By searching for the maximum entropy, the optimal parameter combination (J, β) was determined, and the definition of the fitness function is given by the following formula:

$$d = \arg\max_{(J,\beta)}\left\{G\left(i_j(s)\right)\right\} \tag{8}$$

In the assessment of the effectiveness of vocational education and training based on the time series prediction of mobile applications used by university students, the process of integrating VDM-PSO is detailed as follows:

a) Time series data $a(s)$ from university students' mobile applications, reflecting students' learning behaviors over different periods, was input. The range of values for the VDM parameters (J, β) was set, where J represents the number of modes, ranging from {2, 3, ..., 12}, and β is the penalty parameter, set within the range of [0, 1000]. Subsequently, VDM was used to decompose the input time series data, at which point the PSO parameters needed to be initialized.

b) Following PSO initialization, the fitness of all modes was calculated; that is, the effective information content of each mode was assessed using maximum entropy, with the maximum entropy serving as the initial fitness value. This step ensures that the decomposed modes contain as much information as possible, reducing the impact of redundancy and noise on the decomposition results.

c) For each particle, the global and individual best positions were updated, along with the particle's velocity and position. It is determined whether the change in fitness is less than the set threshold or whether the maximum number of iterations has been reached. If either condition is met, the algorithm concludes and returns the optimal solution; otherwise, iterations continue until the algorithm converges or the maximum number of iterations is reached.

Figure 2 presents the VDM-PSO flowchart. Specifically, for key factors affecting the assessment of vocational education and training effectiveness, such as user activity and learning behaviors, these factors are not represented by a single data point at a given moment s but are composed of multiple data points. To align these data with other variables, these factors should undergo weighted processing. That is, all activity levels prior to moment s are weighted averaged before undergoing time series decomposition. Similarly, learning behavior data is also processed with weights.

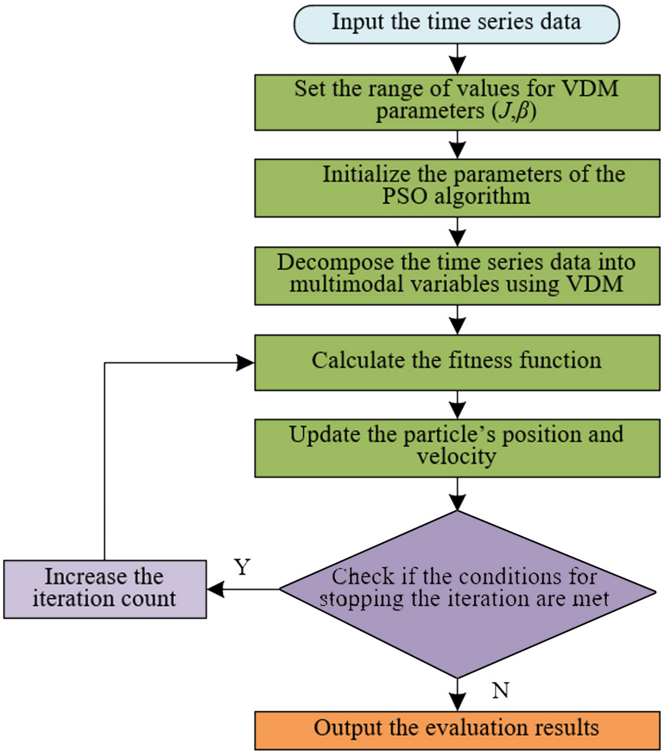

Fig. 2. VDM-PSO flowchart

3 PREPROCESSING OF UNIVERSITY STUDENTS' MOBILE APPLICATION DATA

In the assessment of vocational education and training effectiveness based on the time series prediction of mobile applications used by university students, the data preprocessing step is crucial for ensuring the accuracy and stability of the model. The input data from university students' mobile applications includes factors such as downloads, usage frequency, and activity levels. These data may exhibit significant variations in magnitude across different time points and factors. For instance, the magnitude of learning duration might differ from that of activity levels. To eliminate the impact of these discrepancies, normalization of the time series data is required. Assuming the value of the u-th sub-signal at the k-th time point is represented by a_{uk}, the minimum and maximum values of the u-th sub-signal over the entire time series are denoted by $MIN\{a_{uk}\}$ and $MAX\{a_{uk}\}$, respectively. The normalized value of the u-th sub-signal at the k-th time point is denoted by a'_{uk}. The total number of samples is represented by V, and the number of modal components by J. The normalization is defined as follows:

