Research on the Integration of AI Ancient Literature Models in College Chinese Teaching Practice

Abstract

In recent years, ancient literature has come to be used for an extensive variety of publications, along with poetry, dramas, religious scriptures, and more. The use of artificial intelligence (AI) models to teach historical Chinese literature in a college-level Chinese path. Early Chinese literature and its rich historical heritage and historical importance, offer particular challenges and opportunities for each educator and student. College students' understanding is greatly impacted by the use of ancient literature models, one of the most important skills in Chinese teaching. Students could have a great perception of Chinese concepts and discover ways to connect others with comfort as an outcome. The study's goal is to demonstrate how AI models of historical literature may be included in college Chinese teaching practices. This study proposed a novel drosophila food search fine-tuned intelligent recurrent neural network (DFS-IRNN) to predict the functionality of Chinese teaching practice in college students. This study collects a diverse set of historic Chinese literature texts, consisting of philosophical works. The data become preprocessed using Z-score normalization for the obtained information. By selecting effective teaching techniques and materials based on the outcomes anticipated using the IRNN model, DFS may be used to optimize the layout and delivery of Chinese literary publications. The suggested method scored 98% in critical thinking and 98% in performance ratio. The proposed approach, AI ancient literature methods, is used within the Chinese teaching Implementation. The suggested technique is evaluated in various performance metrics. The result validated that the suggested method outperformed traditional algorithms.

Keywords: Ancient Literature Models, Chinese Teaching, College, Drosophila Food Search Fine Tuned Intelligent Recurrent Neural Network (DFS-IRNN)

1. Introduction

Incorporating the AI model into university Chinese literature education represents a substantial improvement in education practices, aiming to expand each engagement and comprehension. AI-driven model provides cutting-edge tool for reading and interpreting historic texts, offering college students deeper insights into classical Chinese literature **(Chen and Wu 2024)**. By leveraging natural language processing and machine learning techniques, the ones models can take a look at textual patterns, ancient contexts, and linguistic nuances which can be frequently hard to understand through traditional techniques **(Chen et al., 2024).** The method allows in a more interactive analyzing experience, allowing university scholars to explore complex literary works through advanced simulations and contextual analyses **(Zeng 2024)**. The AI model furthermore assists in growing personalized studying paths, adapting to individual student needs and learning of patterns, which could assist to address numerous ranges of familiarity with classical texts. Moreover, the ones models help educators through supplying superior analytical capabilities that may streamline grading and feed practice, allowing more efficient evaluation of student information **(Du 2024)**. The integration of AI in Chinese literature education not only enriches college students' interaction with historical texts but also prepares them for a more tech-centric future through familiarizing them with cutting-edge technological applications. The innovative educational method guarantees that students benefit from a complete knowledge of historical literature while concurrently growing capabilities in generation-driven analysis and interpretation **(Ma 2024)**.Varying levels of student interest and engagement with AI technologies may affect the overall effectiveness of teaching practices.

This research presented a novel drosophila food search fine-tuned intelligent recurrent neural network (DFS-IRNN) to predict the capability of Chinese teaching practice in college students.

The remaining part of the study was organized as follows, part 2 related work, part 3 methodology, part 4 result section, and part 5 conclusion.

2. Related work

Xiao and Yi 2021 to address higher education concerns, higher educational reforms must be implemented at colleges and universities. Customized education has been seen as a novel training technique that stems from individuals' specific desires and social development. Traditional teaching methods in universities and colleges do not enable the implementation of customized training.

Bearman et al., 2023 evaluation methodically scanned important university-level research for references to the keyword 'artificial intellect'. They analyzed terminology and assessed phrases in the relevant literature. Their studies revealed that there were very few if any, clear references to artificial intelligence as a study topic. They distinguished both discourses. That portion of essential shift examines how AI was perceived as an unavoidable development to which everyone must adapt.

Su et al., 2022 evaluated 14 research publications on curriculum for AI for elementary school students published in Asia-Pacific among 2018 and 2021, and determined the selected studies' expertise in the topic, instruments, platforms, operations, models and theories, evaluation procedures, and results for learning. The findings indicated that AI curriculum might assist students improve their AI abilities and expertise, as well as their attitudes toward learning and interests.

