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PAPER

Application of Smart Mobile Devices in Electronic Design Education: Multidimensional Interaction Model and Learning Outcomes Assessment

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ABSTRACT

With the rapid advancement of technology, smart mobile devices are increasingly being integrated into the educational domain, showing significant potential, particularly in electronic design education. Traditional classroom teaching methods face limitations in information delivery and student interaction, while the introduction of smart mobile devices brings new opportunities to classroom instruction. Through smart mobile devices, educators can organize teaching activities more flexibly, and students can engage in classroom interactions in various forms, greatly enhancing teaching effectiveness and learning experiences. Although numerous studies have explored the application of smart mobile devices in education, most focus on single-dimensional interaction models, overlooking the potential of multidimensional interactions. Additionally, traditional methods for assessing learning outcomes often rely on qualitative analysis and post-class tests, which fail to comprehensively and in real-time reflect students' learning states and emotional changes. This paper aims to construct a multidimensional interaction model for electronic design education classrooms based on smart mobile devices and to assess learning outcomes through real-time analysis of students' emotions and feedback data, thereby optimizing teaching strategies. This study not only provides new perspectives and methods for the application of smart mobile devices in education but also offers practical guidance for teaching reforms and innovations in electronic design education, holding significant theoretical and practical value.

KEYWORDS

smart mobile devices, electronic design education, multidimensional interaction model, learning outcomes assessment, emotion analysis

1 INTRODUCTION

With the rapid advancement of technology, the application of smart mobile devices in the field of education is becoming increasingly widespread, especially

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in electronic design education [1–3]. Traditional classroom teaching methods face limitations in information transmission and student interaction, while the introduction of smart mobile devices brings new opportunities to classroom teaching [4, 5]. Through smart mobile devices, teachers can more flexibly organize teaching activities, and students can participate in classroom interaction in various forms, greatly enhancing teaching effectiveness and the learning experience.

The application of smart mobile devices in electronic design education not only revolutionizes traditional teaching methods but also provides technical support for the construction of multidimensional interaction models [6–8]. In a multidimensional interaction model, students can interact through text, voice, video, and other means, effectively enhancing their initiative and participation in learning [9–12]. At the same time, this new teaching mode can also capture and analyze students' emotions and feedback in real-time, providing teachers with an accurate teaching adjustment basis, thereby achieving personalized teaching and promoting the comprehensive development of students.

Although numerous studies have explored the application of smart mobile devices in education, most focus on single-dimensional interaction models, overlooking the potential of multidimensional interactions [13, 14]. Additionally, traditional methods for assessing learning outcomes often rely on qualitative analysis and post-class tests, which cannot comprehensively and in real-time reflect students' learning states and emotional changes [15–17]. The limitations of these research methods have led to the underutilization of smart mobile devices in classroom teaching, requiring more systematic and comprehensive study to address these shortcomings.

This paper primarily includes two parts of study content: first, constructing a multidimensional interaction model for electronic design education classrooms based on smart mobile devices. By comprehensively using text, voice, video, and other interactive forms, a richer and more dynamic classroom interaction environment is established; second, evaluating the learning outcomes of electronic design education using smart mobile devices. By analyzing students' emotions and feedback data in real-time, the learning outcomes are assessed, and teaching strategies are optimized accordingly. This study not only provides new perspectives and methods for the application of smart mobile devices in the field of education but also offers practical guidance for teaching reforms and innovations in electronic design education, holding significant theoretical and practical value.

2 MULTIDIMENSIONAL INTERACTION MODEL FOR ELECTRONIC DESIGN EDUCATION CLASSROOMS BASED ON SMART MOBILE DEVICES

In the context of rapidly developing educational technology, the widespread application of smart mobile devices has brought new interaction methods to electronic design education classrooms. This classroom interaction is no longer limited to the traditional one-way communication of teachers lecturing and students listening but achieves classroom diversification and dynamism through the multidimensional interaction of smart mobile devices. Specifically, the use of smart mobile devices enables students to participate in classroom discussions, ask questions, and express opinions in various forms, such as text, voice, and video. This multidimensional interaction not only enhances students' sense of participation and classroom interaction but also provides teachers with rich classroom data, especially students' emotional data.

In the electronic design education classroom based on smart mobile devices, the key to emotion analysis lies in utilizing these terminal devices to capture and analyze students' multidimensional emotional signals, such as voice, text, and facial expressions, in real-time. Through emotion analysis, teachers can analyze the emotional components in students' voices, such as excitement, calmness, or depression, thereby understanding students' learning status and classroom engagement in real-time. One of the core objectives of this study is to determine the emotional level of the classroom by calculating the classroom emotion conversion rate and classroom excitement.

Assuming the number of emotion conversions is represented by d_t, the duration of the classroom audio is represented by S, and the sampling frequency of the audio is represented by P_Z, the formula for classroom emotion conversion rate is:

$$T = \frac{d_t}{S} \cdot P_Z \tag{1}$$

The duration of the voice segments judged to be excited emotion is represented by dd_γ, and then the formula for classroom excitement is:

$$R = \frac{\sum d_\gamma}{S} \tag{2}$$

Based on the above two formulas, the formula for determining the emotional level of the electronic design education classroom is:

$$L = \begin{cases} Excitement, R > 0.6 \; and \; T > 0.5 \\ Calmness, others \\ Depression, R < 0.3 \; and \; T < 0.3 \end{cases} \tag{3}$$

In the modern educational environment, the application of smart mobile device network analysis provides new study perspectives and methods for electronic design education classrooms. Currently, most smart mobile device network analyses focus on the interactive behaviors in online course forums, studying students' and teachers' learning habits and engagement by analyzing their interactions in these forums. These multidimensional forms of interactive behaviors include various forms, such as text, voice, and video, making classroom interaction richer and more three-dimensional. However, the interactive behaviors in offline classrooms in existing teaching modes are rarely analyzed, mainly because offline classroom data is not as centralized and easy to extract as data in online forums. In offline classrooms, students' interactions and feedback are often scattered across multiple links and forms, and traditional data collection and analysis methods make it difficult to effectively capture this information. This paper innovatively proposes to solve the offline classroom data collection problem by analyzing classroom audio data and applying mobile network analysis to the analysis of offline classroom interactive behaviors. Figure 1 shows an example of a smart mobile device network diagram for interaction in an electronic design education classroom.

