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A Study on Analyzing Physical Education Teachers' Professional Development Trajectories Based on Time Series Prediction Models Driven by Physical Education Reforms

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Abstract This paper focuses on the dynamic characteristics of teachers' professional development in the context of physical education reform, and constructs a career trajectory portrait system based on time series prediction model. A multi-seasonal frequency domain augmented PD-FEformer model is designed to analyze the non-linear evolution law and key turning points of teachers' professional competence. Combined with cognitive network analysis to reveal the hierarchical features of professional competence evolution, the PD-FEformer model is used to capture the barriers to teachers' professional competence development. Physical education teachers had the lowest covariance coefficients for A6-A7 (0.04) and A5-A7 (0.05), and the highest covariance coefficient between A3-A1 (0.46), followed by A2-A3 (0.42) and A3-A4 (0.41). The model identified shortcomings in the development of professional competence of physical education teachers, including 18% of physical education teachers who had not participated in open classes, 26% of teachers who had not won any prizes for their papers in the last three years, and as many as 36% of teachers who had no idea at all about professional development.

Index Terms career trajectory portrait, PD-FEformer model, cognitive network analysis, professional development, physical education teachers

I. Introduction

Under the background of massification of higher education, the issue of professional quality development of college teachers, which is closely related to the improvement of the quality of college education, has been paid more and more attention by the higher education administration, kor school administrators and individual teachers, and has gradually entered into the field of view of higher education researchers [1], [2]. Teachers in higher education, because they directly face students and directly control the education process, undertake the special mission of cultivating high-level talents and determine the quality of higher education talents [3]. As a result, the development of professional qualities they possess, which are in the position of the direct subject of higher education activities, has been the focus of attention from all sectors of society [4]. And the education sector is also in the cultivation and improve the professional quality of college teachers and other aspects of active exploration.

At present, the academic community for the teacher's professional quality of the understanding of the dimension is relatively single, tends to the professional quality of the various parts of the inorganic, simple additive, flowing from the surface, rarely on the professional quality of college teachers to the structure of the logic of the organic sorting [5]-[7]. Take physical education as an example, with the deepening of education reform, physical education in the continuous development and reform at the same time, gradually began to pay attention to the cultivation and improvement of teachers' professionalism [8], [9]. Only with good professionalism, teachers can better adapt to the needs of educational reform and development, and better serve students and education [10], [11]. By constructing a prediction model for the professional development of physical education teachers and analyzing the development trajectory of teachers' professionalism in detail, it can provide guidance for the development of the professional quality of physical education teachers in many colleges and universities in real life [12], [13].

In this paper, we integrate web crawler, natural language processing and deep learning techniques to achieve dynamic association and visual expression of multi-source data. Combining MLP and RevIN to deal with complex trend changes, the Transformer model based on frequency domain enhancement is selected to deal with seasonal sequences. The PD-FEformer model is utilized to solve technical problems and construct a career trajectory portrait system. Taking 50 physical education teachers in City A as research objects, the stage pattern of teachers' professional ability development is resolved by combining cognitive network analysis. The performance level of the model is examined by testing the F1 score index on five data sets. With the anomaly detection ability of the PD-

FEformer model, the core shortcomings in the professional development trajectory of physical education teachers are identified.

II. Career trajectory profiling system based on time series prediction modeling

With the in-depth promotion of physical education reform, teacher professional development has gradually become the core driving force to improve education quality. In the dynamically changing educational environment, constructing a dynamic prediction model of teachers' career development trajectory is of great value for optimizing teachers' cultivation path and realizing accurate career planning. This paper innovatively proposes a career trajectory portrait construction system based on time series analysis, using digital means to form a dynamic career development map with spatial and temporal characteristics.

II. A. Construction of career trajectory portraits

In this paper, we make full use of the existing resume big data and recruitment information big data, and use web crawler technology, natural language recognition, big data analysis and other technologies to construct the career trajectory portrait under the big data view, and the specific design of the technical scheme is shown in Figure 1.

(1) Data collection layer. Using crawler technologies such as Requests, XPath, Scrapy, etc., we regularly crawl the job post information and resume information made public by various job search websites to form a big data set of job and resume information.

(2) Data storage layer. Use MongoDB to store the captured job information and resume information for the first time. Then, use Python language to clean the abnormal data such as mutilated data, wrong data, duplicate data, etc., and do further data organization according to the fields of the career job element information table and career track data table to form the relational data, and then store it into the MySQL database.

(3) Data analysis layer. Use natural language processing technology to further analyze and process the recruitment information and resume information to find out the correlation information between the two, and further mine more information. At the same time, use the deep learning related algorithms in artificial intelligence to carry out the recommendation and prediction of recruitment job demand information, intelligent matching, recommendation and prediction of jobs in resume information, and so on.

(4) Data presentation layer. Mainly using echarts.js, matplotlib and other technologies to achieve visualization, using graphics with weights to display trajectory portraits, including career trajectory portraits at three levels: micro, mid and macro.

