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PAPER

Analyzing the Correlation Between Student Learning Behaviors and Psychological Atmosphere Using Deep Learning

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ABSTRACT

With the rapid development of educational technology, the application of deep learning in analyzing student behavior and psychological states has become a hot topic in the field of education. This study, grounded in deep learning technology, aims to explore the correlation between student learning behaviors and psychological atmosphere, as well as the positive impact of a constructive psychological atmosphere on student learning. The background section discusses the limitations of traditional educational assessment methods and the necessity and urgency of applying deep learning in education. The current state of study section presents the progress in analyzing the correlation between student behavior and psychological states, highlighting the shortcomings in data processing and model construction in existing studies. Addressing these shortcomings, this study proposes a student learning behavior detection scheme based on the lightweight neural network shufflenetV2 and validates through empirical study the positive influence of a constructive psychological atmosphere on student learning behavior. The results show that utilizing a lightweight network model can effectively identify patterns in student learning behavior and, to some extent, predict the students' psychological states. Furthermore, a positive psychological atmosphere indeed enhances students' learning motivation and behavior. The methods and findings of this study hold significant theoretical and practical implications for advancing personalized and intelligent education.

KEYWORDS

deep learning, learning behavior, psychological atmosphere, shufflenetV2, positive psychological atmosphere, educational assessment

1 INTRODUCTION

In the field of education, student learning behaviors and psychological atmosphere are widely considered important factors affecting learning outcomes. With the rapid development of deep learning technology, researchers have begun to seek

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these advanced analytical methods to deeply understand the complex connections between student behavior and psychology [1–4]. Traditional educational assessment methods often focus on learning outcomes, neglecting the changes in student behavior patterns during the process and the psychological motives behind these patterns [5, 6]. Therefore, analyzing the correlation between students' learning behavior and psychological atmosphere through deep learning technology can not only reveal the internal mechanisms of the learning process but also provide possibilities for personalized teaching and intervention.

The significance of this study lies in the use of advanced deep learning models to accurately analyze and identify patterns in students' behavior data, thereby inferring students' psychological atmosphere states. This novel approach could have a profound impact on the field of education [7–10]. Through monitoring student behavior and assessing psychological atmosphere states, teachers and educators can timely adjust teaching strategies, creating a more positive learning atmosphere for students, thereby improving the quality of teaching and students' learning efficiency [11–15].

However, existing research methods have many shortcomings in data processing and model construction. Many studies rely on traditional statistical methods, which often overlook the high dimensionality and non-linearity of data, failing to fully explore the deep information in the data [16, 17]. In addition, existing deep learning models often require a large number of computational resources, which may not be realistic in practical applications, especially for resource-limited educational institutions [18].

To overcome these shortcomings, this paper first introduces a student learning behavior detection method based on the shufflenetV2 lightweight neural network. As an efficient neural network architecture, shufflenetV2 can significantly reduce the consumption of computational resources while ensuring model performance, making it suitable for processing large-scale educational data. Secondly, this study discusses the impact of a positive psychological atmosphere on students' learning behavior intentions and behaviors, which helps to understand and improve the promoting effect of the academic environment on student behavior. The methodology of this paper is novel, and the study content is close to the actual teaching scenario, which has important theoretical and practical value for promoting personalized and intelligent education.

2 STUDENT LEARNING BEHAVIOR DETECTION BASED ON SHUFFLENETV2 LIGHTWEIGHT NEURAL NETWORK

When designing network models for detecting student learning behaviors on mobile devices, several key factors need to be carefully considered to ensure that the model can still operate effectively in a resource-limited environment and provide accurate behavior analysis. Firstly, light weightiness is the primary consideration because the computational resources and battery capacity of mobile devices are far less than those of servers or desktop computers. Therefore, the model must be concise and efficient to fit the processing capabilities of mobile devices. Secondly, low latency is also crucial, especially when the model is used for real-time monitoring and analysis of learning behavior. The model needs to respond quickly so that educators can immediately adjust teaching methods based on feedback about students' behaviors and psychological atmosphere states. In addition, hardware friendliness is a factor that cannot be ignored for models running on mobile devices. The model needs to be optimized for mobile device *CPUs*, *GPUs*, and even *NPUs* to fully utilize these hardware features, thereby improving operational efficiency. For example, choosing network models that support unique instruction sets of the *ARM* architecture can make the model run more efficiently on such devices. However, while pursuing light-weight and efficiency, it is essential to ensure that the model's accuracy is not compromised. In the scenario of student learning behavior detection, accuracy directly relates to the reliability of the analysis results and the effectiveness of implementing educational interventions. Therefore, although lightweight models may sacrifice precision to some extent, they still need to be carefully designed and parameter-adjusted to ensure accurate identification and analysis of student behavior patterns.