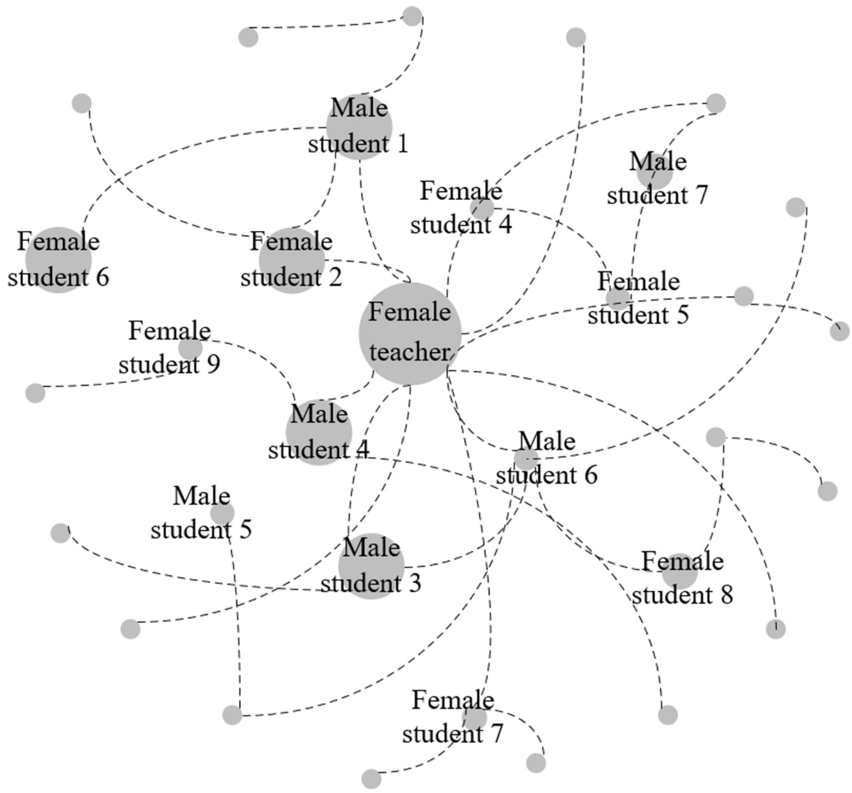

Fig. 1. An example of a smart mobile device network diagram for interaction in the electronic design education classroom

In this multidimensional interaction classroom model for electronic design education based on smart mobile device networks, each speaker is considered a node in the smart mobile device network, with the weight of the node representing the total speaking time of that speaker. The connection between two nodes represents the interaction between the speakers, with the weight of the connection indicating the total interaction time. This method allows for a comprehensive analysis of teacher-student interaction behaviors in the classroom and the construction of a smart mobile device network diagram. Specifically, the conversion rate of teacher-student behaviors in the classroom is first calculated, which refers to the frequency and number of interactions between students and teachers within a specific time period. Second, classroom interaction distance refers to the physical or temporal distance between speakers, which can be determined by analyzing interaction time and speaking intervals. Classroom interaction density reflects the overall activity level of interactions in the classroom, indicating the frequency of interactions within a certain time period. Furthermore, the density of the smart mobile device network is the ratio of the actual number of existing connections to the maximum possible number of connections in the network, reflecting the tightness of overall classroom interactions. The diameter of the smart mobile device network is the shortest path between the two farthest nodes in the network, indicating the farthest distance information travels in the classroom. The degree of a single node represents the number of connections a node has with other nodes, and the average degree of nodes is the average of all nodes' degrees, reflecting the overall level of interaction.

The teacher-student behavior conversion rate measures the frequency of interactions between teachers and students. Its calculation principle is to record the time of each teacher and student's speech, count the number of times students speak immediately after a teacher's speech, and count the number of times a teacher speaks immediately after a student's speech, thereby evaluating the frequency and proportion of teacher-student interactions. Assuming the number of teacher-student interaction behavior conversions is represented by d_{ts}, the duration of classroom audio is represented by S, and the frequency by P_Z, the calculation formula is:

$$Es = \frac{d_{ts}}{S} \cdot P_Z \tag{4}$$

Classroom interaction distance refers to the interaction distance between speakers, usually in terms of time. Its calculation principle is to use the speech times recorded by smart mobile devices to calculate the time intervals between each speech, i.e., the time distance of each interaction. If physical location information is available, the physical distance between speakers can also be calculated, which helps understand the interaction distance and frequency between speakers.