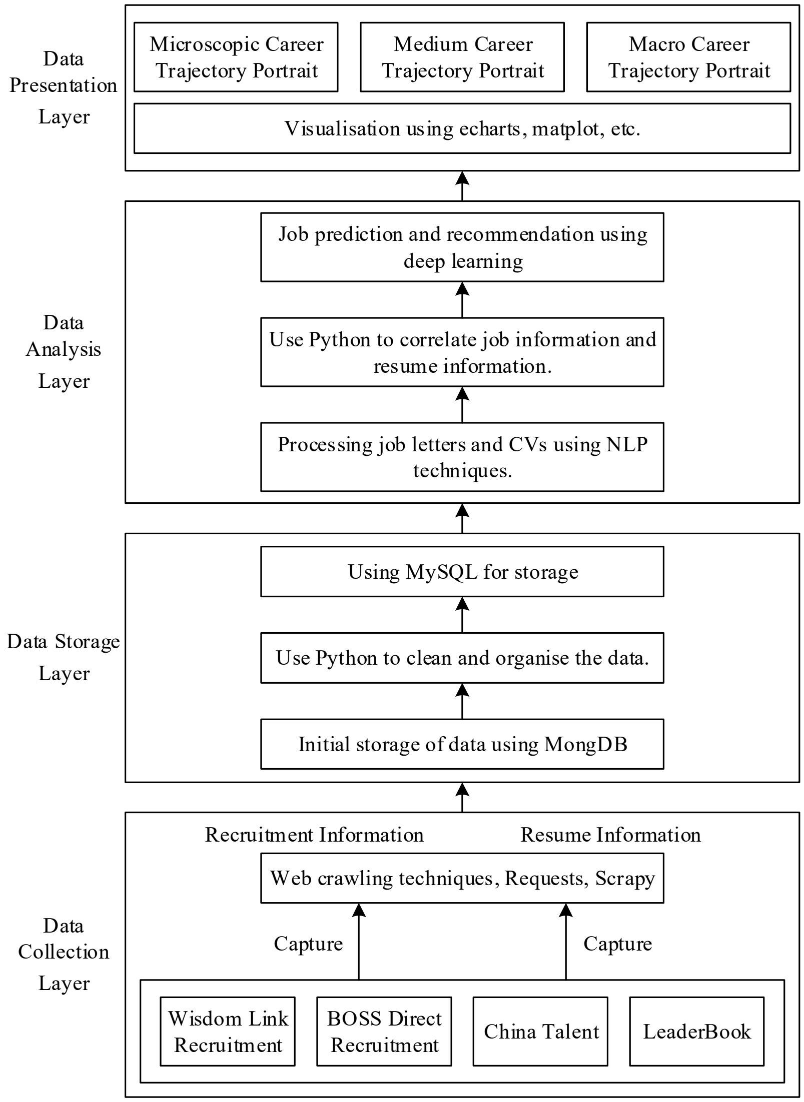


Figure 1: Technical solution for constructing a career trajectory portrait

II. B.Multi-Seasonal Frequency Domain Enhanced PD-FEformer Modeling

In order to analyze the nonlinear evolution law of teachers' professional development, and to address the limitations of traditional time series models in long-range dependency capture and dynamic feature extraction, this paper designs the PD-FEformer model, which ensures the prediction accuracy and at the same time reveals the key turning points and potential paths of career development.The core architecture of the PD-FEformer model is the multi-seasonal frequency domain augmented Transformer module, which is mainly composed of the frequency domain enhancement Transformer component that deals with seasonal sequences and the MLP component that deals with trend sequences. The specific processing flow is as follows:

(1) Processing of trend term series

For the trend term series, the model chooses to use the simple and efficient MLP for modeling and forecasting, and at the same time, in order to deal with the non-stationary information in the time series, the model introduces the reversible instance normalization technique by introducing it prior to the forecasting of the MLP model. The use of RevIN makes it possible to effectively eliminate the interference of nonsmoothness on the forecasting model without changing the distributional characteristics of the data, so that the MLP model can focus more on learning the pattern of the trend itself rather than the noise and irregularity information in the series, and enable it to accurately capture and forecast the complex changes in the trend term. After the prediction is completed, the information about the smooth characteristics of the time series is then recovered through the inverse operation of RevIN to ensure the accuracy and usefulness of the prediction results.

In summary, the trend term model aims to accurately capture and forecast the complex changes in the trend term while effectively addressing the challenge of non-smoothness in the time series by cleverly combining the MLP with the reversible instance normalization technique. Its computational formula can be expressed as follows:

$$Y_{tread} = \operatorname{Re}vIN^{-1}\left(MLP\left(\operatorname{Re}vIN\left(x_{tread}\right)\right)\right) \tag{1}$$

where x_{tread} denotes the input of the trend component and Y_{tread} denotes the predicted output of the trend.RevIN is the normalization layer, denoted as:

$$\hat{x} = \frac{x_{tread} - \mu}{\sigma} \tag{2}$$

where $\hat{x}$ denotes the value of x_{tread} after instanciable normalization, μ is the mean of the instanciable, and σ is the standard deviation of the instanciable.The inverse normalization of RevIN can be expressed as:

$$x' = x\sigma + \mu \tag{3}$$

where x is the input to the back-normalization and x' is the recovered time series forecast.

