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RESEARCH ON THE IMPACT OF GENERATIVE ARTIFICIAL INTELLIGENCE ON LEARNER PSYCHOLOGICAL NEEDS BASED ON LSTM DEEP NETWORKS

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Abstract. In order to clarify the impact of "generative artificial intelligence" on learners' psychological needs, a deep learning method based on LSTM network is proposed. In this method, learners' psychological needs are divided into primary psychological needs, intermediate psychological needs, and advanced psychological needs, which serve as input data for the deep learning process. Input data is then mapped into time data and keyword data, and two weight matrices are generated through the two dimensions of attention mechanism. By fusing two matrices, the final output is the satisfaction level of learners' psychological needs. The experimental results of deep learning show that when using "generative artificial intelligence", learners' pursuit of "satisfying the results of use" has a significant impact on primary psychological needs by 0.74, while when using "generative artificial intelligence", learners' pursuit of "satisfying the process of use" has a significant impact on advanced psychological needs by 0.69. The proposed method can quantify the impact of "generative artificial intelligence" on learners' psychological needs.

1. Introduction

Generative artificial intelligence refers to the technology that generates text, images, sound, video, code, and other content based on algorithms, models, and rules. The ChatGPT released by OpenAI in 2022 belongs to this type of technology [2, 11, 17]. With powerful data, computing power, and excellent content generation capabilities, generative artificial intelligence not only opens up a new human-computer interaction mode, but also has a profound impact on human learning and thinking methods [1, 12, 16]. Especially in the field of education, learners become overly reliant on generative artificial intelligence, which fosters learning inertia. Due to the weakening of critical thinking, incorrect values are generated, leading to a constant stream of problems such as cheating and plagiarism. How to correctly use, manage, and utilize generative artificial intelligence has become a focus of current research [4, 13, 14]. The quantification of psychological needs through generative artificial intelligence has become an important research topic.

Montenegro believes that artificial intelligence reduces the educational subject to an object and elevates the educational object to a subject, leading to a high

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possibility of students losing themselves, and their independence and autonomy will eventually be exhausted [6]. Reda believes that artificial intelligence has brought a series of risks and challenges to education, such as the evolution of rights between artificial intelligence and educational subjects, the alienation of algorithm recommendations and student personality development, and the emotional crisis between artificial emotions and human-computer interaction [8]. Sangavi explored the impact of generative artificial intelligence technology on education and explored the impact of artificial intelligence on the psychological needs of learners [9]. Ibrahim pointed out that the impact of artificial intelligence on human thinking is twofold. On the one hand, artificial intelligence has helped humans improve their perception and thinking abilities, bringing about a deepening of local cognition and guiding people to pay attention to the relationships between things. On the other hand, artificial intelligence is also weakening the thinking habits of human overall cognition and the pursuit of causal relationships, making it less sensitive to the possible consequences of changes in things [3]. Luis uses a deep learning model based on emotional audio and evaluation texts to identify depression, which is a common mental health issue [5]. Rahimi used support vector machines as classifiers to identify mental health status based on audio and video data [7]. Sharma evaluated the performance of a series of machine learning models in mental health status recognition tasks based on personal feature data, including naive Bayes, logistic regression, support vector machines, K-nearest neighbors, random forests, multi-layer perceptrons, sequential minimum optimization, and extreme gradient boosting trees [10]. These works demonstrate that the performance of identifying mental health status in a simple data form such as structured personal characteristics can be comparable to that of mental health status recognition based on images, audio, electroencephalography, and even multimodal data [15].

Generative artificial intelligence, as a new learning tool, is bound to have an impact on the learning habits and psychological needs of learners. However, from existing research, there is currently no deep learning method for quantifying the impact of generative artificial intelligence on psychological needs. In this article, we use LSTM networks to construct deep learning methods and conduct empirical level analysis on this impact.

2. The proposed method

The core research content of this article is the use of generative artificial intelligence by learners to collect, organize, and learn knowledge, as well as the degree to which this process satisfies the psychological needs of learners. Throughout the research process, the satisfaction gained by learners using generative artificial intelligence as a learning tool needs to be reflected in the data obtained from questionnaire surveys. In order to better obtain the data analysis results of this process, we adopted a more effective deep learning network for time series data, Long Short Term Memory Network (LSTM).

2.1. **The deep learning framework based on LSTM networks.** A research method framework based on LSTM deep network was constructed for the problem we need to address, as shown in Figure 1.