$$f_u = \frac{1}{v-1}\sum_{k \neq u} f_{uk} \tag{5}$$

Classroom interaction density reflects the overall activity level of classroom interactions. Its calculation principle is to record the number of speeches and interactions between speakers within a certain period, compare the actual number of interactions with the maximum possible number of interactions, and evaluate the frequency and activity level of interactions. This index helps understand the overall interaction situation in the classroom. Assuming the total number of edges between all nodes is represented by m, the weight of the edges by μ_s, the total number of nodes by v, and the weight of a single node by μ_v, the calculation formula is:

$$U_v = \frac{\sum(m \times \mu_m)}{\sum(v \times \mu_v)} \tag{6}$$

The density of the smart mobile device network is the ratio of actual existing interaction relationships to the maximum possible interaction relationships. Its calculation principle is to construct a network diagram containing all speakers, count the number of actual existing interaction connections, and compare it with the number of all possible interaction connections to obtain the network density. This reflects the tightness of classroom interactions and the breadth of information dissemination.

$$F_v = 2\frac{1}{v(v-1)} \tag{7}$$

The diameter of the smart mobile device network is the shortest path between the two farthest nodes in the network, indicating the farthest distance information travels in the classroom. Its calculation principle is to calculate the shortest path length between all pairs of nodes and find the longest one among them; this path length is the network diameter. This helps evaluate the efficiency of information dissemination in the classroom. Assuming the average degree of the network distance between two nodes is represented by *fua*, the calculation formula is:

$$f_v = MAX\,(fux) \tag{8}$$

The average degree of nodes is the average of all nodes' degrees, reflecting the overall level of interaction. Its calculation principle is to count the degrees of all nodes and then calculate the average of these degrees. Through the average degree, we can understand the breadth of interaction in the entire classroom, providing a reference for improving teaching strategies.

$$F_{AVE} = \frac{\sum F}{v} \tag{9}$$

The degree of a single node represents the number of connections it has with other nodes. Its calculation principle is to count the number of connections between a node and other nodes in the network diagram; these numbers of connections are the degree of that node. The higher the degree, the more interaction relationships that node has, reflecting the breadth of the speaker's interaction in the classroom. Assuming the in-degree of a node is represented by *UF* and the out-degree by *PF*, the calculation formula is:

$$F = UF + PF \tag{10}$$

3 EVALUATION OF LEARNING OUTCOMES IN ELECTRONIC DESIGN EDUCATION USING SMART MOBILE DEVICES

To obtain an accurate evaluation of learning outcomes in electronic design education using smart mobile devices, this paper proposes a spatial attention mechanism bidirectional gated recurrent unit (BiGRU) model based on Spark distributed ensemble empirical mode decomposition (EEMD). The main reason is that learning outcome evaluation in electronic design education involves a large amount of time series data, and this model excels at handling complex time series data. During the data preprocessing stage, student interaction and learning data recorded by smart mobile devices, such as the number of speeches, interaction frequency, and assignment completion times, can be extracted, sorted, grid-matched, and statistically analyzed. Proper preprocessing can provide high-quality input data for subsequent model analysis. In the model construction stage, the combination of EEMD and normalization methods can effectively decompose complex time series data into a finite number of intrinsic mode functions (IMFs) and residual sequences. These decomposed sequences are easier to analyze and predict, especially when combined with the BiGRU algorithm with a spatial attention mechanism, which can better capture spatial interaction information in the classroom, such as the interaction frequency between students and teachers and the intensity of discussions among students. Finally, during the model implementation stage, running the model on the Spark parallel distributed platform can efficiently handle large-scale educational data and achieve real-time evaluation of learning outcomes. The parallel computing capability of the Spark platform can accelerate data processing and model training, ensuring the timeliness and accuracy of evaluation results. Additionally, the model performs denormalization and superposition on the prediction results to provide intuitive learning outcome evaluations, such as learning progress curves and knowledge point mastery levels. Figure 2 shows the flow chart of the EEMD algorithm.

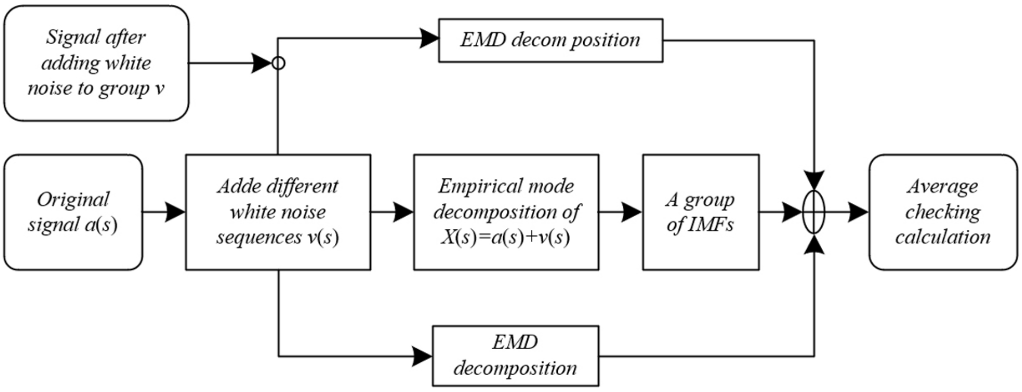

Fig. 2. Flow Chart of the ensemble empirical mode decomposition algorithm

Below are detailed explanations of the four execution steps of the model:

Step 1: Application of the ensemble empirical mode decomposition algorithm in model design: Set the overall average number of times as L, the white noise sequence of the u-th time as $v_u(s)$, the original signal as $a(s)$, and the additional noise signal added to the u-th time as $a_u(s)$. By adding $v_u(s)$ with a standard normal distribution to $a(s)$, an additional noise signal can be obtained. The perturbation characteristics of white noise make the subsequent modal decomposition more stable and accurate.