Overall, the model removes non-stationary information from the data through RevIN, allowing the MLP to more accurately capture and predict complex changes in the trend term. Finally, the non-smooth information is then reintroduced on the model's forecast results through an inverse normalization operation, which restores the smooth forecast values of the model output to the scale and trend of the original data. In this way, the prediction results of the model output contain the core pattern of the trend term and retain the non-smooth characteristics of the original time series, thus improving the stability and accuracy of the prediction.

(2) For the seasonal term series, the Transformer model based on frequency domain enhancement is used for modeling and prediction. The core idea is to use the frequency domain enhanced attention mechanism instead of the traditional time domain attention mechanism, and its basic structure is shown in Fig. 2. Firstly, the input time series x is mapped by the features to get the query matrix q, key matrix k and value matrix v, and then the query, key and value matrices are transformed from the time domain to the frequency domain space by using the Fourier transform. The M patterns are randomly selected to perform an attention computation in the frequency domain, respectively. Subsequently, the attention result is zero-padded to keep the output the same length as the input. Finally, the zero-padded frequency-domain attention result is converted back to the time domain using the Fourier inverse transform to obtain the final attention output.

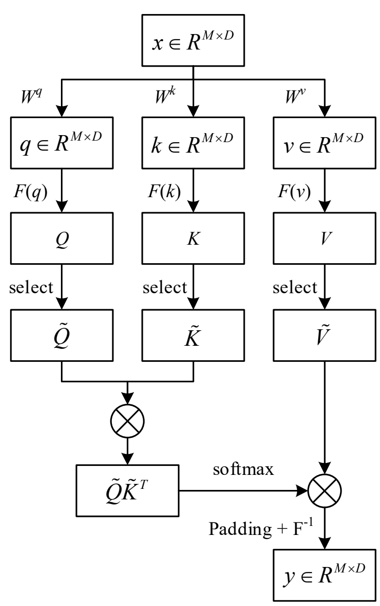


Figure 2: Frequency Domain Enhancement Enhanced Attention Mechanisms

In the model, the Frequency Enhanced Attention Mechanism module is denoted by “FEAttn”, and its specific calculation formula is as follows:

$$FEAttn\left(q,k,v\right) = F^{-1}\left(padding\left(soft\max\left(\tilde{Q}\tilde{K}^T\right)\right)\tilde{V}\right) \tag{4}$$

where q,k,v are the query, key and value vectors in the original data, and $\tilde{Q}$, $\tilde{K}$ and $\tilde{V}$ are the query, key and value vectors after Fourier transform and feature selection, which are used as the feature representation of the original data in the frequency domain. The model still chooses softmax as the activation function to handle the computed similarity between the query and the key.Padding is a padding function used to zero-paddle the result before performing the Fourier inverse transform to ensure that the transformed dimensions are consistent with the original data. $F^{-1}(\cdot)$ is the Fourier inverse transform, which is used to restore the signal volume from the frequency domain space to the original time domain space. In this case, the feature selection module after the Fourier transform randomly selects M modes for each mapping component to compute the attention output. Its $\tilde{Q}$, $\tilde{K}$ and $\tilde{V}$ matrices are computed as follows:

$$\tilde{Q} = S\left(F(q)\right) \tag{5}$$

$$\tilde{K} = S\left(F(k)\right) \tag{6}$$

$$\tilde{V} = S\left(F(v)\right) \tag{7}$$

where $F(\cdot)$ is the Fourier transform and $S(\cdot)$ is the feature selection function, i.e., by randomly selecting M patterns in a way that enables the attention mechanism to focus on these selected features, thus capturing the key information from the data more efficiently, and improving the model's important part of the signal Sensitivity.

In terms of the overall architectural design of the model, the frequency domain enhancement-based Transformer model follows the classical pattern of the traditional Transformer, i.e., a combined encoder and decoder framework is used to construct the model. Specifically, the seasonal item sequences are firstly input into the encoder of Transformer, and the encoder extracts the key features in the sequences through the frequency domain enhancement attention mechanism and the feed-forward neural network and passes this information to the decoder, which will calculate the prediction value of the next time step in sequence according to the previous prediction results and the output of the encoder. The specific process is as follows:

1) In the encoder stage, the preprocessed input sequence first undergoes the frequency domain enhanced attention mechanism for attention computation before entering the feed-forward fully-connected layer, and residual connectivity and normalization are added to each layer. Its calculation formula is as follows:

$$x_{en}^{n+1,1} = Norm\left(\left(FEAttn\left(x_{en}^{n}\right)\right) + x_{en}^{n}\right) \tag{8}$$

$$x_{en}^{n+1,2} = Norm\left(FF\left(x_{en}^{n+1,1}\right) + x_{en}^{n+1,1}\right) \tag{9}$$

where n is the number of layers of the encoder stack, $FF(\cdot)$ is the feed-forward fully connected layer, $FEAttn(\cdot)$ is the frequency-domain augmented-attention mechanism, and $Norm$ is the normalization operation. x_{en} denotes the input to the encoder, which usually refers to the original sequence data or the output of the previous layer of encoder. x_{en}^{n} is the input of the $n+1$th layer of the encoder, and $x_{en}^{n+1,1}$ is the output of the first part of the $n+1$th layer of the encoder after performing the attention computation and using residual concatenation and normalization. The $x_{en}^{n+1,2}$ is the output of the $n+1$th layer of the encoder.