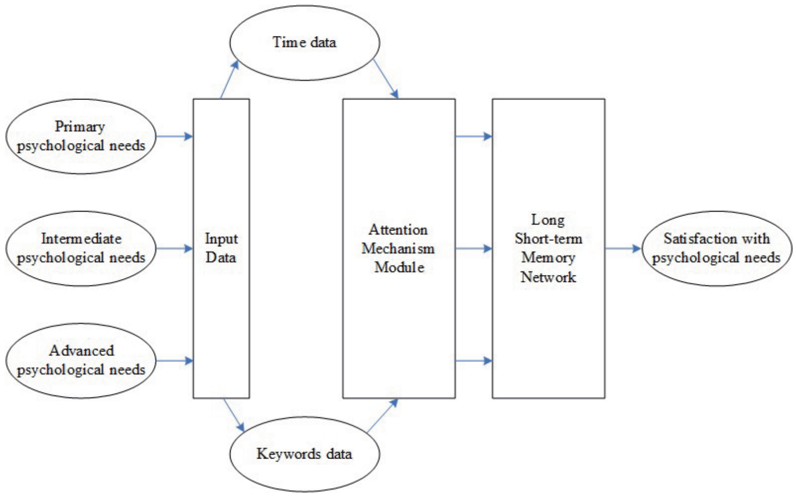

FIGURE 1. Research Method Framework Based on LSTM Deep Network

In the method framework shown in Figure 1, learners can achieve their psychological needs through generative artificial intelligence, which can be divided into three levels: primary psychological needs, intermediate psychological needs, and advanced psychological needs. These three levels of data will be used together as input data for subsequent processing. The input data composed of three types of requirements will be included in the subsequent processing in two forms: first, it will still be expressed according to the time dimension of data, and second, the keyword data extracted from the time data. The simultaneous use of time data and keyword data is to enhance the reliability of the learning process. These two types of data are further transmitted to the attention mechanism module, and then trained, learned, and processed by LSTM deep networks to obtain their weight relationship with psychological satisfaction.

2.2. **Dual channel attention mechanism processing.** From the input unit, it can be seen that the data sent into the deep learning process is divided into three categories: primary psychological needs, intermediate psychological needs, and advanced psychological needs. These data are fused together to form an input data matrix, as shown in Equation (2.1).

$$X = \begin{bmatrix} H_1 & D_1 & R_1 \\ H_2 & D_2 & R_2 \\ \vdots & \vdots & \vdots \\ H_n & D_n & R_n \end{bmatrix}. \tag{2.1}$$

Here, H_1 is the first learner to complete the primary psychological needs data of learning through "generative artificial intelligence", H_2 is the second learner to complete the primary psychological needs data of leaming through "generative artificial intelligence", H_n is the n-th learner to complete the primary psychological needs data of learning through "generative artificial intelligence".

D_1 is the first learner to complete the intermediate psychological needs data of learning through "generative artificial intelligence", D_2 is the second learner to complete the intermediate psychological needs data of learning through "generative artificial intelligence", D_n is the n-th learner to complete the intermediate psychological needs data of learning through "generative artificial intelligence".

R_1 is the first leamer to complete the advanced psychological needs data of learning through "generative artificial intelligence", R_2 is the second learner to complete the advanced psychological needs data of learning through "generative artificial intelligence", R_n is the n-th learner to complete the advanced psychological needs data of learning through "generative artificial intelligence".

In this article, the use of LSTM deep networks aims to establish a connection between input and output data, in order to determine the impact of learners using generative artificial intelligence on psychological needs. However, the input data contains redundant information. There is no expected correlation between these redundant information and outputs. Therefore, before deep learning in LSTM networks, a dual channel attention mechanism is used for processing, with the core purpose of removing redundant information from input data. The reason for setting up two channels here is the bidirectional fission processing of the original data towards time data and keyword data. The attention mechanism framework here is shown in Figure 2.