Holmes and Tuomi 2022 examined current artificial intelligence in learning, as well as their educational and instructional conceptions. They created taxonomy of AIED (AI Education) structures and provided several strategies for utilizing AI in learning and education, highlighting how they were founded on different ideas of what AI and education were or might be, as well as identifying potential bottlenecks on the AIED highway.

XIAO 2024 employed a numerical approach to assess the impact that multimedia enhancements information had on a translator's skill, comprehension, and pleasure of literate settings. They included students engaged in post-secondary education programs. The outcomes revealed a considerable rise in the number of individuals who participated with multimedia-enhanced content, confirming the method's effectiveness as a teaching tool.

Li and Fei 2024 provided a complete framework for a practical teaching program geared toward Chinese Language and Literature students. It has four primary elements, an organization of instructional material, stated operational learning specifications, instructional components, and a goal indicator framework for operational education results. The present research uses single- and two-factor analyses to explore the association between course results to optimize programming patterns and the framework itself.

Wang and Webb 2024 found a number of articles published and a thesis for graduates on the subject. The articles were examined to determine what would represent optimal practices in classroom methods for instruction and learning traditional Chinese music. Depend on the evaluation's criterion for inclusion - presentations were in English, practice-oriented, and evaluated by a peer and provided throughout the previous 30 years- the investigation discovered that the total amount of materials was restricted and that in regards to developed instructional techniques they connected, some gaps developed, certain techniques were essentially constituted, and some were possibly inappropriate to have been experimented.

Zhang 2024 described a comprehensive search throughout the previous 9 several decades of research on instructing Chinese characters yielded 16 peer-reviewed research papers presented since 1937 that addressed learning Chinese personalities at the course and in general educational levels for a Chinese program. Two topics emerged about character education, when and what to educate. Each subject was thoroughly investigated, and a preliminary model was developed as a result.

Lin et al., 2024 look at the links between Chinese high school pupils' capacity for computation reasoning effectiveness for education AI, AI knowledge, and AI methods of learning. The data were collected from 509 Chinese high school pupils, and confirmation factor evaluations revealed that the evaluations were highly reliable and valid. The findings indicated that literacy in artificial intelligence was positively associated with pupils' computational cognitive effectiveness in learning AI.

To estimate the capacity of technical school students in Chinese Traditional Culture (CTC) lessons, **Jiang 2022** introduced Hybridized LSTM-RNN. Standardized datasets, an evaluation tool, and AI technology in the CTC learning program were used in the technique to analyze performance measures and maximize efficacy. The study highlighted how critical it was for students to acquire cultural awareness and comprehend Chinese values.

3. Methodology

A diverse collection of historic Chinese literature texts consisting of philosophical works was collected and pre-processed using Z-score normalization. A novel method DFS-IRNN was proposed to predict the functionality of Chinese teaching practice in college students.

3.1 Dataset

Classical Chinese and ancient poetry are perhaps the most dependable primary historical sources for China. They include stories about ancient kings, God legends, heroic struggles, unrecognized love, how stars look when dynasties fall, and how people whistled, farmed, entertained, and puzzled with algebra thousands of years ago. They have diverse views; some value order and civility, some thrive at deceit in combat, while others believe in balance and nature. They give birth to a language that has evolved into hundreds of live dialects, spoken and written by over a billion people worldwide.**(Data source: https://www.kaggle.com/datasets/raynardj/zh-wenyanwen-wikisource)**

3.2 Z-score normalization

Z-score normalization standardizes the dataset of historic Chinese literature, ensuring comparison, enhancing model convergence, and managing anomalies effectively for robust analysis and insights. Normalization is a pre-processing step that decomposes data into numeric properties and converts values to a certain range. A number of methods are often used in the normalization of data, including min-max standardization, z-score normalization, and normalizing by scaling using decimals. Equation (1) illustrates how Z-score normalization converts a U_j value from element F to U' into a previously unidentified range.

$$U' = \frac{U_j - F_j}{std\,(F)} \tag{1}$$

$U^{'}$ denotes the result of normalizing value, U represents the value to be normalized in element, F_j denotes the average value of a characteristic and $std\ (F)$in this F is the standard deviation.