$$a_u(s) = a(s) + v_u(s),\ u = 1, 2, \ldots, L \tag{11}$$

Empirical mode decomposition (EMD) is performed on $a_u(s)$ to obtain several IMFs and a residual sequence. These IMFs and residual sequences represent different frequency components and trend information in learning outcome data. Assuming the K-th IMF obtained after adding white noise in the u-th time is represented by $z_{u,k}(s)$, the residual function by $e_{u,k}(s)$, and the number of IMFs by K, the formula is:

$$a_u(s) = \sum_{k=1}^{K} z_{u,k}(s) + e_{u,k}(s), u = 1,2,\ldots,L; k = 1,2,\ldots,K \tag{12}$$

Repeat the above steps L times, and by adding different amplitudes of white noise signals multiple times, the influence of noise on the decomposition results can be offset, resulting in a more stable set of IMFs.

$$z_{1,k}, z_{2,k}, z_{3,k}, \ldots, z_{L,k},\ k = 1, 2, \ldots, K \tag{13}$$

To ensure the accuracy and stability of the IMFs, average calculations are performed on the obtained function set, resulting in the final outcome of the modal decomposition functions. Finally, the decomposed IMFs and residual sequences are mapped to [0, 1] for data normalization, facilitating subsequent modeling and prediction. Assuming the k-th IMF of the decomposition is represented by $z_k(s)$, the calculation formula is:

$$z_k(s) = \frac{1}{L}\sum_{u=1}^{L} z_{uk}(s), u = 1,2,\ldots,K \tag{14}$$

Step 2: Constructing spatial attention mechanisms: Grid processing is performed on classroom interaction data to extract the number of student interactions in each grid. Specifically, the classroom is divided into several areas, each representing specific interactive activities such as asking questions, answering, and have discussions. The number of interactions extracted from these areas is used as weights to indicate the interaction frequency in each grid. Further, these interaction frequencies are used as a weight to perform maxpool and avgpool processing on the input feature data. The maxpool operation captures the most frequent interaction behavior in each grid, while avgpool operation calculates the average interaction frequency. Through these two pooling operations, the most important interaction information in each grid can be extracted. The pooled feature data is then convolved to capture the spatial correlation between features. Convolution operations extract local patterns in the data, helping the BiGRU network better understand the important features in student interaction data. Finally, the convolved features are input into the sigmoid function for activation processing to generate spatial attention weights. These weights guide the BiGRU network to pay more attention to the key parts of classroom interaction data. Assuming the feature map is represented by D, average pooling by AP, maximum pooling by MP, convolution operation by fd, sigmoid activation function by δ, and spatial attention parameter matrix by $L_T D$, the construction process of the spatial attention mechanism module is given by the following formulas:

$$L(D) = [AP(D); MP(D)] \tag{15}$$

$$L_T D = \delta(d(L(D))) \tag{16}$$

Step 3: Fusion of the BiGRU Model: In electronic design education, evaluating learning outcomes requires handling complex time series data. This paper selects the BiGRU model, which, by combining two GRU networks with opposite directions, can more effectively capture the information in these time series data. The BiGRU model consists of two unidirectional GRUs, one processing the forward time series information and the other processing the backward time series information. Assuming the update gate is represented by c_s, the reset gate by e_s, the output value at time $(s-1)$ by g_{s-1}, the input value at time s by a_s, the activation functions by δ and tanh, the weight matrix by Q, the update gate weight by Q_c, the reset gate weight by q_e, the tanh output value by $\tilde{g}_s$, and the output result by g_s, the definition of the GRU model is given by the following formulas:

$$C_s = \delta(Q_c \cdot [g_{s-1}, a_s]) \tag{17}$$

$$e_s = \delta(Q_e \cdot [g_{s-1}, a_s]) \tag{18}$$

$$\tilde{g}_s = \tanh(Q \cdot [e_s * g_{s-1}, a_s]) \tag{19}$$

$$g_s = (1 - C_s) * g_{s-1} + C_s * \tilde{g}_s \tag{20}$$

The hidden state of the forward GRU in BiGRU at time s is $\overrightarrow{g_{s-1}}$, indicating that the current time step's state depends on the previous time step's state; the hidden state of the backward GRU at time s is $\overleftarrow{g_{s-1}}$, indicating that the current time step's state depends on the subsequent time step's state. Through this bidirectional structure, BiGRU can consider both past and future contexts, making the model's dependency relationship modeling for time series data more comprehensive. At each time step s, the hidden state of BiGRU is the weighted sum of the forward GRU and the backward GRU. Specifically, this means that at each time step, the model integrates information from the past to the present (forward GRU) and from the future to the present (backward GRU), thereby more accurately capturing the complex temporal patterns in student interaction data. This is especially important for evaluating the multidimensional interaction forms in the classroom, as students' learning behavior is often influenced by both preceding and subsequent activities. Assuming the nonlinear transformation of the input word vectors is represented by the GRU() function, the input value at time s by a_s, the forward output result by $\overrightarrow{g_s}$, the backward output result by $\overleftarrow{g_s}$, the forward and backward output at time $(s-1)$ by $\overrightarrow{g_{s-1}}$ and $\overleftarrow{g_{s-1}}$, the forward hidden state at time s by $\overrightarrow{g_s}$, the backward hidden state at time s by $\overleftarrow{g_s}$, the weights by q_s and n_s, and the bias of the hidden state at time s by y_s. The calculation formulas are as follows:

$$\overrightarrow{g_s} = GRU(a_s, \overrightarrow{g_{s-1}}) \tag{21}$$

$$\overleftarrow{g_s} = GRU(a_s, \overleftarrow{g_{s-1}}) \tag{22}$$

$$g_s = q_s \overrightarrow{g_s} + n_s \overleftarrow{g_s} + y_s \tag{23}$$

Figure 3 shows the flow chart of the constructed evaluation model for learning outcomes in electronic design education using smart mobile devices.