2) Decoder stage

In the decoder stage, the preprocessed sequence is first passed through a masked frequency domain attention module to ensure that the sequence prediction process only sees the output prior to that position, and then, in turn, it enters the frequency domain augmented attention module incorporated into the output of the decoder and the feed-forward fully-connected layer, and again residual concatenation and normalization is introduced at each layer, which is computed using the following formulas:

$$x_{de}^{n+1,1} = Norm\left(FEAttn\left(x_{de}^{n}\right) + x_{de}^{n}\right) \tag{10}$$

$$x_{de}^{n+1,2} = Norm\left(x_{de}^{n+1,1} + FEAttn_{mask}\left(x_{en}^{n+1,2}, x_{de}^{n+1,1}\right)\right) \tag{11}$$

$$x_{de}^{n+1,3} = Norm\left(FF\left(x_{de}^{n+1,2}\right) + x_{de}^{n+1,2}\right) \tag{12}$$

where n is the number of stacked layers in the decoder and $FEAttn_{mask}(\cdot)$ the frequency domain enhanced attention mechanism with masks. $x_{de}^{n+1,1}$, $x_{de}^{n+1,2}$, $x_{de}^{n+1,3}$ are the outputs of each module in the $n+1$th layer in the encoder in turn, and x_{de}^{n} is the input to the $n+1$th layer in the encoder.

In summary, the overall architecture of the frequency domain augmented Transformer model based on multiseasonality is shown in Fig. 3. In particular, for trend term time series, MLP and RevIN are combined to deal with complex trend changes; for seasonal series, the frequency domain enhancement-based Transformer model is used to process them, and a decoder is used to receive the frequency domain information conveyed by the encoder after extracting the frequency domain features and generating the predicted series of seasonal terms. Finally, the final time series prediction results are obtained by fusing the prediction outputs from the trend and seasonal components.