3.3 To predict the capability of Chinese teaching practice in college students using DFS-IRNN

A hybrid approach combining an IRNN with DFS optimization can enhance the study of ancient literature by optimizing the IRNN's education process and output technology. The IRNN effectively analyses and generates classical Chinese texts, whilst the Drosophila food search algorithm, inspired by means of the foraging behaviour of fruit flies, can optimize hyperparameters and refine the model's structure. This synergy permits for extra green exploration of the parameter area, improving the IRNN's performance in capturing contextual relationships and stylistic nuances. As a result, the hybrid model offers custom designed and adaptive learning experiences, offering tailored suggestions and insightful feed backs, thereby enriching college students' engagement with historical literary works.

3.3.1 Intelligent Recurrent Neural Network

An IRNN can significantly enhance the teaching of historical literature by correctly analyzing and producing classical Chinese texts. By utilizing innovative designs, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), the model can capture complicated patterns and long-range dependencies in the data. The research presents an encoder-decoder framework that incorporates an upgraded RNN for fund correlations forecasting. The value of each feature $(w_1, w_2, \ldots, w_s)$ is connected to the value $(z_1, z_2, \ldots, z_{s-1})$and the outcome of the preceding time method, it expressed as equation (2), Figure 1 shows the structure of IRNN.

$$\hat{z}_s = E([z_1, z_2, \ldots, z_{s-1}; w_1, w_2, \ldots, w_s]) \quad (2)$$

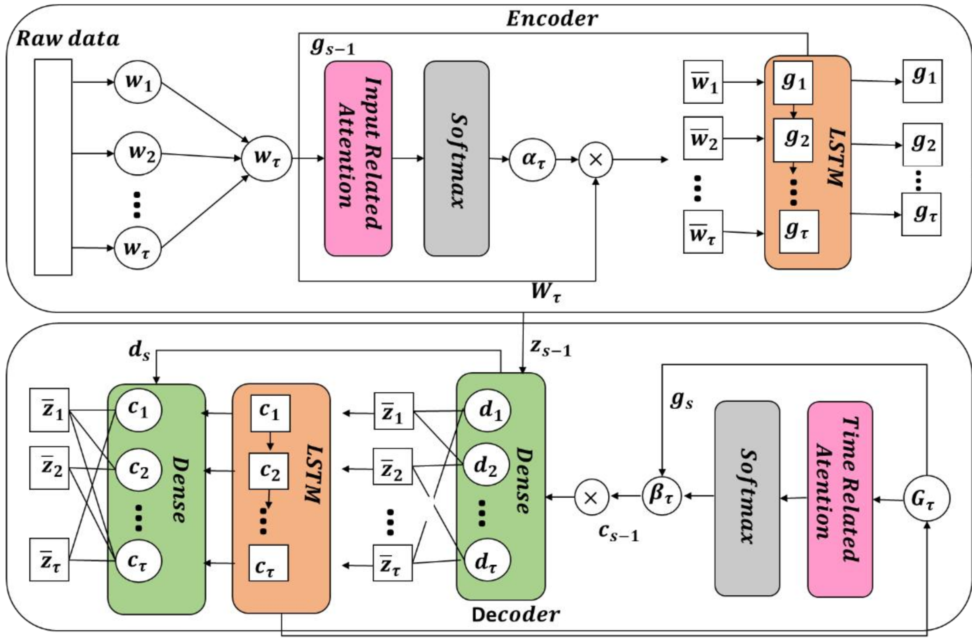

Figure 1 Framework of IRNN

This model distinguishes from others by incorporating attention procedures in both the encoding and decoding process. The encoder employs an attention-related attention method to pick a characteristic a parameter. The decoder employs a temporal-dependent system for attention to assess the relationship between prior time steps. In equations (3) and (4),the encoder uses an attentive-related technique to determine the interest level of the originating fund data $w_s \in \mathbb{R}^n$and the preceding code vector $g_{s-1} \in \mathbb{R}^n$.

$$y_s = \tanh\left(X_\alpha[w_s; g_{s-1}]\right) \quad (3)$$

$$\alpha_s = exp\left(X_{y\alpha}^{S}.\, y_s\right) \quad (4)$$

The link among the actual fund data w_s and previous time procedure coded vector g_{s-1} is represented by $[w_s; g_{s-1}] \in \mathbb{R}^{n\times m}$. X_α is the weighting of the forwarding neural network, and α_s is its focus value. In the received focus value (α_s) is employed to modify the initial inputs, yielding in the equation (5)

$$\overline{W}_s = \sum_{j=1}^{s} \alpha_j w_j \quad (5)$$

In equation (6), $W_s$represents the initial funding data after weighting the attention. The network of LSTM is initialized using the code vectors from the prior processing phase (g_{s-1}) and encodes weighting actual funding data (w_s) to generate the most recent time step's code vectors (g_s).

