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Research article

Neural network dynamics for modeling competency development trajectories in complex social-educational systems

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Abstract: The dynamics of Artificial Neural Networks (ANNs) have emerged as a cornerstone of computational intelligence, providing transformative insights into learning behaviors, stability properties, and predictive modeling in complex systems. In this study, we proposed a dynamic neural network framework designed to model and forecast competency development trajectories in socio-educational environments, situated within the "New liberal arts" paradigm. By synthesizing multi-source behavioral data into longitudinal competency profiles, we characterize evolving collaboration networks through dynamic centrality indicators. Unsupervised learning techniques, specifically DBSCAN and K-means clustering, were implemented to identify and categorize divergent developmental pathways. To encapsulate these temporal fluctuations, a Long Short-Term Memory (LSTM) recurrent neural network was developed, with a rigorous focus on convergence behavior, trajectory forecasting stability, and cross-domain generalization. The results demonstrated robust performance, evidenced by Mean Absolute Errors (MAE) ranging from 0.203 to 0.247 and high correlation coefficients (0.85–0.87), thereby validating the efficacy of ANN dynamics in modeling evolving human competencies. Beyond the educational domain, this framework underscores the broader utility of neural network dynamics for analyzing complex, human-centered systems, furthering the interdisciplinary expansion of ANN applications.

Keywords: neural network dynamics; LSTM; temporal modeling; convergence; competency development; complex systems
Mathematics Subject Classification: 37N40, 62H30, 62M10, 68T07, 91D30, 97P80

1. Introduction

The “New liberal arts” is an emerging educational paradigm that integrates the humanities with digital technology, interdisciplinary sciences, and social practices. Its core characteristics, interdisciplinarity, technological embeddedness, and social responsiveness, are reshaping knowledge production and the cultivation of innovative talent [1,2]. Within this paradigm, the connotation of university teachers’ core competencies has expanded beyond traditional teaching ability to encompass intelligent tool usage, cross-domain collaboration, data-driven thinking, and academic innovation [3]. As pivotal nodes in the new liberal arts ecosystem, teachers’ competency structures directly affect the effectiveness of interdisciplinary learning and the quality of talent cultivation [4–6]. These four competency dimensions are not empirical inductions, but directly stem from the three core elements of new liberal arts Education: Teaching innovation corresponds to “technology embedding”, reflecting teachers' ability to reconstruct curriculum integration with digital tools; academic resilience reflects the continuous inquiry requirements of “interdisciplinary science”, emphasizing the stability rather than peak values of research output; cross-disciplinary collaboration originates from “social responsiveness” and the need for knowledge integration, measuring the breadth of practice in breaking down disciplinary barriers; and digital adaptability permeates all three characteristics, characterizing the ability to quickly adapt to intelligent environments. This mapping relationship ensures the paradigmatic consistency of the competency model. “New liberal arts” originates from the digital and interdisciplinary reconstruction of traditional general education, emphasizing the cultivation of well-rounded talents with critical thinking, digital literacy, and collaborative innovation capabilities driven by technology embedding, social responsiveness, and knowledge integration. This paradigm requires teachers to transform from single knowledge transmitters to multidimensional competency facilitators, thereby directly shaping the theoretical basis for the four competency dimensions of teaching innovation, academic resilience, interdisciplinary collaboration, and digital adaptability in this study. Constructing a computational and dynamic analysis framework based on behavioral data is thus essential for uncovering the laws of competency development, informing precise teacher development policies, and supporting adaptive higher-education systems [7,8].

Despite the growing importance of competency modeling, research faces deep methodological challenges in dynamic representation and predictive accuracy. First, most competency indicators rely on static assessments or aggregate statistics, making it challenging to capture the nonlinear temporal trajectories of teaching, research, and collaboration in real educational contexts [9,10]. Second, cross-domain activities such as teaching input, research output, and collaborative participation are often analyzed independently, lacking time alignment and correlation modeling, which obscures their synergistic effects [11]. Moreover, the temporal features of behavioral data are underexplored: analyses typically remain at cross-sectional comparisons or average trend judgments, failing to address stage transitions and dynamic mutations in competency trajectories [12]. Social network analysis is also limited, as academic collaboration is usually modelled within fixed time windows, thereby neglecting the rhythm and structural fluidity of knowledge exchange and restricting dynamic insights into the role of social capital [13,14]. Traditional clustering emphasizes spatial distribution while ignoring trajectory morphology, leading to weak temporal consistency in developmental pattern recognition [15]. Finally, predictive models are often restricted to historical averages or cumulative values, without incorporating dynamic indicators of coupling, such as fluctuations in research–teaching correlations, resulting in insufficient sensitivity to turning points [16]. The applicability of artificial neural network dynamics to modeling human competence development stems from their inherent ability to model nonlinear, time-varying, and state-dependent processes. Just as synaptic plasticity drives biological learning, Artificial Neural Networks (ANNs) simulate the reconstruction of cognitive structures through weight evolution; their convergence behavior can be analogized to the developmental stage where individual competence tends to stabilize, while trajectory sensitivity maps the perturbation effect of external intervention or collaboration on the growth path. This dynamical-system perspective provides a solid analogical basis for transforming educational behavior into a computable evolutionary process. These limitations hinder the transition from "describing the current state" to "deducing future evolution", restricting the development of intelligent teacher support systems.

The development of intelligent teacher support systems faces significant methodological constraints. To address these challenges, we propose a dynamic neural network–based analytical framework to model and forecast the trajectories of university faculty's core competencies within the "New liberal arts" context. Specifically, comprehensive teacher profiles are synthesized from heterogeneous log data across teaching, research, and collaboration platforms, which are subsequently operationalized into computable competency indicators. A temporal collaboration network is constructed to extract dynamic centrality change rates, elucidating how social interaction dynamics influence competency growth. By applying a hybrid clustering approach (DBSCAN and K-means), we jointly analyze competency and network features to uncover representative developmental archetypes. Crucially, a Long Short-Term Memory (LSTM) recurrent neural network is utilized to capture temporal evolution, with an explicit emphasis on its dynamic learning behavior, convergence properties, and predictive stability.

This closed-loop framework, integrating behavior modeling, network dynamics, and neural network forecasting, offers three major methodological innovations: (1) The establishment of a "behavior–network–trend" trinity model that effectively fuses multi-source heterogeneous data; (2) the introduction of dynamic social-network indicators as external variables to enhance explanatory depth; and (3) the construction of a scalable prediction interface that facilitates individual-level simulations and macro-level policy design. In doing so, we contribute to the methodological foundations of competency development while aligning with broader advancements in neural network dynamics and complex system modeling. Beyond the educational sphere, the framework underscores the interdisciplinary potential of ANN-based temporal modeling in human-centered systems, offering insights for extending neural dynamics research to domains such as organizational development, healthcare, and socio-economic systems.

2. Related work

The professional development of teachers is increasingly intertwined with technological acceptance and trust. Nazaretsky et al. [17] identified "trust in AI" as a critical determinant for technology adoption, suggesting that professional development must explicitly address teachers' confidence in algorithmic decision-making. In parallel, research has moved toward quantifying behavioral patterns through granular log data. Su et al. [18] utilized Learning Management System (LMS) data to map university teachers' engagement, revealing that behavioral intentions are heavily moderated by performance expectancy. To handle the complexity of such behavioral data, scholars have adopted deep learning architectures. Xuan [19] proposed a Deep Residual Network combined with Long Short-Term Memory (DRN-LSTM) units to improve behavior recognition accuracy.