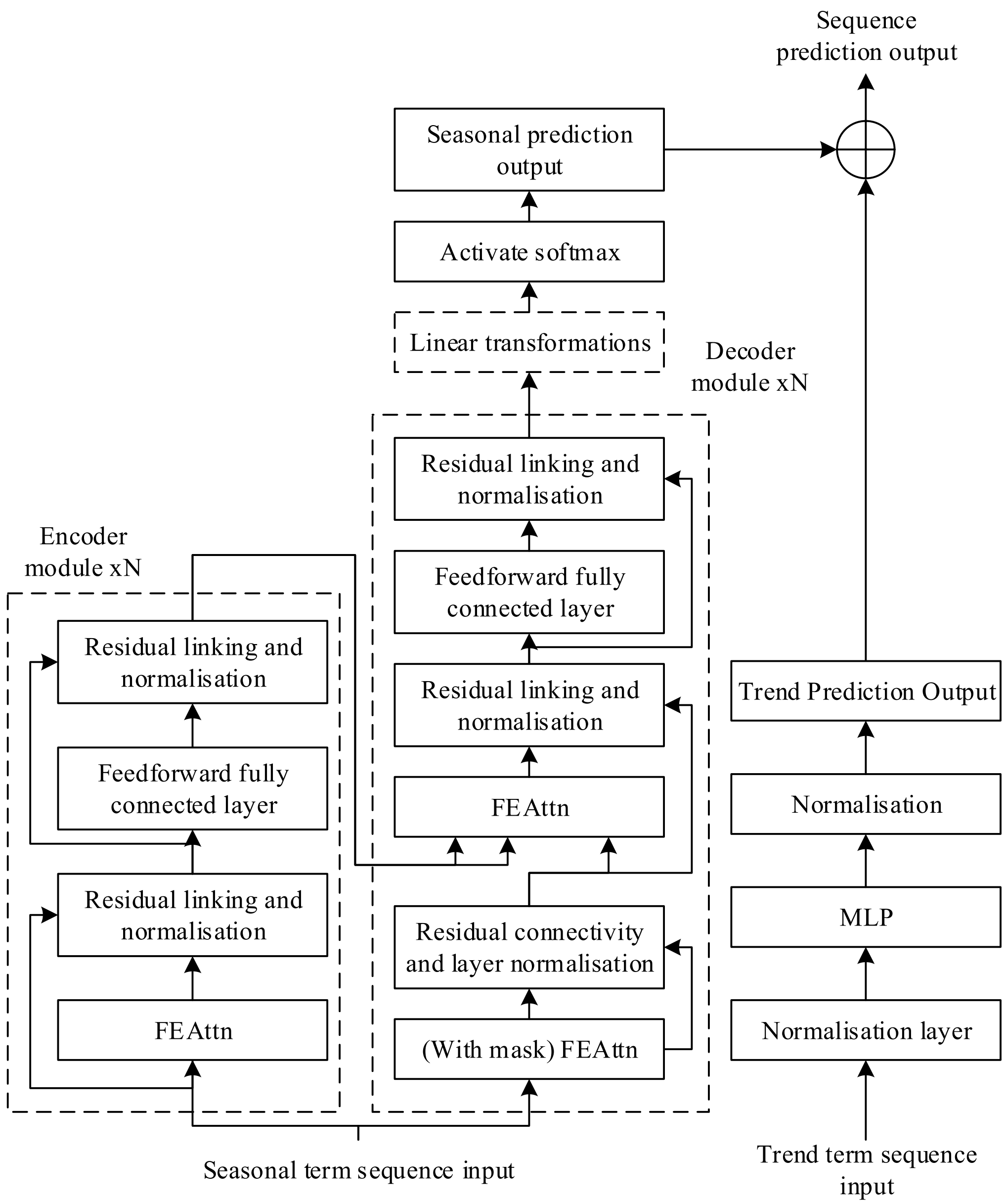


Figure 3: Multi-Seasonal Frequency Domain Enhancement Transformer Module

II. C.Construction of career trajectory portrait system

In order to fully express the three levels of career trajectories and effectively interface with the career position information model, the chained database table structure is used to construct the core database table design of career trajectories. Among them, the previous_career_trajectory_id field in the career trajectory table is used to record the ID of the previous career trajectory (occupational position information) that he or she has served as, and in this way, form a chain of occupational positions, i.e., career trajectory. After using this chained database table to store occupational position information, the statistics and analysis of big data and the visualization technology can be used to well realize the presentation of the micro, meso, and macro level portraits of the occupational trajectories.

III. Analysis of physical education teachers' professional development trajectories based on the PD-FEformer model

In this paper, an empirical analysis was conducted in City A as an experimental field, relying on the cloud teaching and research platform led by the city's education bureau, and a total of 12 online exchange and mutual evaluation activities were conducted.

First, the communication mutual evaluation and reflection data of 50 physical education teachers in the discussion forum were collected, obtaining 250 mutual evaluation seminar texts with a total of 38,584 characters. 65 reflection evaluation texts with a total of 29,753 characters were obtained, in which the ratio of male to female teachers was 7:3. Second, the mutual evaluation seminar text data were explored and analyzed, and 45% of the total teacher review messages were randomly selected for content-independent pre-coding. The consistency test using SPSS yielded a Kappa coefficient of 0.812, indicating that the two coding results were basically consistent, with good reliability, and could be continued to complete the remaining coding work. Finally, the coding results were imported into the Cognitive Network Online Tool to conduct cognitive network analysis by conversational modeling with the elements of professional competence of physical education teachers. The cognitive network connectivity coefficient values were calculated to understand the association between the current status of teacher training and the dimensions of professional competence. Independent samples t-test was used to quantitatively compare teachers' development in terms of time to obtain the trajectory of teachers' professional competence development.

III. A. Cognitive network analysis of professional competence

III. A. 1) Overall

This paper constructs a cognitive network structure model of physical education teachers' professional competence, which contains seven elements, including subject knowledge, technical knowledge, pedagogical knowledge, instructional design ability, instructional implementation ability, instructional evaluation ability, and instructional integration ability, coded as A1~A7 respectively.

The cognitive network connectivity coefficient values are shown in Table 1. It was found that the lowest covariance coefficients were found for A6-A7 (0.04) and A5-A7 (0.05), indicating that teachers' description of technology in the interactive integration of subject content and pedagogy was low, and that the teachers' ability to integrate and apply technology needs to be further strengthened and improved.The highest covariance coefficient was found between A3-A1 (0.46), followed by A2-A3 (0.42) and A3-A4 (0.41). This indicates that physical education teachers have a strong perception of pedagogical knowledge (A3), and are able to interactively connect A3 with other elements and flexibly apply it to actual teaching.