$$g_s = LSTM\left(\overline{Z}_s, c_{s-1}\right) \quad (6)$$

The decoder portion employs a time-related concentration method to calculate the focus worth of the originating fund information encoded vector g_s and the coefficient of regression of the preceding time step fund's encoded vectorsc_{s-1}.

$$y_s^{'} = tanh(X_\beta[g_s; c_{s-1}]) \tag{7}$$

$$\beta_s = exp(X_{d\beta} . y_s^{'}) \tag{8}$$

In equation (7), $[g_s; c_{s-1}]$ represents the link among the actual fund information encoded vector g_s and the preceding step of time investment coefficient of correlation encrypted vectorsc_{s-1}, X_β is the weight of transmitting neural systems, and$\beta_s$is the focus value. β_s rewrites the initial coding vectors g_s to create the contextual vector of the actual funding data c_s.

$$d_s = \beta_s . g_s \tag{9}$$

The contextual matrix (d_s) represents the end transcribed outcome of the initial fund data$(w_1, w_2, ..., w_s)$. In equation (10), to represent a context vectord_s incorporate it with the preceding time-phase funding coefficient of regressionz_{s-1}, and use a computational network with one layer.

$$\overline{z}_{s-1} = X_z[d_s; z_{s-1}] + a \tag{10}$$

To acquire the neural network encoding vector c_{s-1}, initialize a layer of the LSTM network with the prior time-phase fund coefficient of regression z_{s-1} and encode using the network.

$$z_s = LSTM(\overline{z}_{s-1}, c_{s-1}) \tag{11}$$

To rewrite equation (2), use the encoded results $d_s$of the actual fund data $(w_1, w_2, ..., w_s)$and c_s of the fund correlation coefficient $(z_1, z_2, ..., z_{s-1})$.

$$\hat{z}_s = E([d_s, c_s]) \tag{12}$$

Using a model of neural networks to fitting the purpose $E(,)$, the projected value of the fund's relationships factor $(\hat{z}_s)$ is represented as:

$$\hat{z}_s = X_s[d_s, c_s] + a_s \tag{13}$$

The relationship between the initial funding data's contextual vector (d_s) and the preceding time step funds' coefficient of correlation (c_s) is represented by $[d_s, c_s]$in equation (13). The neural network's weight and offsetting are denoted by X_s and a_s respectively, whereas $\hat{z}_s$ represents the expected coefficient of correlation of the end fund.

3.3.2 Drosophila food search optimization

DFS optimization is employed to enhance the performance of an IRNN technique. This optimization approach simulates the foraging behaviour of Drosophila, where the look for food source is guided by the exploration and exploitation techniques. By implementing DFS, the model effectively navigates through the parameter area of the IRNN, systematically exploring capacity configurations at the same time as prioritizing the most promising regions recognized during the quest method. This approach enables optimizing the IRNN's architecture and hyperparameters, and improving its capacity to accurately analyse and interpret historical literature, thereby enriching the coaching practice in a college setting.

The Drosophila optimization technique uses global optimization and foraging habits to identify food sources. This technique uses the Drosophila fly, a 3 mm long and 2 mm wide fruit fly with high eyesight and smelling intensity, to find food. The fly uses its eyesight to locate the best food, with its internal and external sensilla covering its sense of smell. There are two sorts of flies, primers and follower flies. Primer flies hunt for a desirable food supply and choose it at random. Follower flies are drawn to the primer flies rather than the meal itself. Fruit flies perform two sorts of dances, tremble dance and waggle dance. The tremble dancing of the fly indicates the accessibility of food. The waggle dance is performed by flies when there is no food available at the current place and they begin looking for food at the new location. Figure 2 demonstrates the food searching process of drosophila.