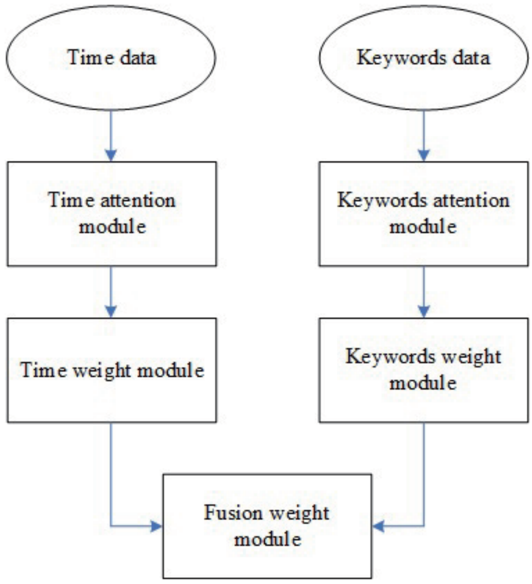

FIGURE 2. Dual channel attention mechanism framework

Because the input data is divided into time dimension and keyword dimension, let's first look at the weight results calculated after the time dimension data is guided to the time attention module and time weight module, as shown in Equation (2.2).

$$\alpha_i = \operatorname{soft\,max}(x_i) = \frac{e^{-x_j}}{\sum_{j=1}^{n} e^{-x_j}}. \tag{2.2}$$

Here, x_i is the psychological demand time data of the i-th learner who completed learning through "generative artificial intelligence", x_j is the psychological demand time data of the j-th learner who completed learning through "generative artificial intelligence", α_i is the weight of the psychological demand time data for the i-th learner to complete learning through "generative artificial intelligence", softmax() is a time attention mechanism function.

The weights of all time dimension data are integrated together, and the result is shown in Equation (2.3):

$$A = \begin{bmatrix} \alpha_1^1 & \cdots & \alpha_i^1 & \cdots & \alpha_n^1 \\ \alpha_1^2 & \cdots & \alpha_i^2 & \cdots & \alpha_n^2 \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ \alpha_1^t & \cdots & \alpha_i^t & \cdots & \alpha_n^t \end{bmatrix}. \tag{2.3}$$

Here, A is the integrated information of all time dimension data, α_i^t is the weight of the psychological demand time data of the i-th learner who completed learning through "generative artificial intelligence" at time t, α_n^t is the weight of the psychological demand time data of the n-th learner who completed learning through "generative artificial intelligence" at time t.

Let's first take a look at the weight results calculated after the keyword dimension data is guided to the keyword attention module and keyword weight module, as shown in Equation (2.4).

$$\beta_i = \operatorname{soft\,max}(f_i) = \frac{e^{-f_i}}{\sum_{j=1}^{n} e^{-f_j}}. \tag{2.4}$$

Here, f_i is the psychological demand keyword data of the i-th learner who completed learning through "generative artificial intelligence", f_j is the psychological demand keyword data of the j-th learner who completed learning through "generative artificial intelligence", β_i is the weight of the psychological demand keyword data for the i-th leamer to complete learning through "generative artificial intelligence", softmax() is a time attention mechanism function.

The weight of all keyword dimension data is integrated together, and the result is shown in Equation (2.5):

$$B = \begin{bmatrix} \beta_1^1 & \cdots & \beta_i^1 & \cdots & \beta_n^1 \\ \beta_1^2 & \cdots & \beta_i^2 & \cdots & \beta_n^2 \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ \beta_1^t & \cdots & \beta_i^t & \cdots & \beta_n^t \end{bmatrix}. \tag{2.5}$$

Here, B is the integrated information of all keyword dimension data, β_i^t is the weight of the psychological demand keyword data of the i-th learner who completed learning through "generative artificial intelligence" at time t, β_n^t is the weight of the psychological demand keyword data of the n-th learner who completed learning through "generative artificial intelligence" at time t.

3. Experimental results and analysis

3.1. **Obtaining experimental variables and data.** In the previous research process, a deep learning method based on LSTM network was constructed to analyze the impact of using generative artificial intelligence on the psychological needs of learners. Under the LSTM deep learning framework we have constructed, the input is the three types of requirements for using Generative Artificial Intelligence, and the output is the satisfaction level of using Generative Artificial Intelligence. In order to meet the requirements of deep learning process, variable settings are first performed to effectively extract data. The variable settings here are shown in Table 1:

Table 1. Indicators of the Impact of Generative Artificial Intelligence on Learner Psychological

symbol	Primary indicators	symbol	Secondary indicators
A1	Primary psychological needs	A11	Are you using Generative Artificial Intelligence (ChatGPT) to complete classroom assignments?
		A12	Are you using Generative Artificial Intelligence (ChatGPT) to complete practical tasks?
		A13	Are you using Generative Artificial Intelligence (ChatGPT) to prepare for exams?
A2	Intermediate psychological needs	A21	Are you using Generative Artificial Intelligence (ChatGPT) to learn knowledge?
		A22	Are you using Generative Artificial Intelligence (ChatGPT) to understand the background of knowledge generation?
		A23	Are you using Generative Artificial Intelligence (ChatGPT) to broaden your horizons?
A3	Advanced psychological needs	A31	Are you using Generative Artificial Intelligence (ChatGPT) to improve learning efficiency?
		A32	Are you using Generative Artificial Intelligence (ChatGPT) to enhance your problem-solving abilities?
		A33	Are you using Generative Artificial Intelligence (ChatGPT) for psychological pleasure?
B1	Process satisfaction	B11	Do you have a better psychological experience using Generative Artificial Intelligence (ChatGPT)?
		B12	Do you have a better user experience using Generative Artificial Intelligence (ChatGPT)?
B2	Result satisfaction	B21	Have you achieved satisfactory performance improvement by using Generative Artificial Intelligence (ChatGPT)?
		B22	Have you achieved satisfactory skill progress by using Generative Artificial Intelligence (ChatGPT)?

In Table 1, A1, A2, A3, B1, and B2 are primary indicators, while A11, A12, A13, A21, A22, A23, A31, A32, A33, B11, B12, B21, and B22 are secondary indicators. According to the secondary indicators, a survey questionnaire can be set up, with scores assigned to five levels of 1, 2, 3, 4, and 5 for each question. Respondents can give scores based on their own experiences.

3.2. **Construction of a relationship model between experimental variables.** From Table 1, it can be seen that A1, A2, and A3 respectively represent the primary psychological needs, intermediate psychological needs, and advanced psychological needs of learners using generative artificial intelligence. They are all input data for deep learning and are further divided into three secondary indicators, which facilitates data acquisition. B1 and B2 respectively represent the process satisfaction and outcome satisfaction of learners using generative artificial intelligence. From this, a variable model during the experimental process can be constructed, as shown in Figure 3.

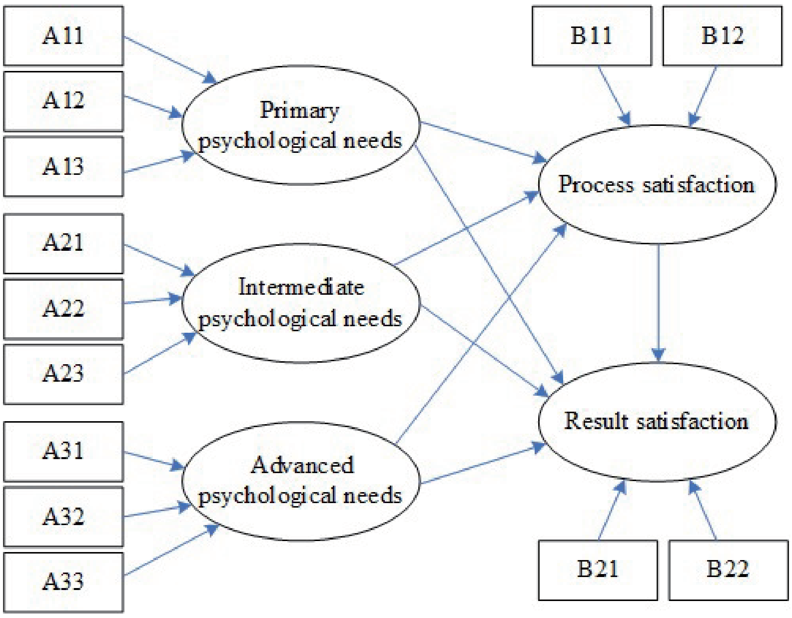

FIGURE 3. Variable model during the experimental process

From the relationship in Figure 3, it can be seen that primary psychological needs can have an impact on both process satisfaction and outcome satisfaction, which is the same for intermediate and advanced psychological needs. Process satisfaction can also have an impact on outcome satisfaction. After obtaining data on various variables through a survey questionnaire, primary psychological needs, intermediate psychological needs, and advanced psychological needs are included in the input of the deep learning network, while process satisfaction and outcome satisfaction are included in the output of the deep learning network. After training the deep learning network to achieve stability, the influence weights between variables can be obtained.

3.3. **Calculation of model weights for the relationship between experimental variables.** In order to obtain the raw data required for deep learning, a survey questionnaire was designed based on the content in Table 1, and 1000 questionnaires were distributed among college students in the Psychology Department of our university. 876 valid questionnaires were collected. The survey method adopted a combination of online electronic questionnaire survey and paper questionnaire survey. Combining the model in Figure 3 with the method in Section 2, the weights between the variables were obtained, and the results are shown in Figure 4.