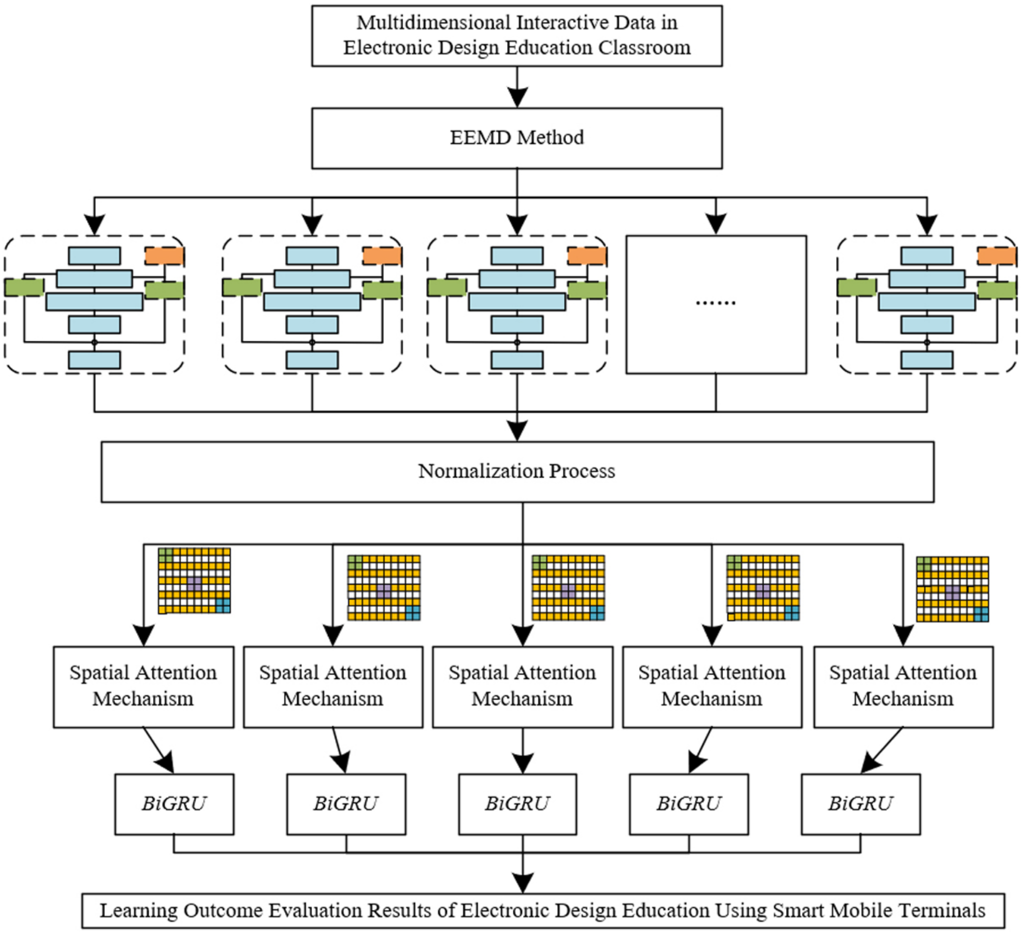

Fig. 3. Flow chart of the constructed evaluation model for learning outcomes in electronic design education using smart mobile devices

4 EXPERIMENTAL RESULTS AND ANALYSIS

According to the data in Table 1, four types of smart mobile terminals used in electronic design education exhibit significant differences in network layer and relationship layer metrics. The Learning Support Tools category has an average degree of 308.252, out-degree centrality of 28.254%, in-degree centrality of 16.245%, betweenness centrality of 3.25%, eigenvector of 74.25%, and density of 18.2359. The Interactive Teaching Tools category performs best in all metrics, with an average degree of 458.236, out-degree centrality of 32.562%, in-degree centrality of 17.325%, betweenness centrality of 1.81%, eigenvector of 70.25%, and density of 26.3241. The Practical Operation Tools category has an average degree of 287.523, out-degree centrality of 23.124%, in-degree centrality of 6.599%, betweenness centrality of 1.43%, eigenvector of 56.32%, and density of 16.2568. The Data Collection and Analysis Tools category has an average degree of 356.324, out-degree centrality of 29.685%, in-degree centrality of 16.235%, betweenness centrality of 1.68%, eigenvector of 72.32%, and density of 20.3214.

Table 1. Relationship layer and network layer metrics of smart mobile terminal networks

	Relationship Layer			Network Layer		
	Average Degree	Out-Degree Centrality	In-Degree Centrality	Betweenness Centrality	Eigenvector	Density
Learning Support Tools	308.252	28.254%	16.245%	3.25%	74.25%	18.2359
Interactive Teaching Tools	458.236	32.562%	17.325%	1.81%	70.25%	26.3241
Practical Operation Tools	287.523	23.124%	6.599%	1.43%	56.32%	16.2568
Data Collection and Analysis Tools	356.324	29.685%	16.235%	1.68%	72.32%	20.3214

From these data, it can be concluded that the interactive teaching tools category plays the most important role in the multidimensional interaction model of electronic design education classrooms. Its high average degree and network layer metrics indicate that these tools are effective in promoting classroom interaction and student engagement. High out-degree and in-degree centrality suggests that interactive teaching tools not only actively guide students to participate in interactions but also effectively receive student feedback. Meanwhile, learning support tools and data collection and analysis tools also show high network centrality and eigenvector values, indicating their significant roles in supporting learning and data analysis. However, the lower betweenness centrality and eigenvector values of Practical Operation Tools suggest that their role in interaction and feedback is relatively weaker.