$$a'_{uk} = \frac{a_{uk} - \underset{k=1,2,\ldots,V}{MIN}\{a_{uk}\}}{\underset{k=1,2,\ldots,V}{MAX}\{a_{uk}\} - \underset{k=1,2,\ldots,V}{MIN}\{a_{uk}\}}, u = 1,2,\ldots,J \tag{9}$$

After normalization, the data was used for parameter optimization in the PSO algorithm and for training the GRU model. After predictions through the VDM-PSO-Att-GRU model, the forecasted downloads remain in normalized form. Therefore, denormalization is necessary to restore the data to its original scale. This step was achieved by multiplying the forecasted values by the standard deviation of the original data and adding the mean, or through a reverse min-max normalization process. Assuming the predicted value of the u-th sub-signal is represented by b_u and the denormalized forecasted value is denoted by a'_u, the equation is as follows:

$$b'_u = b_u \times \left(\underset{k=1,2,\ldots,V}{MAX}\{a_{uk}\} - \underset{k=1,2,\ldots,V}{MIN}\{a_{uk}\} \right) + \underset{k=1,2,\ldots,V}{MIN}\{a_{uk}\} \tag{10}$$

4 EVALUATION OF VOCATIONAL EDUCATION AND TRAINING EFFECTIVENESS USING AN ENHANCED GRU MODEL

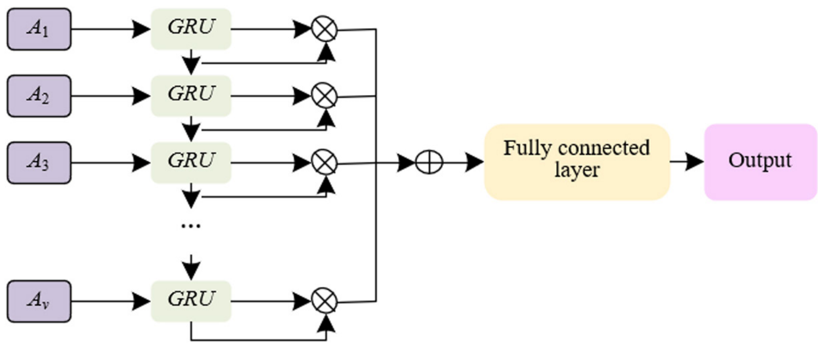

Fig. 3. Structure of the attention-based gated recurrent unit model

The mobile application data series of university students is typically vast and complex, encompassing various factors such as downloads, usage frequency, and activity levels. Furthermore, the assessment of vocational education and training effectiveness involves multiple nonlinear relationships, such as the intricate associations between students' learning behavior patterns and their training outcomes. The GRU model architecture, known for its simplicity and potent time series prediction capability, effectively captures these nonlinear relationships. To further enhance the model's performance, an attention mechanism was integrated into the GRU model. The model structure is depicted in Figure 3. The attention mechanism enables the model to dynamically focus on those aspects of the data that are more crucial for the current evaluation of training effectiveness, thereby enhancing the model's predictive accuracy and interpretability.