In this paper, we use the ShufflenetV2 lightweight neural network as the network model for student learning behavior detection. ShufflenetV2 is designed to run in resource-limited environments, making it very suitable for embedded or mobile devices, whose computing power and storage resources are far less than standard computer systems.

The core advantage of ShufflenetV2 is its lightweight network structure, which significantly reduces the model's parameter amount and computational complexity, allowing the network to operate on lower hardware requirements without sacrificing too much accuracy. This is particularly important for student learning behavior detection models, as such models often need to run in real-time or near-real-time conditions so that teachers can timely receive feedback on student states. ShufflenetV2 promotes information exchange between features by introducing channel shuffling, thereby improving the network's performance while reducing the model size. Furthermore, by using grouped convolutions to reduce computational requirements, ShufflenetV2 can further enhance computational efficiency while maintaining feature effectiveness.

However, ShufflenetV2 also has its disadvantages. Firstly, although channel shuffling can increase the model's representation ability, this operation may lead to a decrease in computational efficiency on some hardware, thereby increasing the model's inference time. Secondly, the random channel dropping in ShufflenetV2 may introduce uncertainty, which in some cases may affect the model's stability and accuracy.

For the special needs of the student learning behavior detection model, we need to ensure that the model remains lightweight and efficient while still accurately identifying and analyzing students' learning behaviors. Therefore, when using ShufflenetV2, we need to make targeted adjustments and optimizations to the network to ensure it can better adapt to the specific tasks of student behavior detection, while minimizing the impact of inference time and uncertainty. Figure 1 shows the schematic diagram of the improved model structure.

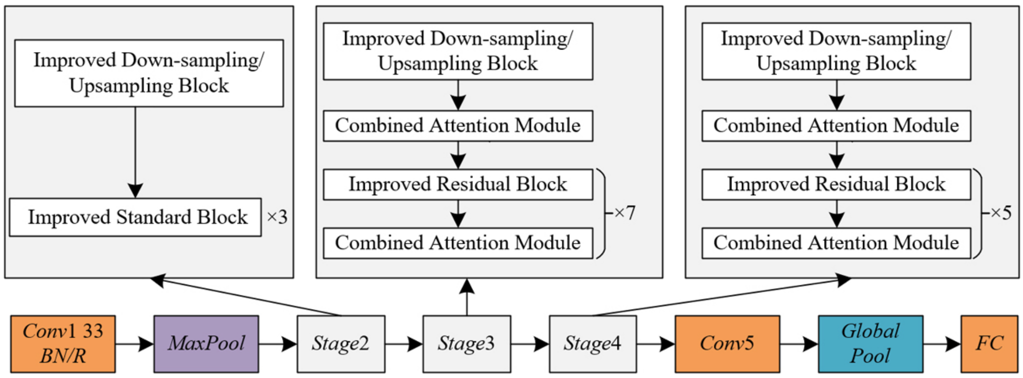

Fig. 1. Schematic diagram of the improved model structure

Firstly, to address the computational performance issues caused by channel shuffling in ShufflenetV2 when applied to student learning behavior detection and to compensate for potential feature loss due to channel reorganization, ensuring a comprehensive understanding and analysis of students' subtle learning behaviors, this paper replaces the 3×3 convolution kernels in the network's building blocks with 5×5 convolution kernels. This increases the receptive field for feature extraction and captures richer contextual information, which is particularly critical. At the same time, to better detect various fine-grained features in student learning behavior, such as attention distribution and subtle psychological changes, an additional 1×1 convolution layer is introduced to enhance the integration ability of information between channels, thereby compensating for the deficiencies of depth wise separable convolutions in channel fusion. Finally, to improve the model's accuracy and robustness in identifying student behavior in practical applications, a stride-1 average pooling layer is added to the first branch of the standard building blocks, smoothing the feature maps and reducing the model's sensitivity to noise and irrelevant information. Figure 2 shows the structure of the improved standard building block and the down-sampling building block.