Moving beyond static snapshots, Harder et al. [20] applied intraindividual temporal network analysis to identify complex regulatory loops in learning resource interactions. The utility of these machine learning techniques extends to broader complex systems; Almetwally et al. [21] illustrated the robustness of ML in predicting physiological outcomes, validating the transferability of these algorithms, while Han et al. [22] leveraged ANNs to model nonlinear interactions between educational resources and achievement, uncovering patterns invisible to linear regression.

The broader landscape of AI in education continues to expand. Chen et al. [23] discussed the era of AI and its challenges for enhancing skills in an international context. Comprehensive reviews by Gavhane and Pagare [24] highlighted AI's emphasis on assessment and adversity quotient, while Mercado-Rojas et al. [25] demonstrated frameworks for integrating AI into citizen science projects. Panchal et al. [26] provided an overview of the opportunities and challenges of machine learning in education, emphasizing the intersection with embedded systems. Theoretically, the field is also evolving. Graesser et al. [27] argued that educational psychology is shifting to accommodate technology and interdisciplinary skills, and Miniankou and Puptsau [28] demonstrated that AI acts not merely as a tool but as a partner in the human-machine educational process.

Despite these advancements, a unified framework for forecasting teacher competency trajectories remains elusive. Most existing models treat teaching, research, and collaboration as isolated domains, neglecting the synergistic coupling—or “cross-domain dynamics”—that characterizes the “New liberal arts” paradigm. Consequently, there is a pressing need for dynamic neural network models capable of synthesizing multi-source behavioral data to deduce future evolutionary paths of professional competence.

3. Dynamic modeling and trend deduction of teachers' core competencies

Figure 1 illustrates the three-layer technical system for digital analysis of core competencies for university teachers in the context of the new liberal arts. The data flow follows a one-way path: Data layer → modeling layer → prediction layer. After cleansing, behavioral logs are fed into the profiling engine to generate competency vectors, which are then used to construct a temporal collaboration network to extract centrality features. These two layers are then integrated into the clustering module to identify development patterns, which serve as historical inputs and covariates for the LSTM model, outputting trend predictions. The data layer integrates multi-source behavioral logs and constructs a temporal behavior matrix through cleansing and semantic mapping. The modeling layer comprises three modules: The teacher profiling engine, the temporal collaboration network, and multimodal feature fusion, enabling competency quantification, network feature extraction, and development pattern clustering. The prediction layer uses an LSTM model with dynamic covariates and an attention mechanism to predict future competency development trends. The system forms a closed loop from multi-source data collection to development prediction, providing precise support for teacher professional development.

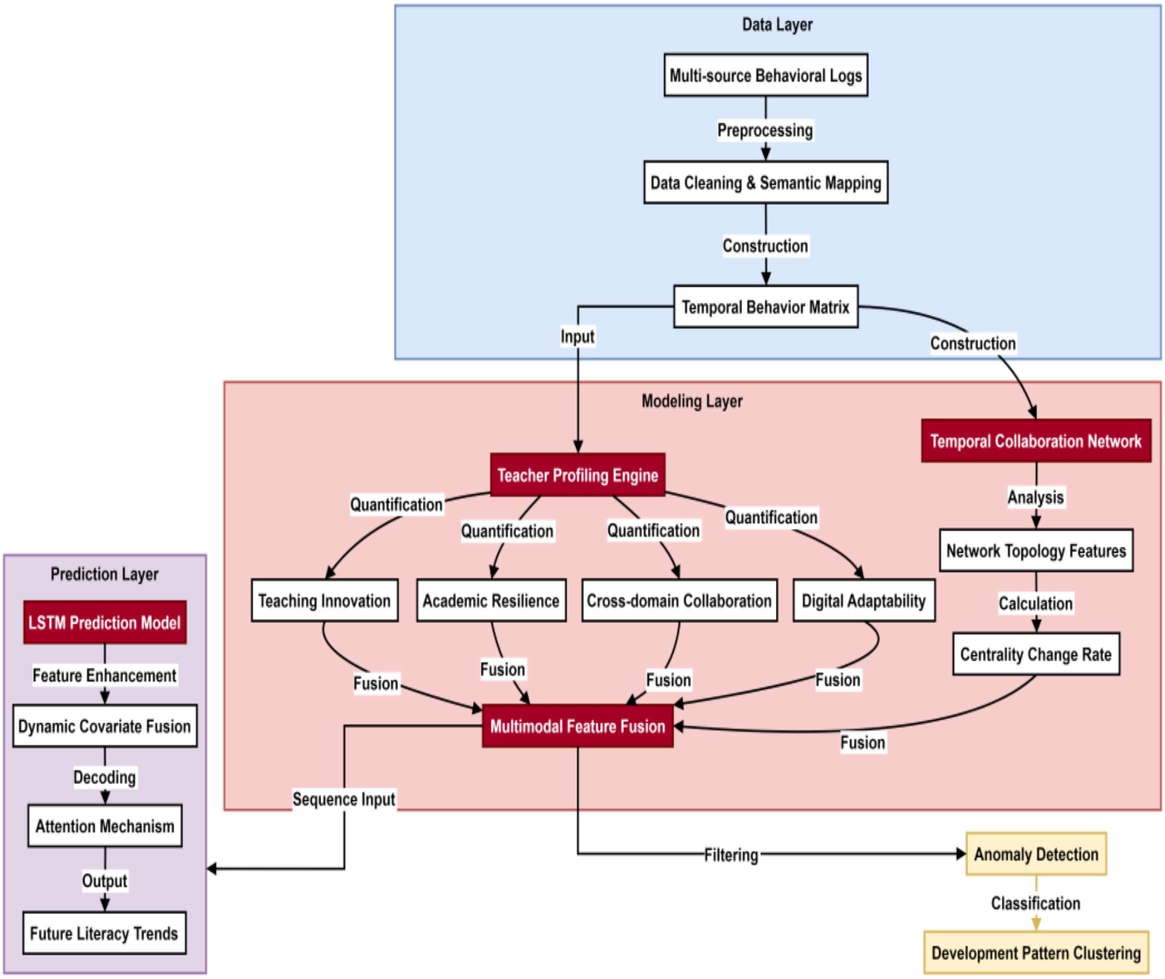

Figure 1. Technical architecture for digital analysis of core competencies of university teachers.

3.1. Construction and quantitative representation of multidimensional teacher portraits

3.1.1. Collection and structural processing of multi-source behavior logs

To objectively quantify teachers' core competencies, we first collected multi-source behavioral logs from university academic administration systems, research management platforms, and internal collaboration tools (e.g., OA systems, online conferencing platforms, and project management software). Data collection covered multiple business processes, including teaching arrangements, course development, research project applications, paper submission, and team collaboration and communication. The data spanned three consecutive years and was recorded at a daily granularity. The raw logs included fields such as behavior type, operation timestamp, associated object (e.g., course number and project ID), participant role (person in charge, participant), interaction frequency, and duration. A unified data cleansing and semantic mapping strategy was employed to address the heterogeneous data formats across different systems. By establishing a behavior coding dictionary, non-standardized operation descriptions (such as "uploading courseware", "revising a paper", and "initiating a meeting") were grouped into predefined behavior categories to ensure cross-platform comparability and consistency. Based on the Ministry of Education's "Guidelines for University

Teacher Workload Accounting" and the log structure of internal business systems, the behavior coding dictionary was revised through three rounds of expert Delphi methodology to define standardized behavior labels for teaching, research, and collaboration, ensuring semantic consistency across platforms.