Table 1: Values of cognitive network connection coefficients

Co-occurrence category	Connection weight	Co-occurrence category	Connection weight	Co-occurrence category	Connection weight
A2-A3	0.42	A3-A1	0.46	A1-A5	0.14
A2-A1	0.29	A3-A6	0.13	A1-A4	0.38
A2-A6	0.11	A3-A5	0.25	A1-A7	0.11
A2-A5	0.15	A3-A4	0.41	A6-A5	0.08
A2-A4	0.32	A3-A7	0.09	A6-A4	0.09
A2-A7	0.11	A1-A6	0.12	A6-A7	0.04
A5-A4	0.07	A5-A7	0.05	A4-A7	0.11

III. A. 2) Phases

In order to explore the structural characteristics of PE teachers' professional competence at different stages, independent samples t-tests were used to quantitatively compare teachers' development in terms of time. The results of the t-test for differences in the structure of teachers' cognitive networks at each stage are shown in Table 2. There was a significant difference between the cognitive networks of less than one year of work and 1~5 years of work on the X dimension (p=0.000) and Y dimension (p=0.001). There is a more significant difference between working 1~5 years and working more than 5 years on the X dimension (p=0.003) and no significant difference on the Y dimension (p=0.382). There was a significant difference between working for more than 5 years and working for 1~5 years on the X and Y dimensions (p=0.000).The results of the t-test indicate that the stages of physical education teachers produce different levels of cognitive development, and there is a significant difference in the development of all dimensions of their professional competence.

Table 2: T-test for differences in cognitive network structure

Work stage	Dimension X					Dimension Y				
	Mean	SD	N	t	P	Mean	SD	N	t	P
Within 1 year	0.83	0.15	50	5.27	0.000	0.15	0.11	50	-2.83	0.001
1 to 5 years	0.59	0.21				0.26	0.09			
1 to 5 years	0.59	0.21	50	2.54	0.003	0.26	0.09	50	-1.28	0.382
More than 5years	0.47	0.16				0.31	0.07			
Within 1 year	0.83	0.15	50	8.93	0.000	0.15	0.11	50	-5.22	0.000
More than 5 years	0.47	0.16				0.31	0.07			

In order to compare the differences in the details of the elements of physical education teachers' training at each stage, the values of the teachers' cognitive network connectivity coefficients were calculated, and the results of the calculations are shown in Table 3. The data show that the maximum A2-A3 and A3-A1 coefficients are both 0.48 for less than one year of work. This is followed by A3-A4 (0.43) and A2-A1 (0.38). The coefficients of A3-A6, A1-A6, A2-A6, A6-A5, A6-A4, and A6-A7 increased from 0 in the middle period. The lowest cognitive network connectivity coefficients were found in the later stages A6-A7 (0.06), A5-A7 (0.06), A4-A7 (0.04), and A2-A7 (0.04), whereas the co-coincidence coefficients between the teaching evaluation skills (A6) and teaching implementation skills (A5) and elements of technological knowledge (A2) and subject matter knowledge (A1) increased.

Table 3: Values of cognitive network connection coefficients at different stages

Co-occurrence category	Within 1 year	1 to 5 years	More than 5 years	Co-occurrence category	Within 1 year	1 to 5 years	More than 5 years
A2-A3	0.48	0.30	0.36	A3-A1	0.48	0.42	0.39
A2-A1	0.38	0.25	0.31	A3-A6	0	0.15	0.11
A2-A6	0	0.11	0.15	A3-A5	0.16	0.21	0.25
A2-A5	0.11	0.15	0.19	A3-A4	0.43	0.38	0.39
A2-A4	0.27	0.30	0.33	A3-A7	0.16	0.18	0.11
A2-A7	0.13	0.09	0.04	A1-A6	0	0.11	0.13
A5-A4	0.09	0.14	0.21	A1-A5	0.11	0.18	0.21
A5-A7	0.03	0.06	0.06	A1-A4	0.24	0.29	0.31
A4-A7	0.07	0.11	0.04	A1-A7	0.12	0.15	0.09
A6-A5	0	0.03	0.05	A6-A7	0	0.05	0.06
A6-A4	0	0.07	0.09				

The study showed that physical education teachers transitioned from learning theoretical aspects such as subject knowledge and pedagogical knowledge in the early stages of their work to applying technology in the middle stages of their work for teaching evaluation and implementation of classroom activities. Teachers' ability to evaluate and implement teaching was developed and the associations with other elements continued to strengthen in the later stages. This also confirms the cognitive network structure characterizing physical education teachers at each stage. In contrast, the association between teachers' instructional integration ability (A7) and other elements was relatively low in the later stages, and the physical education teachers' instructional integration ability in the later stages still needs to be improved.

III. B. Analysis of PD-FEformer model validity

To strengthen the dynamic characterization capability of the trajectory portrait, the timestamp information of the online mutual assessment data is embedded into the multiseasonality processing module of the PD-FEformer model. Time-series features of teachers' interaction behaviors such as weekly participation frequency and response delay of mutual evaluation are inputted into the MLP component as trend items, while periodic signals such as terminology density and course design keyword frequency in the text of mutual evaluation are parsed through the Frequency Domain Enhancement Transformer component, which is used to form a multiseasonal feature fusion with the time-series features of the original recruitment information analysis module of the system, such as fluctuation of job demand and the cycle of the outputs of teaching and research results. Multi-scale feature fusion. In this section, we systematically test the predictive stability and anomaly detection capability of the PD-FEformer model in educational time-series data by constructing model robustness validation experiments under multi-scale perturbation environments.