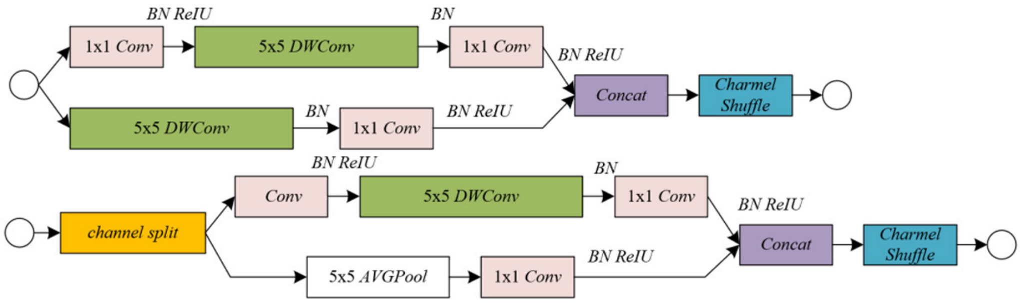

Fig. 2. Structure of the improved standard and down-sampling building block

Compared to network models in other fields, the detection of student learning behavior imposes higher demands on the model's fine understanding and grasp of key information. To address the accuracy loss due to random channel dropping in the ShufflenetV2 lightweight neural network for student learning behavior detection, this paper adopts the strategy of introducing a convolutional attention module, a method that incorporates both *EVA* channel attention and spatial attention mechanisms. Therefore, this paper integrates this attention module into various stages of the ShufflenetV2 network, allowing the model to dynamically assess the importance of each channel and spatial area and allocate weights accordingly. This enables the model to focus more effectively on key features of student learning behavior, such as areas of focused attention and emotional expression, while reducing model parameters and computational resource consumption, and enhancing its ability to capture these details, ensuring accuracy and efficiency in real-time monitoring of student psychological atmosphere states and behavior patterns.

In the student learning behavior detection model based on the ShufflenetV2 lightweight neural network, to more effectively capture and analyze student behavior and psychological atmosphere states, a channel attention mechanism similar to *CBAM* is employed, but optimized for the characteristics of student behavior. Its operation is as follows:

1. Input feature map: The model receives the student behavior feature maps processed by the preceding convolution layers, which contain multiple channels of student behavior signals, such as body posture and facial expression changes.
2. Global pooling: The information in each channel is compressed into a single scalar through global average pooling, helping the model capture global statistical information and providing a basis for subsequent attention evaluation.
3. Weight learning: These scalars are then fed into a fully connected layer designed specifically to learn and evaluate the importance of the weights of each channel.

For student behavior detection, the learning process of this fully connected layer may be optimized to emphasize channels sensitive to learning dynamics and psychological atmosphere changes.

4. Feature map weighting: When the learned channel weights are applied back to the original feature maps, the weighting process enhances those channel features, making them more critical for understanding the student's learning state.
5. Subsequent processing: The weighted feature maps continue to be sent to the network's subsequent convolution layers or fully connected layers for deeper processing, achieving fine-grained identification and analysis of student behavior.

Assuming an input feature map of size $G \times Q \times Z$ is denoted by D, global max pooling and average pooling by AP and MP, the *sigmoid* activation function by δ, and the weight coefficients by L_z, the formula corresponding to the above steps is as follows:

$$\begin{aligned} L_z(D) &= \delta\left(MLP\left(AP(D)\right) + MLP\left(MP(D)\right)\right) \\ &= \delta\left(Q_1\left(Q_0\left(D^z_{AV}\right)\right) + Q_1\left(Q_0\left(D^z_{MAX}\right)\right)\right) \end{aligned} \tag{1}$$

To ensure the efficiency and lightweight nature of the student learning behavior detection model in analyzing the correlation between student behavior and psychological atmosphere states, this study introduces the Efficient Channel Attention (*ECA*) module on top of the ShufflenetV2 neural network. The advantage of the *ECA* module is that it avoids the dimension reduction process present in traditional attention mechanisms, achieving local cross-channel interactions through the use of one-dimensional convolution. This means the module can effectively capture the correlations between different channels without significantly increasing the computational burden. In the context of student learning behavior detection, this approach is particularly effective because it can enhance the model's sensitivity to learning behavior features such as learning posture, gaze focus, facial expression changes, etc., which are often distributed across different channels. Moreover, the efficiency of the *ECA* module particularly meets the needs for real-time monitoring of student behavior and psychological atmosphere states. The formula for this attention mechanism is given by the following equation:

$$L_z(D) = D \otimes \delta\left(conv\_1_j\left(GAP(D)\right)\right) \tag{2}$$

The purpose of introducing a spatial attention mechanism in the model is to enhance the model's ability to recognize local details of student behavior features, which is crucial for analyzing students' learning behaviors and psychological atmosphere states. Minor behavioral changes during learning, such as subtle gestures, shifts in gaze points, or even handwriting habits in note-taking, can manifest as key local features in video or image data. These features are often vital clues for understanding the student's learning state. The spatial attention mechanism helps the model filter out irrelevant background information and reduce noise interference by focusing on these key areas, thus improving the accuracy of the detection model. This is particularly important for the student learning behavior detection model, as the student's learning environment is often filled with various distracting elements, and without an effective mechanism to focus on key behavioral features, the model's performance could easily be affected.

Specifically, the input feature map is processed by max pooling and average pooling operations separately. Both pooling operations are performed independently on each channel, reducing the feature map of each channel (Z, G, Q) to a single-channel feature map (1, G, Q). This way, we obtain two sets of pooled results representing spatial features, capturing different contextual information. Then, these two single-channel feature maps are stacked together to form a dual-channel feature map (2, G, Q). The purpose of this step is to integrate spatial information captured by the two pooling strategies, preparing for generating more comprehensive spatial weights in the next step. Further, a convolution layer processes the dual-channel feature map (2, G, Q) to produce a single-channel spatial weight map (1, G, Q). This convolution layer adjusts feature dimensions and extracts spatial features, where the output weight map indicates the importance of each location on the original feature map. Finally, the calculated spatial weight map (1, G, Q) is element-wise multiplied with the original multi-channel feature map (Z, G, Q). This step assigns a weight to each location of the feature map, allowing the model to focus more on areas that are more important for analyzing student behavior. Assuming the feature map obtained after computation through the spatial attention module is denoted by L_t, then:

$$L_t(D) = E^{G,Q} \tag{3}$$

Two types of pooling methods are used in the channel dimension to produce a two-dimensional feature map:

$$\begin{aligned} D^t_{AV} &\in E^{1\times G\times Q} \\ D^t_{MAX} &\in E^{1\times G\times Q} \end{aligned} \tag{4}$$

Assuming that average pooling of the input feature map D is represented by $AP(D)$ and max pooling of the input feature map D is represented by $MP(D)$, a convolution operation with a kernel size of 7×7 is denoted by $d^{7\times7}$, and the sigmoid function by δ. The formula for the final spatial attention mechanism module is given as follows:

$$L_t(D) = \delta\left(d^{7\times7}\left(\left[AP(D);MP(D)\right]\right)\right) = \delta\left(d^{7\times7}\left(D^t_{AV};D^t_{MAX}\right)\right) \tag{5}$$

This paper proposes the introduction of an improved attention module that combines the *ECA* and the spatial attention mechanism from *CBAM* into a lightweight attention structure embedded between various stages of the ShufflenetV2 lightweight neural network, completing all improvements to ShufflenetV2. Figure 3 shows the structure of the combined attention module.