On this basis, behavioral events were time-aligned and periodized, with quarters being the basic time unit for aggregating behavioral frequency and intensity indicators. Choosing a quarter as the analytical granularity balances the natural cycle of university teaching and research activities (such as semester systems and project application schedules) with data stability, avoiding monthly noise or annual lag. For teaching-related behaviors, indicators such as the number of courses taught per semester, the number of teaching resource updates, and the delay in online interactive responses were extracted. The research dimension focused on variables reflecting sustained input and output efficiency, such as the frequency of project applications, the paper submission cycle, and the interval between research outputs. Collaborative behaviors were quantified through participation in cross-departmental projects, the number of joint lectures, and the density of message interactions within collaborative tools. All indicators were normalized using the Z-score to eliminate dimensional differences, forming a structured temporal behavior matrix, which provided the data foundation for the subsequent mapping of literacy dimensions.

3.1.2. Quantitative mapping of literacy dimensions and generation of portrait vectors

Based on structured behavioral data and in accordance with the theoretical framework of core teacher competencies in the context of the new liberal arts, four operational competency dimensions were set: Teaching innovation, academic resilience, cross-domain collaboration, and digital adaptability, and corresponding quantitative mapping rules were constructed. The teaching innovation score was a weighted synthesis of indicators such as the frequency of course reconstruction, the diversity of digital teaching tools used, and the speed of iterative student feedback responses, reflecting the teacher's ability to proactively adapt teaching design. Academic resilience was measured by the continuity and resistance to volatility of scientific research activities, represented by the inverse of the standard deviation of the interval between paper publications, namely:

$$R_a=\frac{1}{\sigma(T_{\text{gap}})+\varepsilon}. \tag{1}$$

Among them, R_a represents the academic resilience score, T_{gap} is the time interval series between two consecutive paper submissions, is σ its standard deviation, and ε is a smoothing constant to avoid division by zero. Unlike static indicators, such as cumulative output, h-index, or moving average, the reciprocal of the standard deviation focused on the stability of the research rhythm rather than the total amount. It could effectively distinguish "continuously stable" and "burst-intermittent" behavioral patterns. This sensitivity to the time distribution pattern was more in line with the essence of "resilience" that emphasized resistance to disturbances and continuous investment. This design aimed to capture the stable output capacity of teachers in scientific research output rather than simply the accumulation of quantity. The inverse of the standard deviation was used instead of the h-index or the cumulative number to capture the stability of scientific research output rather than total output, thereby avoiding those with high output but sharp fluctuations from being misjudged as "high resilience". This indicator was better suited to identify a continuous investment development model, and its distinction from traditional indicators was defined in the article. The cross-domain collaboration score was composed of the proportion of teachers participating in interdisciplinary projects, the number of co-authored papers, and the proportion of heterogeneous connections in the collaborative network, reflecting the breadth of interaction that breaks down disciplinary barriers. Digital adaptability comprehensively evaluated teachers' speed of adaptation and integration into the technological environment by considering the frequency of use of various intelligent platforms, the time lag in adopting new functions, and the efficiency of multi-system switching.

The scores for each dimension were weighted using the entropy method to avoid subjective bias. Using this method, we calculated the degree of variation for each indicator based on its information entropy. Lower entropy values indicated greater variation within the group and provided more information, thus assigning a higher weight. Finally, the scores from the four dimensions were weighted and combined to generate a quarterly-updated teacher literacy profile vector, which served as the basic unit for subsequent dynamic analysis. This profile vector not only reflected the multidimensionality of individual literacy structures but also provided a traceable quantitative foundation for temporal-evolution modeling.

3.2. Topological feature extraction of teacher interaction network

3.2.1. Construction of a temporal collaboration network and definition of dynamic edge relationships

To accurately depict the evolution of teachers' social interactions in academic and teaching collaboration, we extracted three types of related events with clear cooperation intentions based on structured behavior logs: Joint application for cross-departmental scientific research projects, multiple teachers jointly undertaking course teaching tasks, and publishing academic papers in the form of co-authorship. After entity disambiguation and role identification, the above events were converted into cooperative edge relationships between individual teachers. In order to reflect the temporal and dynamic nature of the interaction, a sliding time-window strategy was used to construct a series of snapshot networks, with each window spanning one quarter to ensure that the network structure was continuously updated over time. In each time window, if two teachers appeared in the same collaborative event, an undirected edge was created between them, with weight proportional to the frequency and duration of their collaboration. The formula is as follows:

$$w_{ij}^{(t)}=\alpha\cdot f_{ij}^{(t)}+\beta\cdot d_{ij}^{(t)}. \tag{2}$$

Here, $w_{ij}^{(t)}$ represents the intensity of collaboration between teacher i and teacher j in the time window, $f_{ij}^{(t)}$ is the frequency of collaborative events in which both teachers participated during that period, $d_{ij}^{(t)}$ is the average duration of all collaborative projects (in months), and α and β are the normalized adjustment coefficient. This was determined using the least-squares method via linear regression of historical collaboration data, with actual collaboration outcomes as the dependent variable, and frequency and duration as the independent variables. The optimal weighted combination was found. This process was implemented using the Python scikit-learn library to balance the contributions of frequency and depth. This weighting mechanism effectively distinguished brief, episodic engagement and sustained, deep collaboration, thereby improving the network representation's realistic fit. Ultimately, a series of weighted undirected graphs was generated, forming a temporal sequence of the teacher collaboration network and providing a dynamic structural foundation for subsequent topological feature extraction.

3.2.2. Time series extraction and change rate modeling of centrality indicators

In each collaborative network snapshot, the degree centrality and closeness centrality of each teacher were calculated to quantify their positional advantages and information accessibility in the organizational collaborative structure. Degree centrality measured the number of collaborators directly connected to an individual and the breadth of their interactions. It was calculated by normalizing the sum of the weighted adjacent edges of the node:

$$C_D(i,t)=\frac{1}{N\text{-}1}\sum_{j\in \mathrm{N}(i)} w_{ij}^{(t)}, \tag{3}$$

where $C_D(i,t)$ represents teacher i's degree centrality in the network at period t, $N(i)$ is its neighbor set, and N is the total number of nodes in the network. Closeness centrality measured the sum of the inverse distances of the shortest weighted paths from an individual to all other teachers, expressing their potential as intermediaries in knowledge flow. for the calculation, we used the Dijkstra algorithm to solve the weighted shortest path matrix, and the output was normalized according to the standard formula. These two metrics were calculated independently within each time window to form a dual series for each teacher.

To further capture the evolving trends in interactive capabilities, a linear slope was fit to each series to extract its direction and rate of change. The slope value served as an indicator of the dynamic trend in the teacher's interactive activity or the diffusion of influence during the observation period. A positive slope indicated continued strengthening of their collaborative status, while a negative slope suggested a risk of marginalization. This rate of change served as an important input variable in subsequent clustering and prediction models, enabling the transformation from static network position to dynamic social capital evolution and enhancing the ability to analyze the structural drivers of teacher development paths.

Figure 2, using grouped bar charts, illustrates the specific scores of four types of teachers across competency dimensions. Research-oriented teachers (blue bars) excelled in academic resilience (0.9), reaching the advanced level, but were relatively weak in cross-domain collaboration (0.5), remaining at the basic level. Balanced teaching teachers (red bars) achieved a high score of 0.9 in teaching innovation, demonstrating relatively balanced development across all dimensions. Collaboration-driven teachers (green bars) excelled in cross-domain collaboration (0.9), but were relatively weak in digital adaptability (0.6). Digital pioneer teachers (orange bars) excelled in digital adaptability (0.9), but were relatively weak in academic resilience (0.6). Reference lines for competency levels (basic: 0.3, proficient: 0.6, advanced: 0.8) were included in the chart to facilitate intuitive assessment of competency levels in each dimension.