III. B. 1) Stability

The experiments use five different publicly available datasets such as PSM, SWaT, DSADS, GECCO, and SWAN to evaluate the model performance. In the training phase, 32 samples are processed in each batch. For parameter optimization, the Adam optimization algorithm with a learning rate of 0.0001 is used Sequence length L is set to 50. In the classification training phase, binary cross-entropy is used as the loss function and F1 scores are recorded in each round of training, and the trend of the F1 scores in each iteration is shown in Fig. 4. To prevent overfitting, an early stopping strategy is introduced to monitor the training efficiency and effectiveness of the model. As can be seen in Fig. 4, the F1 scores all stabilize at 350 iterations in the five datasets and eventually reach more than 0.6, proving the stability of the PD-FEformer model.

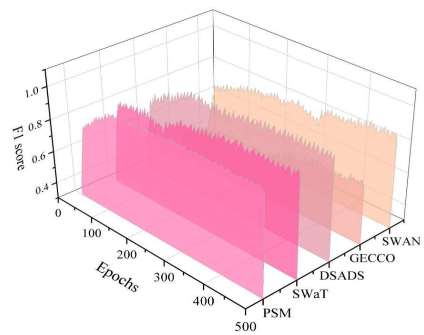
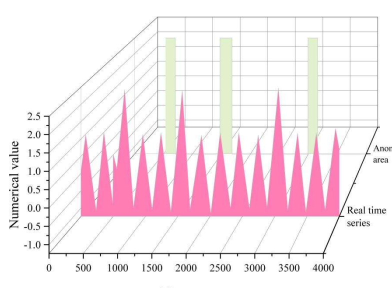


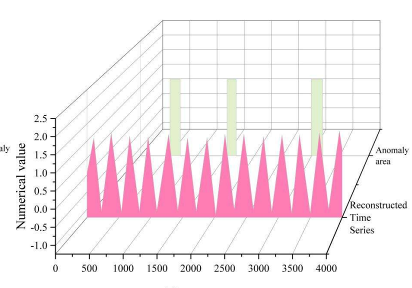
Figure 4: Trends in F1 scores

III. B. 2) Abnormality detection capability

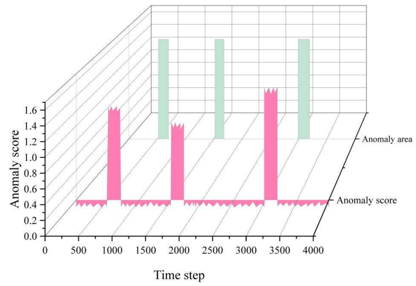
By learning the normal distribution and pattern of the samples, Transformer is able to effectively reconstruct anomalous data segments. Since anomalous data usually deviates from the normal distribution, significant differences between the reconstruction results and the original data can occur. The PD-FEformer model is used to generate univariate time series containing anomalous data segments, and the method helps to visualize the effectiveness of the time-series reconstruction network and the anomaly detection mechanism. The results of the original sequence, reconstructed sequence and anomaly score visualization are shown in Fig. 5(a~c). Comparing Fig. 5(a) and (b), it can be observed that the anomaly region in the original sequence is significantly deviated from the corresponding region of the reconstructed sequence. Figure 5 (c) demonstrates the degree of deviation between the original sequence and the reconstructed sequence, and quantifies the degree of deviation as the anomaly score. The results show that the anomaly scores of the anomalous data segments are significantly higher than those of the normal data segments, which verifies that the PD-FEformer model is able to learn the distributional features and patterns of the normal sample data and effectively predict the performance of the anomalous data in normal scenarios at the reconstruction stage. The experiments show that the PD-FEformer model is able to quantify the recognition sensitivity of key events such as delayed policy response and sudden change in professional competence in educational scenarios.



(a) Original sequence



(b) Reconstructed sequence



(c) Abnormality score

Figure 5: Original sequence, reconstructed sequence and abnormality score

III. C. Analysis of barriers to professional capacity development

The previous section reveals the stage differences in teachers' professional competence and the weakness of technology integration ability through cognitive network analysis, and verifies the effectiveness of the PD-FEformer model in capturing temporal features and abnormal events. This section combines the multi-scale predictive ability of the PD-FEformer model with the results of cognitive network analysis to reveal persistent barriers to teachers' professional development by correlating the heterogeneous characteristics of behavioral indicators such as public class participation and research output with professional development expectations.

III. C. 1) Professional competence

(1) Participation in open classes

The statistics of physical education teachers' participation in open classes are shown in Figure 6, which shows that only 8% of teachers have participated in city-level open classes, 14% have participated in district-level open classes, 60% have participated in school-level open classes, and the remaining 18% have not participated in open classes. It can be seen that physical education teachers in City A did not show strong motivation and initiative to participate in open classes.