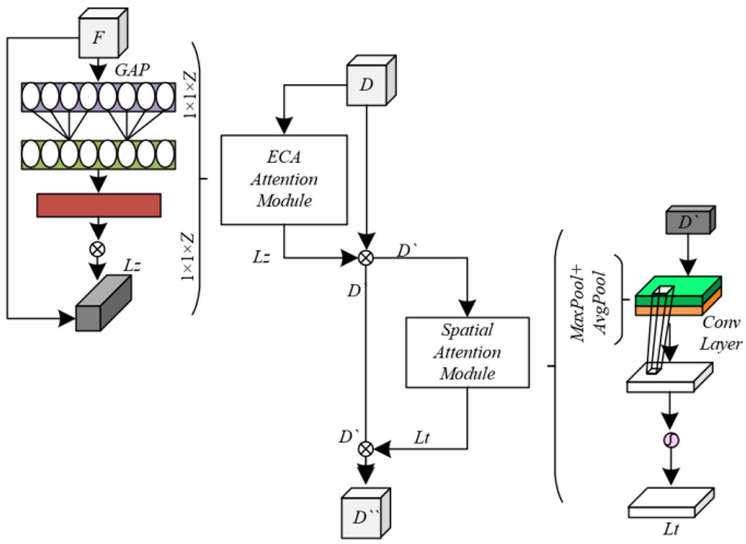

Fig. 3. Structure of the combined attention module

To improve the model's generalization ability and prevent overfitting, the model chooses a smooth loss function as the optimization objective function. Because students' behaviors and psychological atmosphere states are diverse and subtle, they may not always clearly correspond to a specific category. Moreover, there may be a certain degree of imbalance in student behavior data, meaning some behavior patterns are more common than others. In this case, the smooth loss function helps the model better capture less obvious or less common behavioral features, thus showing higher sensitivity and accuracy in predictions. Assuming the value for label smoothing is represented by γ, the number of label classifications by v, and the current category by *target*, the expression for smoothing the classification labels is given as follows:

$$b(u)=\begin{cases}\dfrac{\gamma}{v}, u \neq \text{target} \\ 1-\gamma+\dfrac{\gamma}{v}, u=\text{target}\end{cases} \tag{6}$$

After completing the above smoothing operation, the loss function calculation is then performed as shown in the following equation.

$$LOSS=-\sum_{u}^{v} b(u)\log\left(o\left(a_u\right)\right) \tag{7}$$

3 ANALYSIS OF THE IMPACT OF A POSITIVE PSYCHOLOGICAL ATMOSPHERE ON STUDENT LEARNING BEHAVIOR INTENTIONS AND ACTIONS

In the educational environment, a positive psychological atmosphere significantly influences students' learning behavior intentions and behaviors, similar to how organizational atmosphere influences employee behavior in organizational behavior studies. A positive psychological atmosphere involves students' perceptions and interpretations of the school environment, including perceptions of educational goals, teaching strategies, and assessment standards. When students learn in a positive atmosphere, they typically feel supported and encouraged, making them more willing to participate in learning activities and have a positive attitude towards learning outcomes. This psychological atmosphere is closely linked to the personal level of students because it directly affects their cognition, emotions, and behaviors. Research indicates that a positive and supportive learning environment can promote students' sense of self-efficacy, increase their learning motivation, and help form positive behavioral intentions, ultimately translating into actual learning behaviors.

In the school environment, students' perceptions of a positive learning atmosphere may affect their views on learning behavior norms, thus forming a state of positive psychological atmosphere. This state promotes the formation of specific learning behaviors and intentions among students. The perception of a positive learning atmosphere can shape their cognition of learning behavior norms, further constituting a positive psychological atmosphere. When students experience a high level of positive psychological atmosphere, they may realize the importance their teachers and peers place on learning. These signals encourage students to consider more positive approaches in their learning decisions because they believe such positive attitudes towards learning are expected by the school, teachers, and peers. These positive signals, by conveying which behaviors can meet the expectations of the school and teachers, thus enhance or weaken their intention to implement specific learning behaviors. On one hand, when students perceive a high level of positive psychological atmosphere, they might realize that their teachers and peers tend to actively engage in learning. To gain recognition and avoid exclusion, students may prefer to consider positive ways of learning before making learning decisions. This forms positive learning behavior intentions, striving to achieve behaviors consistent with the school's learning goals. On the other hand, when students are in a highly positive psychological atmosphere, they might also realize that the school supports and values their positive learning behaviors, possibly offering more resources and opportunities. This enhances students' perception of the importance of their learning behaviors to the school, which may, in turn, increase their intention to display more positive learning behaviors.

In the field of environmental psychology, the specific psychological atmosphere an individual experiences are seen as a key factor influencing their behavior. A specific psychological atmosphere can have a strong predictive effect on behavior because individuals' behaviors tend to follow their internal cognitions and feelings. When students perceive a highly positive learning psychological atmosphere, they recognize that positive learning behaviors are not only part of the school culture but also central to their educational experience. Students may thus feel normative pressure to achieve these positive behaviors to match the expectations of their environment. That is, students' perceptions of a positive learning atmosphere may directly impact their learning behavior intentions and actual behaviors. In a learning environment, if students perceive that the school advocates positive learning behaviors, they might also internalize such behaviors as their own behavior patterns. Therefore, this study proposes the following hypotheses: *Ha*: Students' perception of a positive psychological atmosphere will have a significant positive impact on students' learning behavior and intentions. *Hb*: Students' perception of a positive psychological atmosphere will have a significant positive impact on students' learning behaviors. By analyzing how a positive psychological atmosphere influences students' behavior, intentions, and practices by shaping students' learning norms and providing positive learning role models, this study will explore in depth the mechanism of this atmosphere in promoting students' academic achievements.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Comparison of accuracy before and after improvements to the student learning behavior detection model