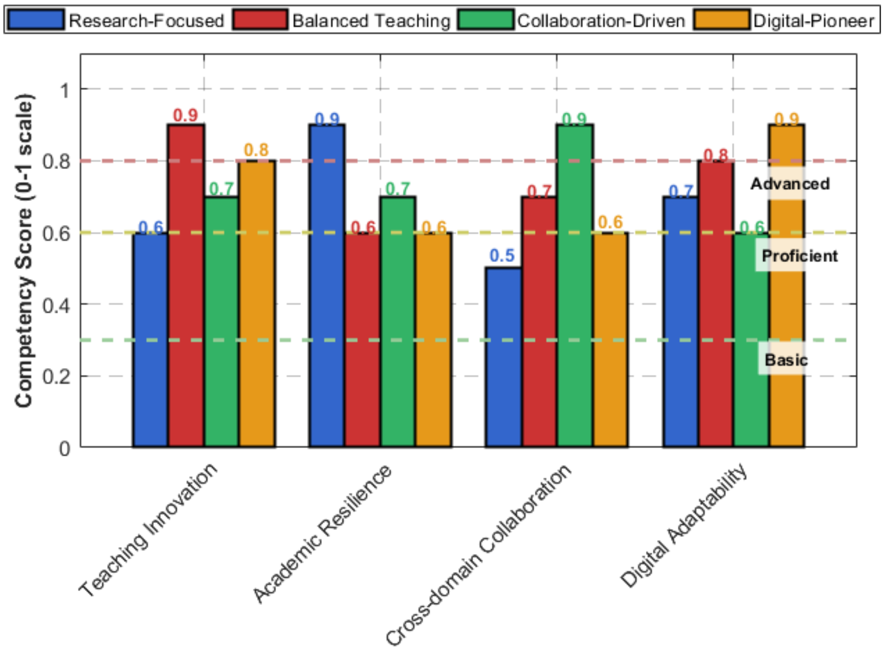

Figure 2. Multidimensional competence profile by teacher type.

3.3. Cluster identification of literacy development models

3.3.1. Construction of multidimensional feature matrix and abnormal pattern separation

To reveal the structural differences in teachers' core literacy development, we integrated the quantitative indicators generated in the previous stage and constructed individual-level analysis units. The literacy development status of each teacher at the end of the observation period was composed of four core dimensions: Teaching innovation score, academic resilience level, time-series mean of degree centrality, and slope of change in proximity centrality. These four variables together formed a four-dimensional feature vector that captured the dual attributes of ability performance and social interaction, reflecting the comprehensive positioning of teachers in knowledge production and organizational collaboration. All original features were normalized using Z-scores to eliminate dimensionality effects and ensure comparability of spatial distributions across dimensions. The transformation form is:

$$x'_{ij}=\frac{x_{ij}-\mu_j}{\sigma_j}. \tag{4}$$

Here, x_{ij} represents the original value of the i-th teacher on the j-th feature, and μ_j and σ_j are the mean and standard deviation of the feature in the sample, respectively x'_{ij}. The standardized data constitutes the feature matrix, which serves as the input basis for cluster analysis.

In this high-dimensional space, the developmental trajectories of individual teachers exhibit a non-uniform distribution, with some individuals deviating from the mainstream group due to extreme behavioral patterns or unique evolutionary paths. To identify these anomalous developmental patterns and prevent them from disrupting the overall clustering structure, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm was used to detect outlier patterns. Based on the principle of density connectivity, this method divided the space into a core region, boundary points, and noise points by setting a neighborhood radius and a minimum point count threshold. Individuals who were not reachable by any core point were classified as noise, corresponding to atypical developmental patterns, such as those with long-term low collaboration and high productivity or those who were intensive in teaching but stagnant in research. These individuals, labeled outliers, were removed from the main clustering process, while the main group remained and entered the next stage of structured classification, thus ensuring the representativeness and stability of the clustering results for the mainstream developmental path.

3.3.2. Subject group classification and pattern label generation

After eliminating abnormal development patterns, the K-means clustering algorithm was used to classify the remaining teachers' development patterns. This method achieves a compact partitioning of samples in the feature space by minimizing the within-cluster sum of squares (WCSS). The objective function is defined as:

$$\min \sum_{k=1}^{K} \sum_{\mathbf{x}_i \in C_k} \| \mathbf{x}_i - \boldsymbol{\mu}_k \|^2. \tag{5}$$

Here, C_k represents the kth cluster, $\mathbf{x}_i$ is the standardized eigenvector of the i-th teacher, $\boldsymbol{\mu}_k$ is the cluster center vector, and K is the preset number of clusters. The initial selection of the K value was based on theoretical assumptions: New liberal arts education emphasizes the balance among four dimensions of capabilities, teaching, research, collaboration, and technology, and anticipates the existence of corresponding dominant types. The optimal number of clusters, K = 4, was determined by combining the elbow rule and the silhouette coefficient to ensure clear inter-class distinction and strong intra-class cohesion. After the algorithm's iterative convergence, each teacher was assigned to a development type, forming several internally consistent group structures. K-means clustering uses the k-means++ initialization strategy to select initial cluster centers to reduce the impact of random initialization on the stability of the results. This setting uses the scikit-learn default parameters, as stated in the paper, to improve the standardization and reproducibility of the algorithm.

Based on the coordinate distribution of each cluster center in the four-dimensional feature space and the dimension contribution weights, the pattern interpretation was conducted. One cluster significantly outperformed the others in academic resilience and degree centrality, but experienced slow growth in teaching innovation, thus being defined as “research-led”. Another cluster showed stable scores in teaching and research, with a moderate rate of change in proximity centrality, indicating a balanced development trend and thus being classified as “teaching-balanced”. The third cluster excelled in indicators related to cross-domain collaboration, with a significantly steeper slope in proximity centrality, reflecting strong social embeddedness and being defined as “collaboration-driven”. The fourth cluster exhibited low to medium levels across all indicators, lacked development momentum, and was labeled “potentially sluggish”. These pattern labels not only reflected the structural differences between groups but also provided a classification basis for subsequent prediction of differentiated trends and the design of intervention strategies. The clustering process achieved a semantic mapping from continuous behavioral data to discrete development paths, enhancing the ability to analyze the diverse mechanisms of teacher growth.

Table 1 summarizes the parameter settings and evaluation metrics for DBSCAN anomaly detection and K-means clustering. DBSCAN, using Epsilon = 0.35 and Minimum Points = 5, identified 12.3% of teachers with atypical development patterns, effectively separating noise samples. The Epsilon value was determined using the k-distance curve method. The inflexion point value of the fifth-nearest-neighbor distance was selected, and a grid search over 0.3–0.4 confirmed the highest clustering stability. The clustering results were comprehensively evaluated using the silhouette coefficient (0.61), the intra-class sum of squares (2.87), and the inter-class separation (1.94), indicating that the identified teacher development patterns exhibited good internal consistency and external distinguishability. These indicators collaboratively validated the rationale of the clustering scheme, providing a reliable basis for categorization for subsequent prediction of differentiated trends and enhancing the ability to analyze the heterogeneity of core competency development among university teachers.

Table 1. DBSCAN and K-means clustering parameter settings and evaluation indicators.