Specifically, the model comprises four layers: the input layer, the GRU layer, the attention mechanism layer, and the output layer. The input layer selects the time series of mobile applications used by university students as the input feature matrix. These feature matrices represent critical information such as emotional feedback on mobile applications, diversity of app functions, and frequency of use. These features are treated as fundamental units and are sequentially fed into the next layer for processing. Following this, the GRU layer, which is the core part of the model, contains multiple GRU units, each corresponding to a time step. In this layer, the input feature matrices are fed into the GRU units, which utilize the output from the previous time point as the input for the current time point, thereby capturing the dynamic changes within the time series data. This mechanism enables the model to effectively learn and remember the learning behaviors of students at different time points and their trends. Next is the attention mechanism layer, whose primary function is to allocate weights to the information at each time step. By analyzing the information output from the GRU layer, the attention mechanism identifies which time steps have a more significant impact on the effectiveness of vocational education and training, assigning higher weights to these pieces of information. This enables the model to focus more on the time points that are most crucial to the assessment outcomes, thereby enhancing the accuracy and interpretability of the predictions. Finally, the output layer uses the output from the attention mechanism layer, applying an activation function to predict the outcomes of the vocational education and training effectiveness evaluation. The attention probability value corresponding to g_s is denoted by α_s, the attention weight by x_s, the weight coefficients by w and μ, and the bias coefficient by y. The computation method for the attention layer is as follows:

$$\alpha_s = w \tanh\left(\mu g_s + y\right) \tag{11}$$

$$x_s = \text{softmax}\left(\alpha_s\right) = \frac{e^{\alpha_s}}{\sum_{u=1}^{v} e^{\alpha_s}} \tag{12}$$

$$X = \sum_{k=1}^{v} x_k g_k \tag{13}$$

5 EXPERIMENTAL RESULTS AND ANALYSIS

Based on the time series data of downloads for vocational education and training mobile applications shown in Figure 4, significant fluctuations and periodic changes in download volumes are observed. Within the initial 16 time periods, downloads were zero. Thereafter, a sudden increase in downloads was noted between the 31st and 76th periods, particularly reaching peaks of 5,000 and 8,000 downloads in the 46th and 61st periods, respectively. Subsequent periods displayed distinct periodic fluctuations. For example, between the 91st and 121st periods, downloads were 4,000 and 500, respectively, indicating considerable variance. From the 151st period, a sharp rise in downloads began, peaking at 24,000 downloads in the 181st period and continuing to rise until reaching the highest peak of 36,000 downloads in the 226th period. Thereafter, despite fluctuations, downloads remained at a high level, particularly reaching another peak between the 256th and 286th periods with 28,000, 26,000, and 25,000 downloads, respectively. In the final stages, the download volume reached its highest peak of 52,000 downloads in the 346th period. From the analysis of the above time series data on downloads, it is concluded that downloads of mobile applications for vocational education and training exhibit clear periodic fluctuations and phase-wise growth characteristics. In the initial phase (from the 0th to the 76th period), downloads were low and highly fluctuating, indicating an initial exploration and acceptance process by the users. Over time, as the application's downloads gradually increased and reached multiple peaks, this correlated with factors such as promotional activities, course updates, or increased demand for educational training. In the middle to later stages (after the 151st period), downloads consistently remained high, showing a trend of gradual acceptance and sustained usage by more users. Particularly in the 226th and 346th periods, where downloads reached their highest peaks, this reflected significant updates or the launch of attractive new content at these moments, further enhancing users' willingness to download and use the application.

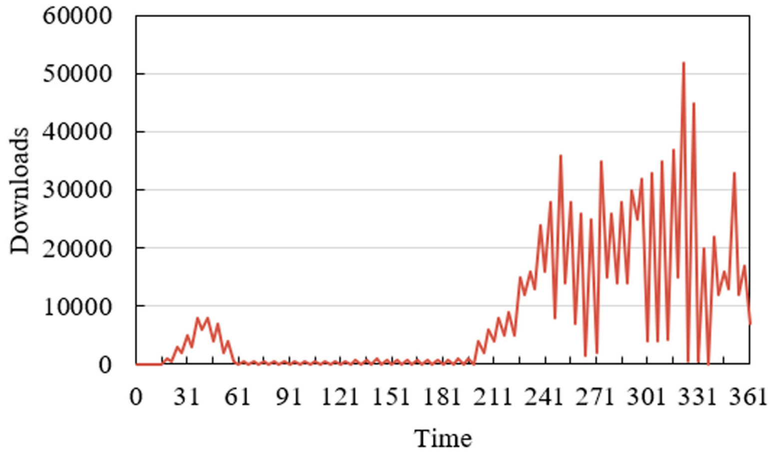

Fig. 4. Time series of downloads for vocational education and training mobile applications