Network Structure	*TOP-1 Accuracy*
Basic Model + Improvement 1	0.8895
Basic Model + Improvement 1	0.9214
Basic Model + Improvement 1 + Improvement 2	0.9156

According to the comparison data of the accuracy of the student learning behavior detection model before and after improvements shown in Table 1, the improvements aimed at addressing the two shortcomings of ShufflenetV2 are referred to as Improvement 1 and Improvement 2 in the table, with the basic model being ShufflenetV2. Analysis of Table 1 leads to the conclusion that the initial basic model, ShufflenetV2, after the application of Improvement 1, saw its *TOP*-1 accuracy increase from an unreported baseline to 0.8895. This significant accuracy enhancement validates the effectiveness of Improvement 1 in improving the efficiency of student learning behavior detection. Further, when the model only applied Improvement 1, the *TOP*-1 accuracy further increased to 0.9214, indicating the positive impact of Improvement 1 on model performance when dealing with large-scale educational data. However, when the basic model combined both Improvement 1 and Improvement 2, the accuracy slightly decreased to 0.9156. Although still higher than the initial increase achieved by applying Improvement 1 alone, this result suggests that there may be some compatibility issues between Improvement 1 and Improvement 2, or that under certain conditions it may lead to a slight performance decrease. From analyzing these results, it can be concluded that the method for detecting student learning behavior based on the improved ShufflenetV2 lightweight neural network proposed in this paper is effective. The significant improvement in model performance through the application of Improvement 1 demonstrates that the improvement measures successfully enhanced the basic model's capacity, making it more suitable for the task of learning behavior detection. Although there was a slight decrease in accuracy when Improvement 2 was used in conjunction with Improvement 1, the performance of the model still exceeded that of the version using only Improvement 1. This may suggest the need for optimizing the compatibility of these two improvement measures in future research.

Table 2. Comparison of experimental results of different student learning behavior detection methods

Method	Number of Parameters	*Flpos (M)*	*ToP*-1 *Accuracy*
Random Forest	1256856	145.23	0.8751
Kernel SVM	234556	326.68	0.9236
Dynamic Bayesian Networks	12356842	178.21	0.9154
FP-Growth Algorithm	1365248	145.23	0.8745
Gradient Boosting Machines	1658569	154.69	0.8895
Spectral Clustering	1256124	149.36	0.9261
The proposed model	1265894	152.32	0.9154

From the comparison of the experimental results of different student learning behavior detection methods in Table 2, the model proposed in this paper, based on the improved ShufflenetV2, shows a relative advantage in terms of the number of parameters compared with other methods, with only 1,265,894 parameters, slightly higher than *Kernel SVM* and much lower than *dynamic Bayesian networks*. In terms of computational load (*FLOPs*), the proposed model requires 152.32 million *FLOPs*, close to *Random Forest* and the *FP-Growth algorithm* but slightly higher than these two methods. In terms of *TOP*-1 accuracy, the proposed model, with a result of 0.9154, is in the upper-middle level, although slightly lower than *kernel SVM* and *spectral clustering* but still significantly higher than *Random Forest* and *FP-Growth Algorithm*. Furthermore, considering the highest accuracy of *Spectral Clustering*, its number of parameters and computational load are also relatively large, showing that the proposed model achieves a balance of high accuracy with fewer parameters and reasonable computational demand. Overall, the improved ShufflenetV2 model proposed in this paper demonstrates good performance in all aspects. With relatively high accuracy, the model also boasts a lower number of parameters and reasonable computational requirements, which is particularly important for processing large-scale educational data as it implies less resource consumption and faster processing speed. These characteristics make this paper's model highly valuable for practical applications, especially in resource-constrained environments.