Parameter/Indicator	Value / Setting	Description
DBSCAN Epsilon	0.35	Radius defining the neighborhood for density connectivity
Minimum Points	5	Minimum number of points required to form a dense region
Noise Point Ratio	12.30%	Proportion of teachers identified as outliers
Silhouette Coefficient	0.61	Measure of clustering compactness and separation
WCSS	2.87	Total dispersion within clusters
Inter-Cluster Separation	1.94	Degree of differentiation between development patterns

3.4. Training of a time series prediction model for development trajectory

3.4.1. Sliding window-based literacy sequence modeling and LSTM network structure design

To dynamically predict the development trajectory of teachers' core competencies, constructed a time-series prediction model with a quarterly time step. The input data consisted of a sequence of each teacher's competency scores over a continuous observation period, covering four dimensions: Teaching innovation, academic resilience, cross-domain collaboration, and digital adaptability, forming a multivariate time series $\mathbf{s}_t=\left[s_t^{(1)},s_t^{(2)},s_t^{(3)},s_t^{(4)}\right]$. To capture long-term evolutionary patterns and preserve nonlinear dynamic characteristics, a LSTM network was employed as the underlying architecture. This network effectively mitigates the vanishing gradient problem through a gating mechanism, memorizing key historical states and selectively updating current outputs. This made it suitable for teacher development processes characterized by periodic transitions and trend inertia. In the model, we assigned higher historical weights to periods of abrupt changes in the relevance of research and teaching through the attention mechanism, indicating its ability to identify key windows for cross-domain integration; simultaneously, the LSTM gating structure dynamically adjusts the degree of historical information retention, focusing predictions on the time segments most explanatory to capability leaps, thereby mitigating the “black box” problem to some extent. We chose LSTM over GRU or Transformer primarily because of its ability to stably model long-term dependencies in medium-length sequences, its robustness to training with limited samples, and its sensitivity to nonlinear trends and phase transitions. In comparison, GRU's simplified gating mechanism may weaken its ability to distinguish complex trajectories. Furthermore, Transformer is prone to overfitting on small-scale time-series data and lacks an inherent temporal inductive bias.

Model training uses a sliding window strategy to construct a sample set, with a window length set to six consecutive periods. This means using literacy data from the first six quarters to predict development levels for the next two quarters. A six-quarter window covers at least one full academic year and the summer research period, sufficient to capture the inertial trend in capability development, while avoiding excessive length that could reduce dynamic sensitivity. Specifically, each training sample consists of an input sequence $\mathbf{S}_{\text{in}}=[\mathbf{s}_{t\text{-}5},\mathbf{s}_{t\text{-}4},\ldots,\mathbf{s}_t]$ and a target sequence $\mathbf{S}_{\text{out}}=[\mathbf{s}_{t+1},\mathbf{s}_{t+2}]$, ensuring the model's multi-step forward prediction capabilities. The LSTM layer consists of two stacked layers with 128 hidden units. A dropout mechanism (with a ratio of 0.3) is introduced to prevent overfitting. The output layer is mapped to a four-dimensional continuous space via a fully connected layer. Mean squared error is used as the loss function for optimization. The AdamW optimizer is used during training, combined with a learning rate decay strategy to enhance convergence stability. The model iteratively updates weight parameters on the training set until the prediction error on the validation set converges, achieving the ability to fit the literacy evolution path nonlinearly.

Thus, we employed five-fold time-series cross-validation in the model to ensure that the time order within each fold was not disrupted, and final evaluation was performed on an independent test set (20% of the total samples).

To test model robustness, a brief ablation analysis was performed: Reducing the number of LSTM layers from 2 to 1 increased the MAE by approximately 0.03, while increasing it to 3 did not significantly improve performance but increased training time by 40%; adjusting the learning rate from $1e^{-3}$ to $5e^{-4}$ or $5e^{-3}$ exacerbated the fluctuations in validation loss; and replacing the dynamic collaborative network with a static snapshot (fixed window) decreased cross-domain prediction relevance by 0.12. This indicated that the configuration achieved a reasonable balance between efficiency and stability.

3.4.2. External covariate fusion and cross-domain collaborative dynamic embedding

The centrality dynamics in temporal collaborative networks not only reflect the accumulation process of teachers' social capital but also directly affect their ability development trajectory: An increase in degree centrality is usually accompanied by enhanced cross-domain resource acquisition capabilities, thereby promoting teaching innovation; the slope of proximity centrality characterizes information flow efficiency and is positively correlated with academic resilience. These evolutionary features, as external covariates, are Z-normalized and concatenated into the ability vector of each period, constituting the five-dimensional input of the LSTM, enabling the neural network to simultaneously perceive the co-evolution of individual behavior and social embedding.

In order to further enhance the model's explanatory power and predictive sensitivity for teacher development mechanisms, we introduced the scientific research-teaching correlation as a key external covariate into the LSTM input structure. This indicator characterized the behavioral coupling strength between teachers' scientific research input and teaching practice and reflected the dynamic changes in their cross-domain resource integration capabilities. The scientific research-teaching correlation was calculated using a sliding window with a lag of 1 period; that is, when predicting period t+1, only historical data up to period t were used to prevent future information leakage from the covariate. This processing method was clarified in the data preprocessing to avoid forward-looking bias in time-series prediction. The correlation calculation was based on the standardized scientific research activity frequency series, r_τ, and teaching behavior intensity series, d_τ, using the dynamic correlation coefficient within the sliding window:

$$\rho_t = \frac{\sum_{\tau=t-2}^{t}(r_\tau - \bar{r})(d_\tau - \bar{d})}{\sqrt{\sum_{\tau=t-2}^{t}(r_\tau - \bar{r})^2} \cdot \sqrt{\sum_{\tau=t-2}^{t}(d_\tau - \bar{d})^2}}. \tag{6}$$

Here, ρ_t represents the research-teaching correlation in quarter t, and $\bar{r}$ and $\bar{d}$ are the means within the corresponding third-order windows. This indicator is generated period by period, in a sliding window, forming a time series synchronized with the literacy sequence. It serves as the fifth input channel and is concatenated with the original four-dimensional literacy vector to form an extended input sequence. This design enables the model to perceive the coordinated fluctuations between teachers' dual responsibilities when learning literacy evolution patterns, enhancing its ability to identify turning points (such as when research feeds back into teaching or when teaching burdens suppress research).

In the model architecture, the covariate and primary competency sequences were simultaneously fed into the LSTM encoder, enabling information fusion through shared hidden states. Furthermore, an attention mechanism was introduced during the decoding phase, enabling the model to dynamically weigh the input contributions of different time steps within the historical window when predicting the following two periods, particularly strengthening the influence of highly correlated periods on subsequent development. The final output was a four-dimensional vector of predicted competencies for the next two quarters, supporting forward-looking deduction of individual-level developmental paths. This fusion strategy not only improved prediction accuracy but also enabled the model to respond to cross-domain interactions, furthering the transition from “black-box prediction” to “mechanism-embedded deduction”.

The interpretability of this model was reflected in the structural alignment between neurodynamic features and educational behavior mechanisms: The long-term memory units of the LSTM hidden states corresponded to the persistent inertia of teachers' research output; the time-varying pattern of gating weights reflected the sensitivity of teaching innovation to external interventions; and the peak of attention scores often appeared at the abrupt change point in research-teaching relevance, revealing a key window for cross-domain integration. Dynamic centrality, as an external input, shaped the strength of social capital's influence on competence trajectories by modulating the forgetting gate, thereby enabling semantic coupling between neural mechanisms and the educational process.

Figure 3 shows the quarterly trends in the four dimensions of teacher core competencies and the predictions from the LSTM model. The left-hand sub-figure reflects the quarterly changes in scores for these four dimensions, demonstrating ongoing efforts and fluctuations in teachers' performance across these competencies. For example, scores for cross-domain collaboration and digital adaptability exhibit varying degrees of fluctuation, likely related to the challenges and changes teachers face in multidisciplinary collaboration and technological adaptation. The right-hand subfigure shows the LSTM model's predictions of future quarterly competency scores. By analyzing historical data, the LSTM model effectively captures the long-term dependencies and cyclical changes in competency development, providing relatively accurate forecasts of future trends. The volatility of the predicted results aligns with the actual data, demonstrating that the LSTM model, while accounting for interdependencies among dimensions, can provide strong support for the future development of teacher competencies. These data provide a dynamic perspective on the development of teacher competencies, highlighting the complex interactions between different competency dimensions and the importance of predictive power.