By analyzing the EEMD and actual data in the one-day and 10-day datasets shown in Figure 4, it is evident that the EEMD algorithm fits the actual data very closely. In the 1-day dataset, the values from the EEMD algorithm are almost identical to the actual data at each time point. For example, at time points 10, 20, 30, 40, 50, 60, 70, and 80, the EEMD values are 4, 1, 8, 4, 16, 10, 70, and 170, which match exactly with the actual data. Similarly, in the 10-day dataset, the fit between the EEMD algorithm and actual data is also very good. For instance, at time points 200, 400, 600, 800, and 1000, the values are 176, 18, 71, 52, and 158 for both the EEMD and actual data, indicating strong consistency. This high level of consistency suggests that the

EEMD algorithm performs well in capturing data trend changes. Based on this fitting performance, it can be inferred that the EEMD algorithm can be effectively applied in electronic design education to provide accurate learning effect evaluations through the decomposition and analysis of student interaction and feedback data.

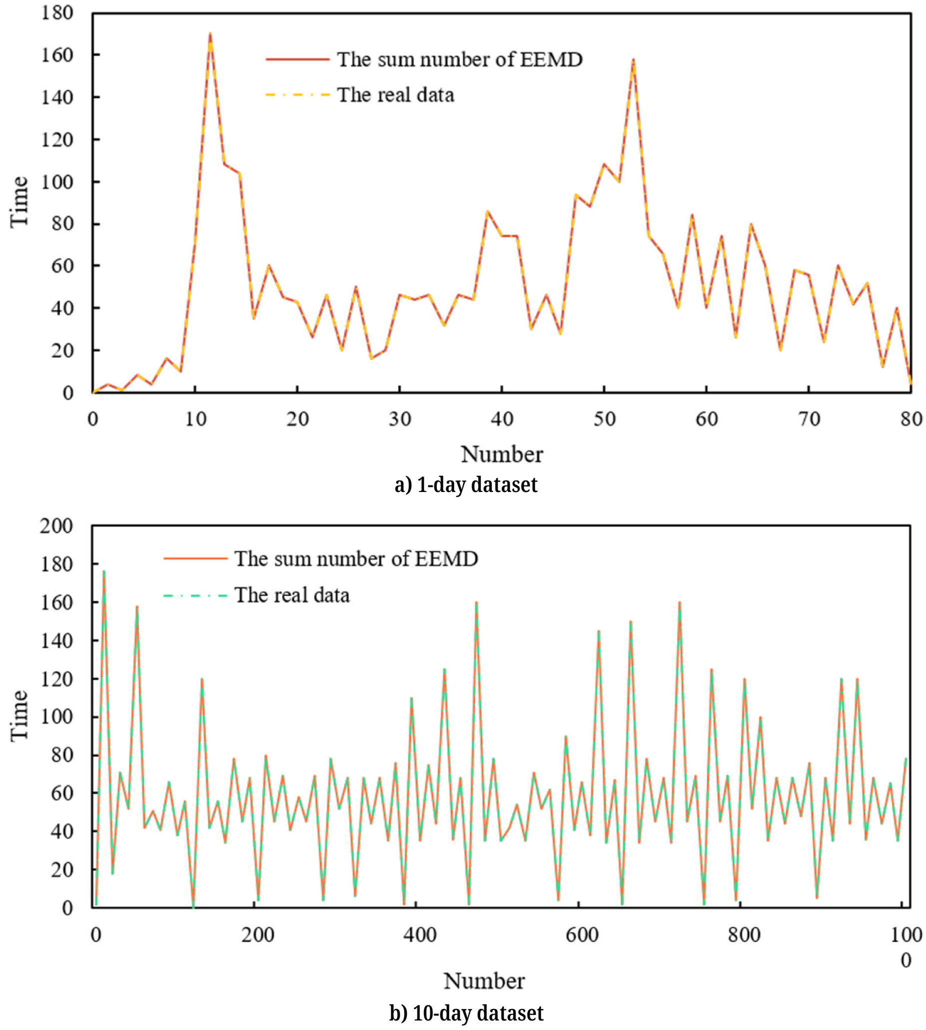

Fig. 4. Fitting situation of the empirical mode decomposition algorithm

Table 2. Forecasting of sequences before normalization using empirical mode decomposition

IMF	MOEs			
	MAPE (%)	MAE	RMSE	ME
1	7.302%	1.625	3.124	9.562
2	8.215%	0.489	0.712	2.324
3	31.235%	0.926	0.956	1.225
4	90.312%	6.012	8.415	14.236
5	12.512%	8.265	8.325	9.562
6	2.842%	1.689	1.825	2.785
7	32.62%	12.456	13.562	22.136

According to the data in Table 2, the predictive performance of each IMF varies significantly. In terms of prediction error, IMFs one and six have the lowest mean absolute percentage error (MAPE) at 7.302% and 2.842%, respectively, indicating good prediction accuracy. IMFs two and five have MAPEs of 8.215% and 12.512%, showing relatively small prediction errors. Conversely, IMFs three and seven have higher MAPEs of 31.235% and 32.62%, respectively, indicating lower prediction accuracy. Additionally, IMF four has the highest MAPE of 90.312%, showing the largest prediction error. Other error metrics such as mean absolute error (MAE), root mean square error (RMSE), and mean error (ME) also reflect similar trends, with IMFs six and one performing the best across all metrics, while IMFs four and seven perform the worst.