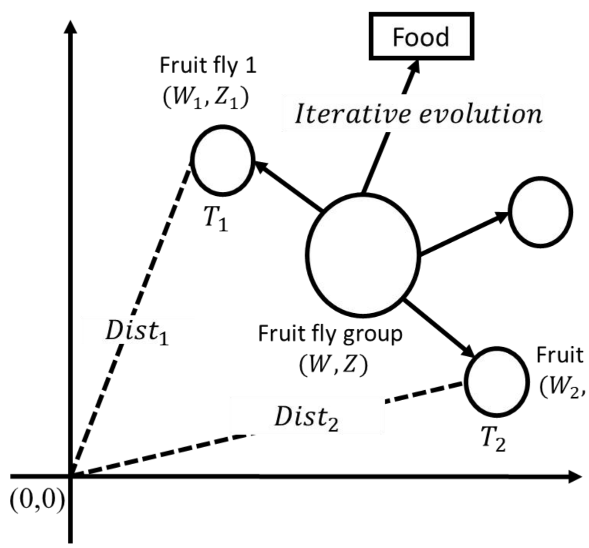

Figure 2 Food searching process of drosophila

The standard Drosophila optimization method involves the following steps with its equations, During the stage of initialization, the swarm location is chosen at random to begin the search process.

$$W_0 = InitW_{axis}$$

$$Z_0 = InitZ_{axis} \quad (14)$$

Equation (15), assignments phase, provide an improbable direction and distant for food search utilizing osphresis.

$$W_j = W_0 + randValue\ Z_j = Z_0 + randValue \quad (15)$$

Equation (16), during the assessment phase, calculate the distance between the food source and its origin.

$$Dis_j = \sqrt{W_j^2 + Z_j^2} \quad (16)$$

Equation (17), the predicted distance will be used to determine the scent intensity judgment estimate T.

$$T_j = 1/Dist_j \quad (17)$$

Substitution phase, Determine the scent intensity of each drosophila site, using the estimated value T as input.

$$Smell_j = Fitness\ Function\ (T_j) \quad (18)$$

During the stage of identification, use equation (18) to determine the optimal scent intensity.

$$[BestSmell_{BestIndex}] = \max\ (Smell) \quad (19)$$

During the decision-making phase, fruit flies utilize their eyesight to choose the greatest food sources equation (20).

$$W_0 = W(BestIndex)$$

$$Z_0 = Z(BestIndex) \quad (20)$$

4. Result

Python 3.12.6 was used to finish tasks on Windows 11. The processor was an Intel Core i7 12th Gen, and there was 32 GB of RAM. The test under examination was a contemporary laptop setup that would enable performance measurements for intensive multitasking and development workloads.

The outcomes of the pupil's abilities, which were assessed utilizing the IRNN-DFS technique, will be compared in this part. The suggested technique to existing methods like Hybridization LSTM-RNN

(HLSTM-RNN) (Jiang 2022) was compared. Figures 4 and 5 show the students' critical thinking skills and performance ratio. The suggested technique performs better than the current methodology.

4.1 Accuracy and loss

Accuracy loss calculates a model's departure from the ideal, perfect accuracy throughout the entire dataset. The forecast accuracy of a specific model varies from the ground truth throughout the entire dataset. Despite the accuracy loss, Figure 3 is a crucial metric for evaluating the model's overall performance and comprehending its level of precision. It takes on particular significance in applications to predict Chinese teaching proficiency. The proposed method is effectively performed in predicting Chinese teaching proficiency in college students.