Table 1. Error comparison of evaluation results of time series decomposition models

	Traditional VDM	EEMD	VDM-PSO
MAE	1.02	1.26	0.77
RMASE	1.68	2.07	1.62
MAPE	4.26	4.56	3.89

Based on the data in Table 1, the performance of three different time series decomposition models, i.e., traditional VDM, ensemble empirical mode decomposition (EEMD), and VDM-PSO, can be observed in terms of error evaluation metrics. Among them, the VDM-PSO model exhibits relatively lower error values across all three error indicators. Specifically, the VDM-PSO model's mean absolute error (MAE) is 0.77, which is lower than the traditional VDM's 1.02 and EEMD's 1.26. In terms of root mean square absolute error (RMASE), the VDM-PSO model scores 1.62, also lower than the traditional VDM's 1.68 and EEMD's 2.07. For the mean absolute percentage error (MAPE), VDM-PSO records an error of 3.89%, outperforming traditional VDM's 4.26% and EEMD's 4.56%. These results indicate that the VDM-PSO model demonstrates higher accuracy and stability in processing time series data from university students' mobile applications.

Table 2. Performance comparison of different models assessing the effectiveness of vocational education and training

		ARIMA	LSTM	GRU	Att-LSTM	Att-GRU
Evaluation window 1	MAE	33.25	5.07	6.02	0.27	0.08
	RMASE	12.56	8.89	8.87	0.83	0.13
	MAPE	28.69	4.89	9.78	2.77	1.22
Evaluation window 5	MAE	41.02	12.45	10.23	0.05	0.44
	RMASE	13.25	14.58	12.25	1.35	0.83
	MAPE	31.26	19.68	17.56	3.87	2.88
Evaluation window 10	MAE	43.25	9.88	13.25	0.77	0.87
	RMASE	23.68	10.23	15.26	1.23	1.65
	MAPE	28.65	12.26	16.36	5.89	5.89

(Continued)

Table 2. Performance comparison of different models assessing the effectiveness of vocational education and training *(Continued)*

		ARIMA	LSTM	GRU	Att-LSTM	Att-GRU
Evaluation window 30	MAE	50.23	12.25	15.26	1.25	1.21
	RMASE	34.56	14.56	16.35	2.03	2.87
	MAPE	32.69	22.36	25.69	15.69	16.59

According to the data in Table 2, significant differences are observed in the performance of various models across several evaluation windows. Notably, the Att-GRU model demonstrates the best performance in evaluation window 1, with a MAE of only 0.08, an RMASE of 0.13, and a MAPE of 1.22, significantly outperforming other models. The attention-based long short-term memory (Att-LSTM) model follows closely with a MAE of 0.27, an RMASE of 0.83, and a MAPE of 2.77. In contrast, the traditional autoregressive integrated moving average model (ARIMA) exhibits the poorest performance across all evaluation windows, with significantly higher values of MAE, RMASE, and MAPE. In evaluation of Windows 5 and 10, the Att-GRU and Att-LSTM models continue to excel, with markedly lower values of MAE, RMASE, and MAPE compared to other models. However, as the evaluation window size increases, such as in Evaluation Window 30, errors for all models rise, yet the Att-GRU and Att-LSTM models still maintain relatively low error values, with MAEs of 1.21 and 1.25, respectively. These results indicate that long short-term memory (LSTM) and GRU models equipped with attention mechanisms exhibit higher accuracy and stability across different evaluation windows, particularly more pronounced in smaller windows.