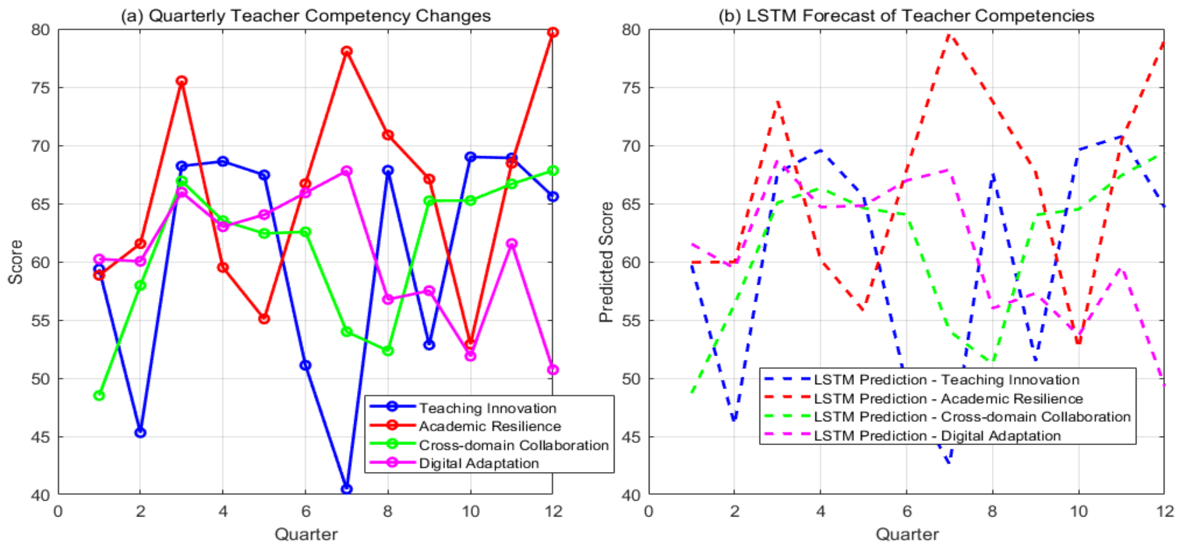

Figure 3. Time series trend and prediction effect of the LSTM model.

4. Comparative verification of the teacher competency development model

4.1. The relationship between standardization effect, teacher social interaction, and teaching evaluation

During the data cleaning phase, a unified behavioral coding dictionary was established, mapping heterogeneous operations to a standardized behavioral classification system. Behavior frequency and intensity indicators were then aggregated by quarterly time windows to calculate the course load and interactive response speed of teaching activities, as well as the output interval and project participation density of scientific research activities. To eliminate dimensional differences, all indicators were normalized using Z-scores to ensure numerical comparability across behavior types. Through time-series alignment and period division, the process constructed a structured temporal behavior matrix, providing a standardized data foundation for subsequent literacy quantification.

Figure 4 compares the effects of time series processing and standardization on multi-source behavioral logs. The left panel (a) shows changes in the original teaching behavior frequency and research behavior duration over 12 quarters. Teaching frequency exhibits cyclical fluctuations, peaking at the beginning and end of each academic year, while research duration shows a moderate upward trend but a slight decline in the first six quarters. The right panel (b) shows the data after Z-score standardization. This converts behavioral indicators across dimensions to a common scale, making the patterns of change in teaching and research activities clearer and more comparable. The standardized data reveals greater variability in research during the mid-quarters, while teaching is more stable. This indicates that standardization effectively eliminates dimensional differences between behavioral indicators, enabling teaching and research behaviors to be compared and analyzed under the same standards, providing a reliable data foundation for subsequent quantitative mapping of literacy dimensions.

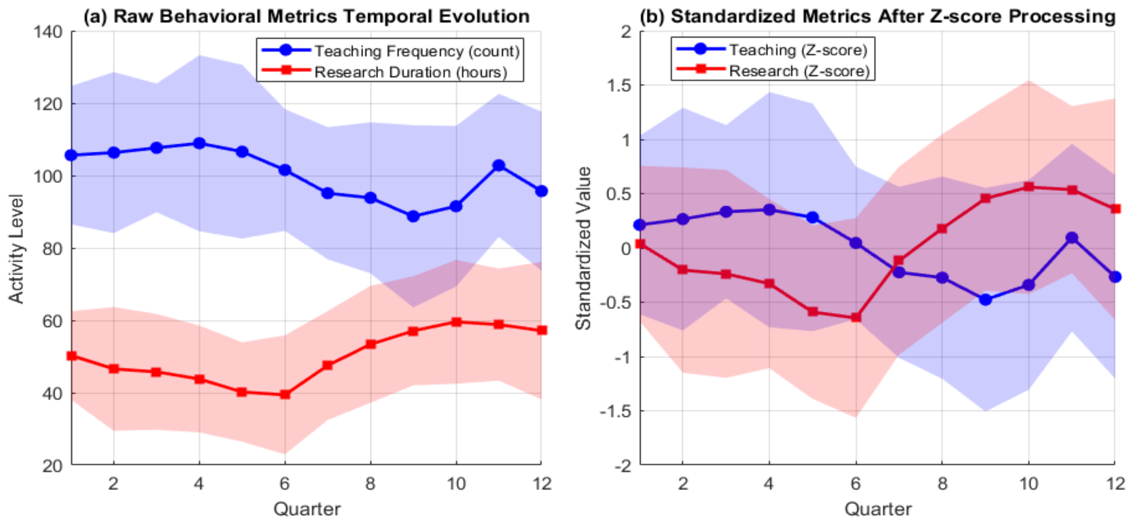

Figure 4. Time series processing and standardization effects of multi-source behavior logs.

We collected data on each teacher's degree centrality and closeness centrality at different time points. We used social network analysis to assess their influence and connection density within the teaching network. Degree centrality reflects the number of connections a teacher has with other nodes, while closeness centrality measures the average distance between a teacher and other educational entities. Next, we calculated the rate of change in social interactions among teachers, using changes in the frequency of interactions between each teacher and their colleagues and students to determine whether social interactions were strengthening or weakening. Finally, we combined the teacher's teaching innovation score and academic resilience score with correlation analysis to explore the correlation between changes in social interactions and these teaching evaluation indicators.

Figure 5 shows the temporal changes in teachers' degree centrality and closeness centrality, as well as the relationship between the rate of change in social interaction and scores on teaching innovation and academic resilience. First, in Figure 5(a), degree centrality and closeness centrality show an upward trend over time, indicating that teachers' importance and connectivity in the teaching network are gradually increasing. The increase in degree centrality indicates that teachers are connected to more nodes in the network, reflecting their active participation in classroom activities. The increase in closeness centrality suggests that the distance between teachers and other educational entities is gradually decreasing, potentially leading to more frequent interactions and improved information dissemination efficiency. These changes may be related to increased collaboration among teachers and strengthened sharing of teaching resources, which promotes the healthy development of the academic environment. Figure 5(b) reveals the relationship between the rate of change in social interaction and scores on teaching innovation and academic resilience. The increase in the rate of social interaction is positively correlated with the score on teaching innovation, indicating that interaction between teachers and students enhances the stimulation of innovative thinking. Increased social interaction also promotes teachers' greater academic resilience in the face of educational challenges, enabling them to adapt more effectively to and overcome educational uncertainty. The increase in social interaction may be due to teachers' adaptation to educational reforms and the increased use of technological tools, which make teaching methods more inclusive and flexible, thereby improving teaching quality and student learning outcomes.