Table 3. Forecasting of sequences after normalization using empirical mode decomposition

IMF	Measures of Effectiveness (MOEs)			
	MAPE (%)	MAE	RMSE	ME
1	3.602%	0.856	1.125	2.214
2	1.315%	0.332	0.356	0.652
3	4.121%	0.235	0.265	0.421
4	3.912%	1.021	1.325	2.652
5	0.024%	0.031	0.031	0.048
6	0.021%	0.007	0.009	0.026
7	3.412%	1.265	1.526	2.785

Table 4. Performance of different models on learning effectiveness evaluation across various datasets

Days		1-Day				5-Day				10-Day			
MOEs		MAPE (%)	MAE	RMSE	ME	MAPE (%)	MAE	RMSE	ME	MAPE (%)	MAE	RMSE	ME
Algorithms	EMD-LSTM	12.121	2.236	2.458	6.352	11.456	2.158	2.562	6.485	18.526	2.658	4.325	28.265
	EEMD-LSTM	5.784	2.456	4.125	7.895	12.154	0.956	1.289	6.021	8.124	13.25	2.458	18.125
	EMD-GRU	10.265	3.895	4.652	9.874	28.326	5.685	4.125	10.262	22.235	3.895	6.235	37.451
	EEMD-GRU	8.125	2.652	3.265	6.021	26.254	3.589	3.987	21.235	22.315	2.895	4.125	21.365
	EMDN-GRU	3.658	1.236	1.658	3.254	6.789	1.845	2.562	9.124	4.365	1.895	2.895	14.265
	The Proposed Model	1.512	0.725	0.936	2.151	3.124	0.445	0.562	1.895	2.561	0.715	0.978	3.458

Table 3 shows the results of forecasting using the EMD algorithm after normalization for each IMF. It is evident that normalization significantly improved prediction accuracy. The MAPE values for functions one, two, three, four, and seven are 3.602%, 1.315%, 4.121%, 3.912%, and 3.412%, respectively, all of which are lower than before, indicating a reduction in prediction errors. In particular, functions five and six have MAPEs of 0.024% and 0.021%, demonstrating extremely high prediction accuracy with errors nearly negligible. For other error metrics such as MAE, RMSE, and ME, the values for each function also significantly decreased after normalization, with functions five and six showing the best results: MAE of 0.031 and 0.007, RMSE of 0.031 and 0.009, and ME of 0.048 and 0.026. These results indicate that normalization has significantly enhanced the predictive performance of the EMD algorithm. Especially for functions five and and, the near-zero prediction errors after normalization demonstrate their effectiveness in capturing data features and providing highly accurate predictions. This is of significant importance for real-time assessment and feedback in electronic design education based on smart mobile terminals, as high-precision predictions can more accurately reflect students' emotions and learning outcomes, helping educators adjust teaching strategies promptly.

Table 4 shows the performance of different datasets and different algorithms in learning outcome evaluation. From the 1-day dataset, the proposed model performs well in all error indicators, with MAPE being only 1.512%, significantly lower than other algorithms. The MAE is 0.725, the RMSE is 0.936, and the ME is 2.151, all of which are the lowest values, indicating that the proposed model has the highest accuracy in short-term prediction. In the five-day dataset, the proposed model also performs excellently, with MAPE being 3.124%, significantly better than other algorithms. The MAE is 0.445, the RMSE is 0.562, and the ME is 1.895. These data again verify the high accuracy of the proposed model. For the 10-day dataset, the proposed model's MAPE is 2.561%, MAE is 0.715, RMSE is 0.978, and ME is 3.458, which is also the best among all algorithms. These data indicate that, whether it is a short-term or long-term prediction, the proposed model has high accuracy and stability. Based on the above results, it can be seen that the proposed model, based on Spark distributed ensemble EMD with a spatial attention mechanism and BiGRU, has significant advantages in learning outcome evaluation. Compared with traditional long short-term memory (LSTM), GRU, and convolutional neural network (CNN) algorithms, the proposed model shows the lowest MAPE, MAE, RMSE, and ME in datasets of various time spans, indicating that it can more accurately capture and predict complex time series data characteristics.

5 CONCLUSION

This paper focuses on the application of smart mobile terminals in electronic design education, mainly including two parts: First, a multidimensional interaction model for electronic design education classrooms based on smart mobile terminals was constructed. By comprehensively utilizing multiple interactive forms such as text, voice, and video, a richer and more dynamic classroom interaction environment was established. This multidimensional interaction model can effectively enhance student engagement and learning experiences, providing a new teaching model for electronic design education. Secondly, this paper conducted an evaluation of learning outcomes in electronic design education using smart mobile terminals. Through real-time analysis of students' emotional and feedback data, learning outcomes were evaluated, and teaching strategies were optimized accordingly. The experimental results show that the proposed model, based on Spark distributed EEMD with a spatial attention mechanism and BiGRU, outperforms traditional methods in terms of prediction accuracy and stability, having significant advantages.

This study not only provides new perspectives and methods for the application of smart mobile terminals in the field of education but also offers practical guidance for teaching reform and innovation in electronic design education, with important theoretical and practical value. By constructing a multidimensional interaction model and a precise learning outcome evaluation model, this paper provides a systematic solution for how to use smart mobile terminals to improve educational outcomes. These study results can be applied to actual teaching, helping teachers better understand and meet students' learning needs, thereby improving overall teaching quality. Despite the significant achievements of this study, there are still some limitations. First, the diversity and scale of experimental data may not fully reflect the effects in all teaching scenarios. Secondly, the adaptability and stability of the model in different teaching environments and student groups need further verification. Future study can be expanded in the following directions: First, expand the scale and diversity of datasets to verify the model's generalizability and robustness; second, integrate more advanced machine learning and deep learning techniques to further optimize the model's performance; Third, conduct larger-scale field teaching experiments to verify and improve the practical application of the multidimensional interaction model and learning outcome evaluation model, thereby promoting further innovation and development in electronic design education.