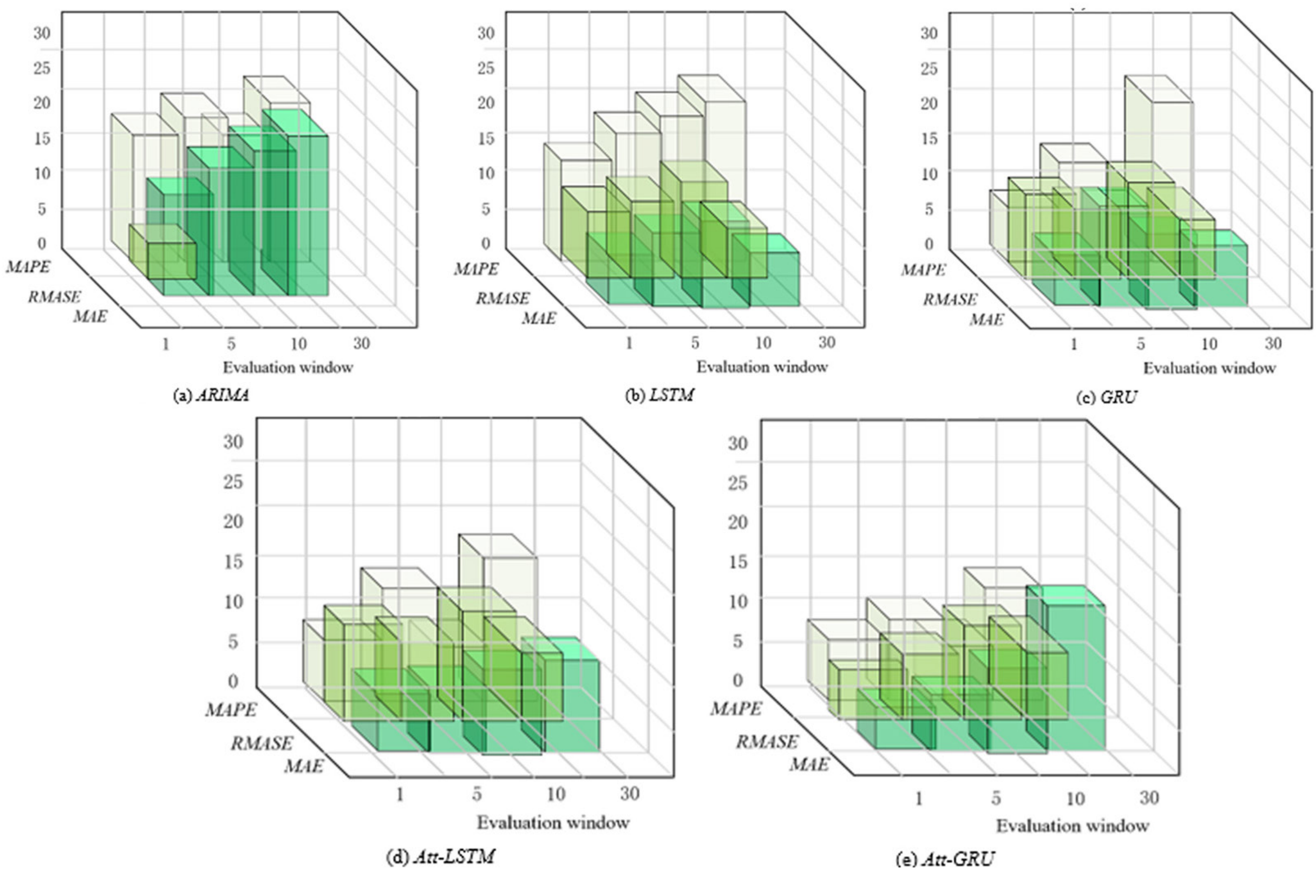

Fig. 5. Experimental results across different evaluation windows

According to the experimental results shown in Figure 5, significant variations in model performance across different evaluation windows are observed. It is evident that the GRU and LSTM models exhibit distinct characteristics when processing time series data from university students' mobile applications. The GRU model, with its fewer gating units, captures key patterns and trends more effectively in short-term evaluations (one day and five days), thus performing best in these shorter windows. For long-term evaluations (10 days and 30 days), the LSTM model, due to its more complex gating mechanisms, handles and retains longer-term dependencies better, hence showing relatively superior performance in longer windows. Furthermore, by comparing the performance of attention-enhanced models, Att-LSTM and Att-GRU, with their non-attention counterparts, LSTM and GRU, the critical role of attention mechanisms in enhancing model performance was validated. Attention mechanisms aid the models in better capturing important modes and the relationships between modes in the time series data of university students' mobile applications, significantly enhancing the models' expressive power and learning capabilities, thereby improving the accuracy and effectiveness of time series predictions. In contrast, the ARIMA model performs poorly in such tasks due to its insufficient capability to model complex patterns and long-term dependencies. This further demonstrates the superiority of attention-based deep learning models in handling complex time series data.