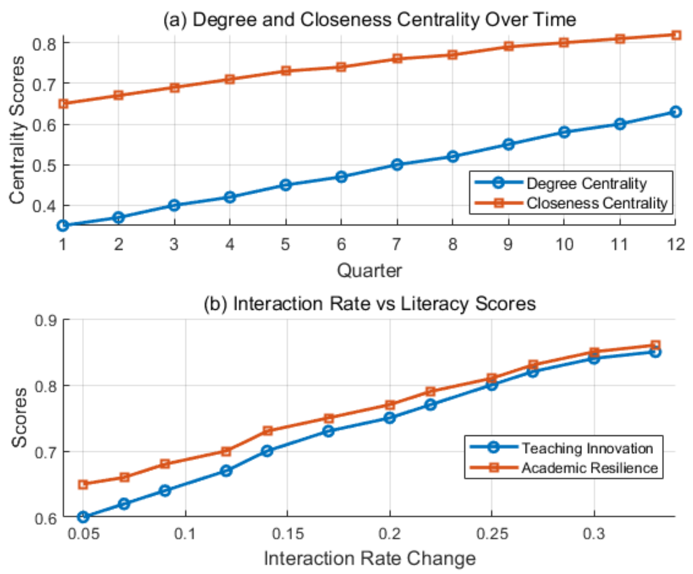

Figure 5. The relationship between teachers' social interaction and teaching evaluation.

4.2. Literacy level prediction accuracy performance

All prediction performance is reported based on an out-of-sample test set that has never been used in training or hyperparameter tuning. Using mean squared error (MSE) and mean absolute error (MAE) to measure prediction bias, we compared the prediction results of our Teacher Portraits + LSTM model with those of ARIMA (Autoregressive Integrated Moving Average), SVR (Support Vector Regression), and random forest (RF) models for faculty in three disciplines: Engineering, humanities, and management. These three disciplines, representing technology application, theoretical construction, and practical integration, respectively, tested the model's robustness under different knowledge production logics.

Figure 6 compares the prediction performance of the proposed Teacher Portraits+LSTM model with ARIMA, SVR, and Random Forest (RF) for faculty in three disciplines: Engineering, humanities, and management. Evaluation metrics were MSE and MAE. Overall, Teacher Portraits+LSTM demonstrates optimal prediction stability and accuracy across both error metrics, with MSEs ranging from 0.083 to 0.118 and MAEs ranging from 0.203 to 0.247, indicating stronger generalization capabilities in cross-disciplinary comparisons. For engineering faculty, given the relatively standardized behavioral data structure and stable research output cycles, the errors of various models are generally low. However, traditional methods show significant performance degradation for the humanities and management groups. This is due to the more nonlinear and intermittent development paths of humanities faculty. In contrast, management faculty are significantly affected by fluctuations in collaborative networks, placing higher demands on the model's dynamic modeling capabilities. Teacher Portraits+LSTM effectively captures the development heterogeneity under different knowledge production logics by integrating multi-source behavior sequences and cross-domain collaborative dynamic covariates, alleviating the traditional model's reliance on linear trends and stationary assumptions. It can, thus, maintain robust predictive performance in complex educational settings, reflecting its methodological advantages and its potential for modeling the evolution of teacher literacy.

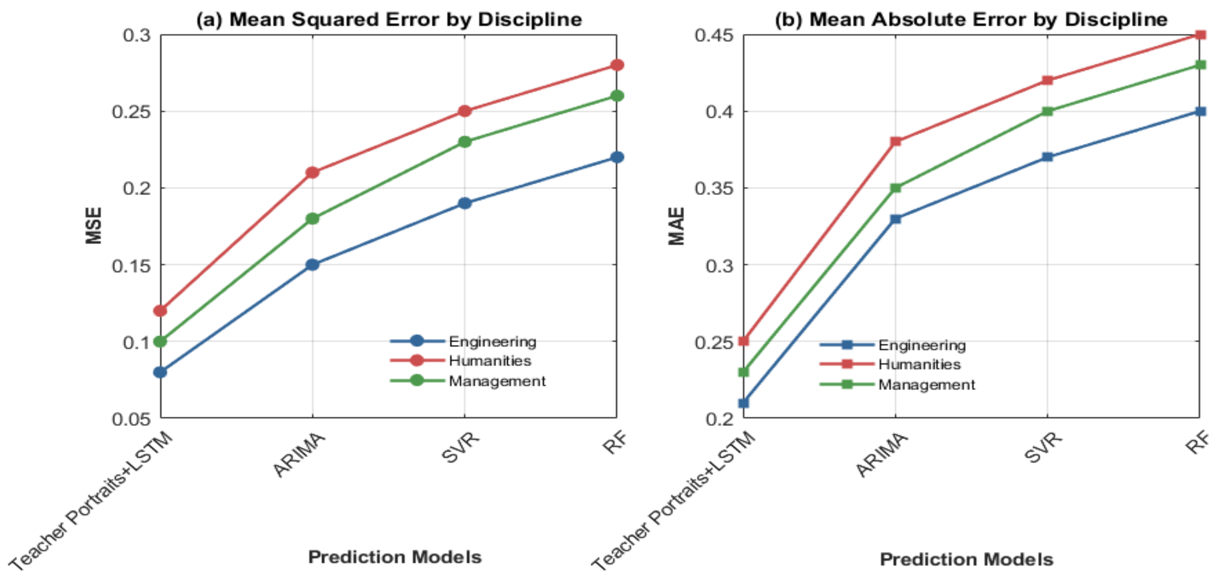

Figure 6. Literacy level prediction accuracy.

4.3. Developing pattern recognition accuracy

To test the robustness of clustering methods under conditions of uneven teacher digital engagement, we divided the sample into high-density (>80%) and low-density (<50%) subsets based on behavioral log coverage, representing comprehensive digital footprints and sparse observation conditions, respectively. The silhouette coefficient was used to measure the cohesion and separation of cluster structures, reflecting the clarity of category boundaries. The adjusted Rand index measures the consistency of clustering results based on known developmental pattern labels to correct for random-matching bias. The proposed DBSCAN+K-means hybrid strategy was compared with traditional K-means, hierarchical clustering, and spectral clustering methods. Standardized feature inputs and parameter optimization were performed under two data densities to ensure fair comparison. Through two-metric cross-validation, the stability of each algorithm under varying information richness was systematically evaluated, revealing the mechanism by which data sparsity influences the accuracy of developmental pattern recognition.

Figure 7 compares the performance of our proposed hybrid DBSCAN+K-means clustering method with traditional clustering algorithms in developmental pattern recognition accuracy across data densities, using the Silhouette Coefficient and Adjusted Rand Index as evaluation metrics. High behavioral log coverage (>80%) indicates sufficient digital engagement among teachers, with complete behavioral trajectories and highly distinguishable features. All methods achieve relatively straightforward cluster structures. However, under low coverage (<50%), data sparsity results in a discrete distribution in the feature space. Traditional methods such as K-means and hierarchical clustering, which are sensitive to initial centers and distances, significantly degrade in performance and are prone to blurred boundaries or misclassification. In contrast, our proposed method uses DBSCAN first to identify and remove noise points, effectively mitigating the impact of sparse data on cluster stability while preserving the compactness of the main structure. This results in more interpretable clustering during the K-means phase, with Silhouette Coefficients ranging from 0.51 to 0.68 and Adjusted Rand Indexes ranging from 0.53 to 0.72. This advantage is demonstrated by both metrics, with particularly strong robustness in low-density subsets. The results show that integrating density recognition and partitioning clustering can better address the modeling challenges posed by the uneven digital participation of university teachers and improve the applicability and credibility of development pattern recognition in real educational scenarios.