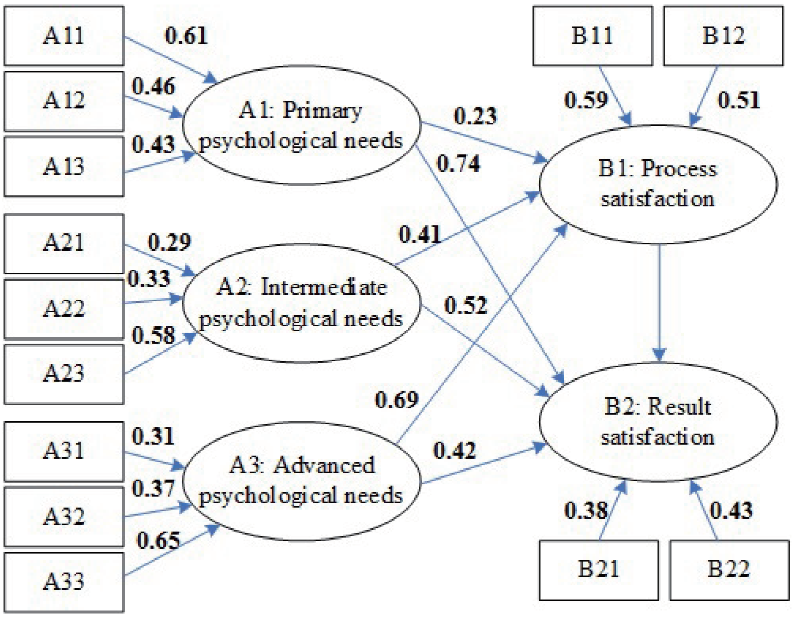

FIGURE 4. Weight calculation results of the relationship model between experimental variables

4. DISCUSSION

According to the weight calculation results between the variables in Figure 4, it can be seen that:

Firstly, through LSTM deep learning calculations, the impact of variable A11 on variable A1 is 0.61, the impact of variable A12 on variable A1 is 0.46, and the impact of variable A13 on variable A1 is 0.43. This indicates that the primary psychological need for learners to use "generative artificial intelligence" comes more from the need to complete classroom assignments. The demand for exams is the weakest, as "generative artificial intelligence" can only be used during exam preparation and cannot be used during exams.

Secondly, through LSTM deep learning calculations, the impact of variable A21 on variable A2 is 0.29, the impact of variable A22 on variable A2 is 0.33, and the impact of variable A23 on variable A2 is 0.58. This indicates that the intermediate psychological needs of learners using generative artificial intelligence are more aimed at expanding their horizons. As for the needs of learning knowledge and understanding the background of knowledge, the impact is relatively weak.

Thirdly, through LSTM deep learning calculations, the impact of variable A31 on variable A3 is 0.31, the impact of variable A32 on variable A3 is 0.37, and the impact of variable A33 on variable A3 is 0.65. This indicates that learners use advanced psychological needs of generative artificial intelligence more to obtain psychological pleasure. As for improving learning efficiency and problem-solving ability, the impact is relatively weak.

Regarding the relationship between the above variables, neural network methods such as CNN and RNN were used to compare with the proposed method. The comparison results are shown in Table 2.

Table 2. Comparison of several methods

Index	Method		
	CNN	RNN	OURS
Accuracy(%)	86.4	90.2	94.1
Convergence time(s)	0.598	0.602	0.477

5. Conclusions

The emergence of generative artificial intelligence (such as ChatGPT) has brought new experiences and technological means to the learning process of learners. However, learners face the problem of psychological imbalance through the use of generative artificial intelligence. In order to analyze the impact of generative artificial intelligence on the psychological needs of learners, a deep learning method based on LSTM network was constructed. The three psychological needs of learners are used as inputs, mapped into time data and keyword data, and incorporated into attention mechanisms. The two dimensions of attention mechanisms generate weight matrices and then fuse them to ultimately form the satisfaction level of learners' psychological needs. Under the LSTM deep learning framework, the required variable system for research was designed, and a variable relationship model was constructed. The experimental results show that the influence of variable A1 on variable B2 is as high as 0.74, indicating that learners who use "generative artificial intelligence" have a primary psychological need and prefer to be satisfied in the use results; The impact of variable A3 on variable B1 is 0.69, indicating that learners prefer to meet the advanced psychological needs of using "generative artificial intelligence" during the use process.

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