Table 3. Descriptive statistics of variables (N = 356)

Variable	Min Value	Max Value	Mean	Standard Deviation
Environmental Self-Identity	1.000	7.000	5.231	1.245
Positive Psychological Atmosphere	1.500	5.000	3.698	0.712
Self-Efficacy	1.600	5.000	3.654	0.536
Positive Learning Behavior Intentions	1.000	5.000	3.895	0.528
Positive Learning Behavior	1.200	5.000	3.789	0.521

Table 4. Correlation coefficients among variables (N = 356)

	Environmental Self-Identity	Positive Psychological Atmosphere	Self-Efficacy	Positive Learning Behavior Intentions	Positive Learning Behavior
Gender	0.037*	0.002	0.004	0.023	0.016
Age	0.022	0.087	–0.008	0.087	0.125**
Grade	–0.046	–0.047	–0.042	–0.015	–0.016
Major Type	–0.011	0.087	0.057	0.012	0.022
Learning Style	–0.021	0.125***	0.102*	0.128**	0.125**
Academic Achievement	–0.088	0.098*	–0.054	0.011	0.001
Environmental Self-Identity	1.000	0.365***	0.256***	0.578***	0.526***
Positive Psychological Atmosphere	0.369***	1.000	0.275***	0.612***	0.536***
Self-Efficacy	0.235***	0.256***	1.000	0.369***	0.489***
Positive Learning Behavior Intentions	0.554***	0.614***	0.356***	1.000	0.721***
Positive Learning Behavior	0.524***	0.528***	0.489***	0.725***	1.000

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, two-tailed test.

According to the descriptive statistical results shown in Table 3, it can be observed that the mean value of environmental self-identity is 5.231, the highest among all variables, with a standard deviation of 1.245, indicating that individuals' scores on this variable are relatively dispersed but generally tend towards a higher environmental self-identity. The mean values of positive psychological atmosphere and self-efficacy are 3.698 and 3.654, respectively, close to each other, but the standard deviation of the positive psychological atmosphere (0.712) indicates more variability among individuals compared to self-efficacy (0.536). The means for positive learning behavior intentions and positive learning behavior are 3.895 and 3.789, respectively, both close to the full score of 4, and with relatively small standard deviations (0.528 and 0.521), suggesting that most students tend to show positive learning behavior intentions and behaviors, and this tendency is relatively consistent across the sample. It can be concluded that the students participating in the study generally have a higher sense of environmental self-identity, possibly because students can find their positioning in the learning environment and feel a sense of belonging. The existence of a positive psychological atmosphere has a positive impact on students' positive learning behavior intentions and actual behaviors. Despite some variability among individuals in these two variables, overall, students generally exhibit positive learning motivation and behaviors.

Table 4 presents the correlation coefficients between different variables. Gender shows a low positive correlation with environmental self-identity ($r = 0.037$, $p < 0.1$) but is not significantly correlated with other variables. Age shows a moderately positive correlation with positive learning behavior ($r = 0.125$, $p < 0.05$). Additionally, learning style significantly correlates positively with a positive psychological atmosphere ($r = 0.125$, $p < 0.01$), positive learning behavior intentions ($r = 0.128$, $p < 0.05$), and positive learning behavior ($r = 0.125$, $p < 0.05$). Among core variables, environmental self-identity shows strong positive correlations with positive psychological atmosphere ($r = 0.365$, $p < 0.01$), self-efficacy ($r = 0.256$, $p < 0.01$), positive learning behavior intentions ($r = 0.578$, $p < 0.01$), and positive learning behavior ($r = 0.526$, $p < 0.01$). Positive psychological atmosphere has the strongest correlations with positive learning behavior intentions ($r = 0.612$, $p < 0.01$) and positive learning behavior ($r = 0.536$, $p < 0.01$). These data indicate the crucial role of a positive psychological atmosphere in students' positive learning behavior intentions and actual behaviors, with strong positive correlations with both. This suggests that a more positive psychological atmosphere in the academic environment could enhance students' learning behaviors and intentions. Environmental self-identity also shows significant positive correlations with students' positive learning intentions and behaviors, indicating a close connection between students' sense of belonging in the educational environment and their learning behaviors.

Table 5 shows the results of the multicollinearity test, including *tolerance* and the variance inflation factor (*VIF*). Generally, a tolerance value less than 0.1 or a *VIF* value greater than 10 may indicate a serious multicollinearity problem among variables. In this data set, all variables have tolerance values well above 0.1, and all *VIF* values are well below 10, suggesting that multicollinearity is not a significant issue. Nonetheless, the statistics for learning style (Tolerance = 0.432, *VIF* = 2.369) and positive learning behavior intentions (Tolerance = 0.459, VIF = 2.236) are relatively low, which may indicate slight collinearity between these variables but not to a severe degree. In summary, the multicollinearity test indicates that there is no serious multicollinearity problem among the independent variables in this data set, suggesting that the model's estimation results are reliable. Statistically, the independence among the variables is sufficient for further regression analysis. Therefore, it is reasonable to expect that the information provided by these variables is independent, making the analysis results regarding the impact of a positive psychological atmosphere on students' positive learning behavior intentions and behaviors robust.