Table 3. Evaluation results of vocational education and training effectiveness across different sample categories

Categories of Mobile Application Data Samples	Analysis of Learning Behavior	Analysis of Learning Outcomes	Learning Engagement	Learning Satisfaction	Long-term Impact Assessment
Behavioral data	0.2015	0.1235	0.0685	0.0045	0.3859
Interaction data	0.1425	0.1425	0.0821	0.0321	0.3784
Performance data	0.1428	0.1456	0.0723	0.0232	0.3625
Content access data	0.1985	0.0235	0.0289	0.0352	0.2854
Feedback data	0.1425	0.0856	0.0287	0.0115	0.2695
Social data	0.1369	0.0257	0.0932	0.0654	0.2568

Data from Table 3 reveal significant differences in the results of vocational education and training effectiveness evaluations across different sample categories. In the analysis of learning behavior, behavioral data (0.2015) and content access data (0.1985) scored relatively higher, whereas interaction data (0.1425), performance data (0.1428), and feedback data (0.1425) scored lower. Regarding the analysis of learning outcomes, performance data (0.1456) and interaction data (0.1425) performed better, while content access data (0.0235) and social data (0.0257) scored lower. In terms of learning engagement, social data (0.0932) and interaction data (0.0821) achieved higher scores, whereas content access data (0.0289) and feedback data (0.0287) scored lower. In the long-term impact assessment, behavioral data (0.3859) and interaction data (0.3784) excelled, while social data (0.2568) and feedback data (0.2695) scored relatively lower. The analysis of these results indicates that behavioral and interaction data excel across multiple assessment dimensions, demonstrating their high representativeness and practical value in evaluating the effectiveness of vocational education and training. Particularly in the analysis of learning behavior and long-term impact assessment, behavioral data scored the highest, indicating its significant advantages in capturing actual student behaviors and long-term learning effects. Interaction data performed well in the analysis of learning outcomes and engagement, underscoring the critical role of interaction in enhancing learning effects and student engagement. In contrast, content access data and feedback data scored lower across most dimensions due to their limitations in reflecting actual learning effects and long-term impacts.

6 CONCLUSION

This study presents a method for assessing the effectiveness of vocational education and training based on an improved GRU model, which encompasses three main aspects of study. Firstly, the time series data from university students' mobile applications was decomposed using the VDM to extract more representative and interpretable information. Secondly, the decomposed data was preprocessed to enhance the quality and effectiveness of the model inputs. Lastly, the enhanced GRU model was employed for effectiveness assessment, where the incorporation of an attention mechanism boosted the model's predictive performance. The experimental results include time series analyses of mobile application downloads for vocational education and training, evaluation error comparisons of time series decomposition models of mobile applications used by university students, performance comparisons of different models assessing the effectiveness of vocational education and training, experimental outcomes across various evaluation windows, and assessment results of vocational education and training effectiveness across different sample categories.

From the study content and experimental results of this study, several conclusions were drawn. The method proposed in this study excels in evaluating the effectiveness of vocational education and training, particularly in handling diverse data types. Through the VDM and preprocessing steps, the quality and representativeness of model inputs are effectively enhanced, thereby boosting the predictive capabilities of the model. The improved GRU model, combined with the attention mechanism, not only enhances the accuracy of assessments but also provides more detailed assessment results, especially prominent in long-term impact assessments and analyses of learning behaviors. However, this study has certain limitations, such as the diversity and volume of sample data, which may not be sufficient to fully verify the universality of the model. In addition, the performance of the model under extreme conditions still requires further study. Future study directions could include expanding the diversity and scale of datasets, improving the robustness of the model, exploring more complex deep learning models, and further optimizing the attention mechanism, thereby enhancing the precision and comprehensiveness of vocational education and training effectiveness assessments.

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