6 REFERENCES

[1] P. J. Arul Leena Rose and T. Ananthi Claral Mary, "Accelerating the move towards online learning through cloud platforms in higher education sectors using smart devices during COVID-19," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 15, no. 10, pp. 33–48, 2021. https://doi.org/10.3991/ijim.v15i10.22163

[2] A. A. Adegbenjo *et al.*, "Design and analysis of an automated IoT system for data flow optimization in higher education institutions," *Journal Européen des Systèmes Automatisés*, vol. 56, no. 5, pp. 889–897, 2023. https://doi.org/10.18280/jesa.560520

[3] X. Zhang, Y. J. Hai, and C. Li, "Learning management system in education via mobile app: Trends and patterns in mobile learning," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 9, pp. 19–34, 2024. https://doi.org/10.3991/ijim.v18i09.49027

[4] L. Sharafeeva, "The study of teaching staff motivation to use mobile technologies in teaching mathematics," *International Journal of Education in Mathematics, Science and Technology (IJEMST)*, vol. 10, no. 3, pp. 604–617, 2022. https://doi.org/10.46328/ijemst.2364

[5] J. M. Romero-Rodríguez, I. Aznar-Díaz, F. J. Hinojo-Lucena, and G. Gómez-García, "Mobile learning in higher education: Structural equation model for good teaching practices," *IEEE Access*, vol. 8, pp. 91761–91769, 2020. https://doi.org/10.1109/ACCESS.2020.2994967

[6] S. Blondin and J. Letouzey-Pasquier, "Teaching primary geography through mobile methods: Didactic reflections and insights from collaborative research with Swiss teachers," *Transfers*, vol. 13, nos. 1–2, pp. 68–81, 2023. https://doi.org/10.3167/TRANS.2023.13010206

[7] V. Dear, N. Dedi, A. S. Mardiani, and H. Nugroho, "Trends in IT strategy implementation: A systematic review across education and industry (2000–2022)," *Ingénierie des Systèmes d'Information*, vol. 28, no. 6, pp. 1643–1651, 2023. https://doi.org/10.18280/isi.280622

[8] M. Budiarti, M. Ritonga, Rahmawati, Yasmadi, Julhadi, and Zulmuqim, "Padlet as a LMS platform in Arabic learning in higher education," *Ingénierie des Systèmes d'Information*, vol. 27, no. 4, pp. 659–664, 2022. https://doi.org/10.18280/isi.270417

[9] P. S. Tsai and C. C. Tsai, "Preservice teachers' conceptions of teaching using mobile devices and the quality of technology integration in lesson plans," *British Journal of Educational Technology*, vol. 50, no. 2, pp. 614–625, 2019. https://doi.org/10.1111/bjet.12613

[10] Y. Wang and J. Talim, "Online mobile teaching methods based on Android in the 5G environment," *International Journal of Continuing Engineering Education and Life Long Learning*, vol. 30, no. 2, pp. 133–147, 2020. https://doi.org/10.1504/IJCEELL.2020.106346

[11] M. Tepla, P. Distler, and P. Smejkal, "The overview and use of mobile applications in chemistry education," *Chemicke Listy*, vol. 115, no. 12, pp. 679–684, 2021.

[12] G. Aimicheva, Z. Kopeyev, Z. Ordabayeva, N. Tokzhigitova, and S. Akimova, "A spiral model teaching mobile application development in terms of the continuity principle in school and university education," *Education and Information Technologies*, vol. 25, pp. 1875–1889, 2020. https://doi.org/10.1007/s10639-019-10051-z
[13] M. N. Davids, M. Van Wyk, Z. M. Jojo, M. J. Taole, M. Sethusha, and K. Prins, "The feasibility of digitalizing teaching practice through mobile app development: Supervisors' reactions," *International Journal of Information and Communication Technology Education (IJICTE)*, vol. 19, no. 1, pp. 1–15, 2023. https://doi.org/10.4018/IJICTE.324717
[14] S. Vehapi, E. Asafova, K. Erdyneeva, A. Tyazhelnikov, S. Zhdanov, and A. Shaidullina, "Comparative analysis of mobile learning trends of physical education teaching students: Republic of Kosovo and Russia example," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 19, pp. 44–58, 2021. https://doi.org/10.3991/ijet.v16i19.26023
[15] K. Michos, A. Cantieni, R. Schmid, L. Müller, and D. Petko, "Examining the relationship between internship experiences, teaching enthusiasm, and teacher self-efficacy when using a mobile portfolio app," *Teaching and Teacher Education*, vol. 109, p. 103570, 2022. https://doi.org/10.1016/j.tate.2021.103570
[16] O. Iskrenovic-Momcilovic, "Contribution of using mobile application on botanical fieldwork in primary school," *Interactive Learning Environments*, vol. 31, no. 2, pp. 1186–1198, 2023. https://doi.org/10.1080/10494820.2020.1826531
[17] I. Aznar-Díaz, F. J. Hinojo-Lucena, M. P. Cáceres-Reche, and J. M. Romero-Rodríguez, "Analysis of the determining factors of good teaching practices of mobile learning at the Spanish University. An explanatory model," *Computers & Education*, vol. 159, p. 104007, 2020. https://doi.org/10.1016/j.compedu.2020.104007

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