Table 5. Multicollinearity test (N = 356)

Variable	Multicollinearity Statistics	
	Tolerance	*VIF*
Gender	0.956	1.035
Age	0.512	0.895
Grade	0.778	1.236
Major Type	0.632	1.524
Learning Style	0.432	2.369
Academic Achievement	0.925	1.125
Environmental Self-Identity	0.659	1.523
Positive Psychological Atmosphere	0.612	1.648
Self-Efficacy	0.834	1.128
Positive Learning Behavior Intentions	0.459	2.236

Note: Dependent variable: positive behavior.
Source: Analysis results organized from SPSS20.0 software.

Table 6. Results of hierarchical regression test for mediating effect on positive learning behavior intentions (N = 356)

Variable	Positive Behavior Intentions			
	Model 1	*Model* 2	*Model* 3	*Model* 4
Gender	0.037	0.006	0.032	0.035
Age	0.011	–0.044	0.014	0.054
Education Level	0.013	0.061	0.048	0.006
Job Type	–0.061	–0.074	–0.112**	–0.048
Tenure	0.154*	0.214*	0.097	0.123
Company Type	–0.005	0.056	–0.054	–0.021
Pro-environmental Self-Identity		0.568***		
Positive Psychological Atmosphere			0.612***	
Positive Behavior Intentions				
F-value	1.125	24.568***	28.698***	1.256
R^2	0.021	0.345	0.378	0.021
ΔR^2	0.021	0.356	0.356	0.021

Notes: ***p < 0.01, **p < 0.05, *p < 0.1, two-tailed test.

Table 6 presents the results of the hierarchical regression test for the mediating effect, analyzing the impact of a positive psychological atmosphere on positive behavior intentions. In Model 1, without considering the impact of pro-environmental self-identity and a positive psychological atmosphere, the overall variance explained (R^2) is quite low, at only 0.021. After entering Model 2 and including pro-environmental self-identity, R^2 significantly increases to 0.345, indicating that pro-environmental self-identity has a significant impact on positive behavior intentions ($\beta = 0.568$, $p < 0.01$). In Model 3, with the further addition of a positive psychological atmosphere, R^2 increases again to 0.378, showing a very significant positive impact of a positive psychological atmosphere on positive behavior intentions ($\beta = 0.612$, $p < 0.01$). This suggests that a positive psychological atmosphere has a direct and strong impact on positive behavior intentions. The additional variables introduced in Model 4 do not significantly change the R^2 value, indicating their limited explanatory power for positive behavior intentions. Additionally, job type shows a significant negative correlation in Model 3 ($\beta = -0.112$, $p < 0.05$). The analysis results indicate that a positive psychological atmosphere plays a key role in positive learning behavior and intentions. High levels of pro-environmental self-identity and a positive psychological atmosphere can significantly enhance students' positive learning behavior intentions. This finding highlights the importance of psychological atmosphere in the academic environment, especially for improving students' willingness and behavior towards positive learning.

5 CONCLUSION

The study content of this thesis can be divided into two main parts: First is the introduction and experimentation with a method for detecting student learning behaviors based on the lightweight neural network, shufflenetV2. The application of shufflenetV2 in this study significantly improved the efficiency of processing large-scale educational data while ensuring the accuracy of the learning behavior detection model. Through experimental comparisons of the model's accuracy before and after improvements, as well as the effectiveness of different methods for detecting student learning behaviors, the study confirmed the practicality and effectiveness of shufflenetV2 in the field of education. Secondly, the study deeply explored the impact of a positive psychological atmosphere on students' learning intentions and behaviors through descriptive statistics of variables, correlation analysis, multicollinearity tests, and hierarchical regression tests for mediating effects. Through these analyses, the study not only revealed the important facilitating role of a positive psychological atmosphere on students' positive learning behaviors but also verified the significance of its mediating effects through the Bootstrap method.

The key conclusions affirm the efficiency and effectiveness of shufflenetV2 in detecting student learning behaviors and the positive influence of a positive psychological atmosphere on student learning behaviors. These findings hold significant implications for guiding educational practice, urging educators and technology developers to focus on creating a positive psychological atmosphere in the learning environment and utilizing efficient technological means to monitor and promote student learning behaviors.

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