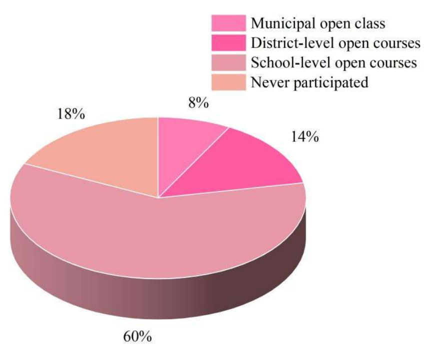


Figure 6: Statistical results of attending open classes

(2) Thesis awards in the last three years

The statistics of physical education teachers' thesis awards in the past three years are shown in Figure 7. It can be seen that 18% of the teachers won in 1 paper, 26% of the teachers won 1-3 papers, 18% of the teachers won 3-6 papers, 12% of the teachers won more than 7 papers, and the number of teachers who did not win any awards accounted for 26%. It shows that physical education teachers in City A do not have high initiative and ability to study research. Through the survey found that many teachers' awards are the school to pass the documents of the education department, are mandatory requirements, with the change of the times, in the society of such a large amount of information, the lack of knowledge, the education concept of obsolete, will be abandoned by this society. Physical education teachers should be fully mobilized to learn, work enthusiasm and enthusiasm, to stimulate their potential motivation, to play their existing knowledge and experience in an effort to improve the training system to promote the professional development of teachers themselves.

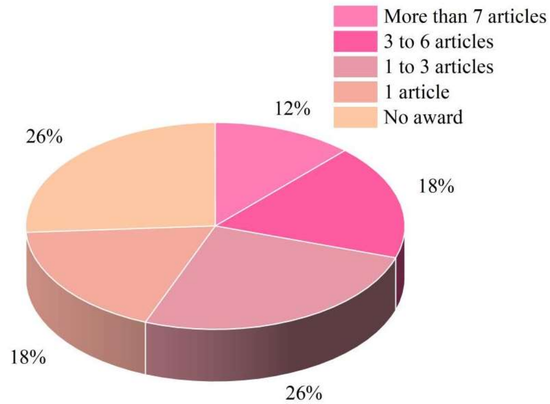


Figure 7: Statistical results of paper awards in the past three years

III. C. 2) Development expectations

The statistical results of physical education teachers' development expectations are shown in Figure 8. Only 12% of physical education teachers want to get further training in their academic qualifications, and 26% of physical education teachers want to become subject leaders, which shows that only a minority of physical education teachers have plans and ideas for their future development. There are 14% of physical education teachers hope that the teaching results can be assessed as excellent, 12% of physical education teachers hope to get further training in business, and as high as 36% of teachers have no idea at all and have given up on their professional development.

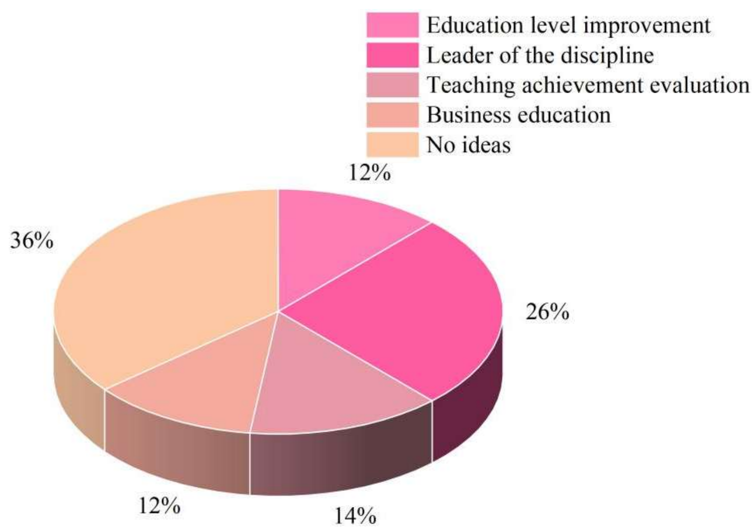


Figure 8: Statistical results of development expectations

IV. Conclusion

In this paper, we constructed a career trajectory portrait system based on the PD-FEformer model to systematically analyze the dynamic characteristics and internal laws of the professional development of physical education teachers.

Cognitive network analysis showed that the covariance coefficients of physical education teachers A6-A7 (0.04) and A5-A7 (0.05) were the lowest, and the covariance coefficient between A3-A1 was the highest (0.46), followed by A2-A3 (0.42) and A3-A4 (0.41). The stages of physical education teachers produce different levels of cognitive development and significant differences in the development of all dimensions of professional competence. The transition from learning theoretical aspects such as subject knowledge and pedagogical knowledge in the early stages of the work period to applying technology in the middle stages for teaching evaluation and implementation of classroom teaching activities. Teachers' competencies in teaching evaluation and implementation of teaching were developed, and the associations with other elements continued to strengthen in the later stages.

Experiments demonstrated that the PD-FEformer model had better predictive stability and anomaly detection in educational time-series data, identifying shortcomings in the development of physical education teachers' professional competence. The percentage of physical education teachers who had not participated in open classes was 18%, the percentage of teachers who had not won any prizes for their papers in the last three years was 26%, and as many as 36% of teachers had no idea about professional development at all.

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