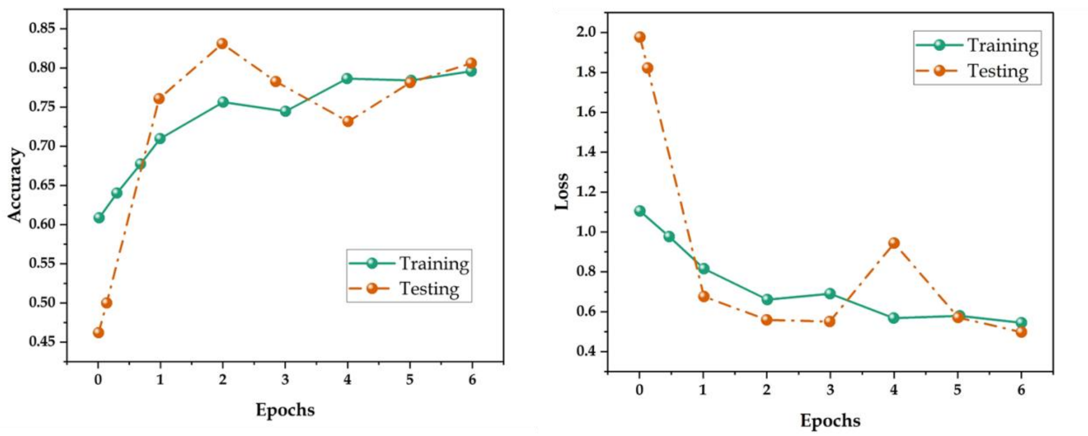

Figure 3 Accuracy and Loss

4.2 Creative thinking Skill

To illustrate the comparative effectiveness of various methodologies in enhancing creative thinking skills (CTS) within the context of integrating AI historic literature models into university Chinese teaching practice. By offering the overall performance of current techniques, HLSTM-RNN (97%) alongside the proposed approach DFS-IRNN (98%), Figure 4 demonstrates the superiority of the proposed approach. This highlights its ability to significantly improve college students' innovative thinking abilities, thereby improving the overall learning experience in college Chinese courses that contain ancient literature through AI models.

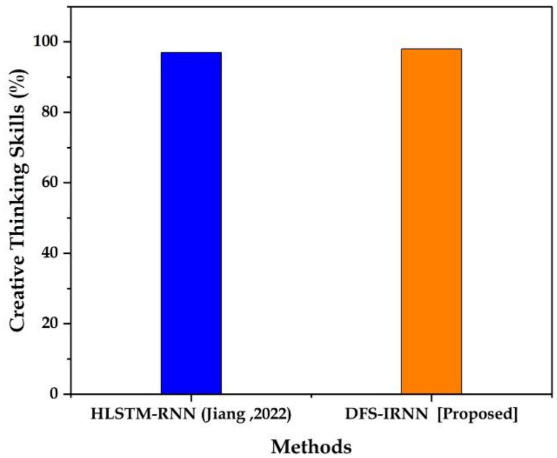

Figure 4 Outcome of CTS

4.3 Performance ratio

By presenting the overall performance of present strategies, HLSTM-RNN (96%) along the proposed method DFS-IRNN (98%), Figure 5 demonstrates the superiority of the proposed approach. This highlights its capacity to significantly enhance students' performance ratio, thereby improving the overall learning experience in university Chinese courses that include ancient literature through AI models.

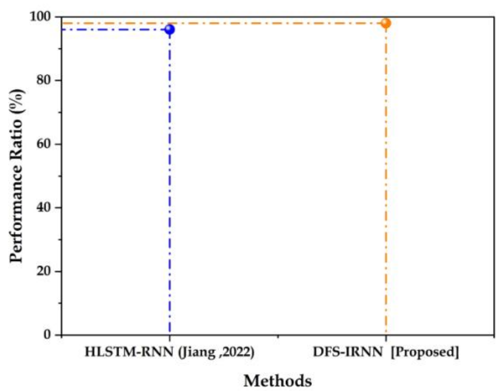

Figure 5 Result of performance ratio

5. Conclusion

In recent years, ancient literature has been utilized to publish a variety of works, including poetry, plays, religious scriptures, and more. Using artificial intelligence (AI) models to teach ancient Chinese literature in a college-level Chinese class. Ancient Chinese literature, with its rich cultural background and historical relevance, presents unique problems and possibilities for both teachers and students. The project aims to show how AI models of ancient literature might be incorporated into college Chinese teaching techniques. This study presented a unique drosophila food search fine-tuned intelligent recurrent neural network (DFS-IRNN) to predict Chinese teaching proficiency in college students. In this research, collect a diverse level of ancient Chinese literature texts, including philosophical works. The acquired data was pre-processed with Z-score normalization. DFS may optimize the design and delivery of Chinese literature courses by picking the most successful teaching tactics and materials based on IRNN model predictions. The suggested technique, AI ancient literary models, is implemented in a Chinese teaching application. The suggested technique is assessed using several performance criteria such as critical thinking and performance ratio. The proposed method achieved 98% in critical thinking and 98% in performance ratio, the results revealed that the suggested technique outperformed other existing algorithms. Limited access to numerous ancient literature datasets may prevent the model's effectiveness in numerous teaching contexts. Future research could explore integrating AI models into curricula, enhancing the relevance of ancient literature in contemporary contexts.

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