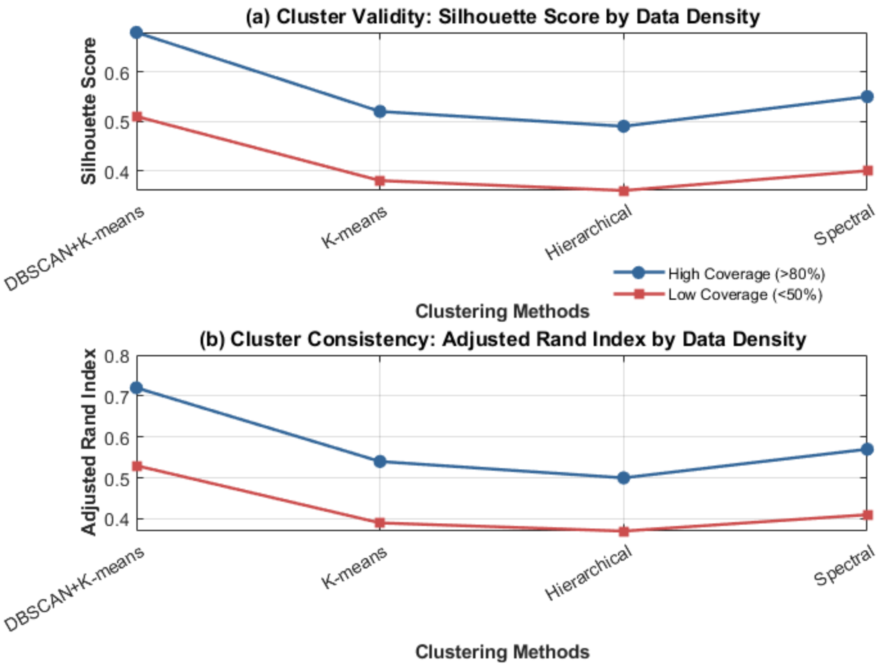

Figure 7. Silhouette coefficient and adjusted rand index.

4.4. Comparison of dynamic fitting capabilities of network centrality evolution prediction

To test the accuracy of the model's modeling of the dynamic evolution of teacher social capital, the time-series forecasting performance of the change rates of focal centrality and closeness centrality was studied. The Pearson correlation coefficient (r) and the coefficient of determination (R^2) were used as goodness-of-fit metrics. A three-period series of observed centrality change rates was used as a benchmark, and the predicted values from each model were compared point by point. r reflects the consistency between the predicted trend and the actual direction of change, while R^2 measures the model's ability to explain the variation. Together, these two factors assess the fidelity of the prediction results in terms of dynamic morphology. The comparison models included ARIMA, SVR, random forest, and the proposed Teacher Portraits + LSTM model. Multi-step forward estimates were generated using the same training set and sliding forecast mechanism. All model inputs were time-aligned, and the outputs were denormalized before comparison.

Table 2 shows the dynamic fit of different models in predicting the evolution of teacher network centrality, focusing on the long-term accuracy of the rate of change of degree centrality and closeness centrality. Compared with traditional methods, the proposed Teacher Portraits+LSTM model demonstrates significant advantages in both Pearson correlation coefficients (0.85–0.87) and coefficients of determination (0.72–0.75), demonstrating that it not only more accurately captures the directional trends of centrality changes but also provides a stronger explanation of dynamic fluctuations. This advantage stems from the model's ability to deeply encode multi-source behavioral sequences and explicitly model cross-domain coordination mechanisms, enabling it to identify nonlinear transitions and structural shifts in social capital accumulation. ARIMA, constrained by its linear assumption, struggles to respond to sudden increases in interactions or ruptures in cooperative relationships. Moreover, while SVR and random forests possess nonlinear fitting capabilities, they lack mechanisms for modeling temporal dependencies and are prone to trend drift in multi-step forecasts. In contrast, the LSTM architecture effectively preserves key states in the long-term evolutionary path through gated memory units. Combined with high-order feature inputs from teacher portraits, it enhances sensitivity and adaptability to social network dynamics. The results show that this method has a stronger mechanism-restoration ability for depicting the evolution of teachers' social embeddedness as knowledge nodes and provides a more dynamic explanatory computational tool for understanding the formation and change of the academic collaboration structure.

Table 2. Comparison of dynamic fitting capabilities.

Prediction model	Metric type	Degree centrality change rate	Closeness centrality change rate
Teacher Portraits+LSTM	r	0.87	0.85
	R^2	0.75	0.72
ARIMA	r	0.62	0.58
	R^2	0.49	0.45
SVR	r	0.68	0.64
	R^2	0.53	0.5
RF	r	0.71	0.67
	R^2	0.56	0.52

4.5. The effectiveness of multi-source information fusion in cross-dimensional correlation analysis

To test the model's ability to reveal cross-domain synergy among teachers' core competencies, the we focused on the strength of the nonlinear associations between research-teaching correlation and other competency dimensions. Mutual information measures the degree of nonlinear information sharing between two variables, with higher values indicating stronger dependence. The Spearman rank correlation coefficient reflects the monotonic relationship between variables and is robust to outliers. Combining these two factors comprehensively assesses the dynamic correlation structure among competency dimensions. This note has been added to the table to improve readability. Comparisons were conducted independently among young teachers (<35 years old) and experienced teachers (⩾50 years old) to reveal heterogeneity in cross-domain integration patterns across career development stages.

Table 3 shows the performance differences among models in revealing cross-dimensional mechanisms underlying the correlation between faculty research and teaching activities, focusing on their ability to capture the collaborative behavior patterns of young and experienced faculty. The results show that the proposed Teacher Portraits+LSTM model significantly outperforms ARIMA, SVR, and random forest in terms of mutual information (0.42–0.48) and Spearman correlation coefficients (0.55–0.62), demonstrating that its multi-source information fusion architecture can more realistically reproduce the nonlinear dependency structure and dynamic coupling trends between literacy dimensions. This advantage stems from the model's joint modeling of behavioral temporal sequences, network evolution, and cross-domain covariates, which preserves key correlation features during prediction. The correlation strengths of various models for young faculty are generally higher than those for experienced faculty, reflecting their stronger need for functional integration and behavioral plasticity in the early stages of their careers. The more rigid the patterns of experienced faculty are, the higher the sensitivity of the model is. Traditional methods, lacking explicit encoding of cross-domain dynamics, struggle to capture complex mechanisms, such as research feedback to teaching or the transfer of technological tools, resulting in a weakened correlation structure. In contrast, Teacher Portraits+LSTM significantly improves the ability to analyze the inherent collaborative logic of the educational behavior system by introducing scientific research-teaching correlation as a time-varying covariate and combining it with the attention mechanism to enhance a cross-dimensional response, providing a more explanatory analytical perspective for understanding the role integration mechanism of teachers at different development stages.

Table 3. Group comparison of multi-source information fusion efficiency in cross-dimensional correlation analysis.

Faculty Group	Model	Mutual Information Mean	Spearman's ρ Mean
Early-career (<35 years)	Teacher Portraits+LSTM	0.48	0.62
	ARIMA	0.31	0.41
	SVR	0.35	0.45
	RF	0.37	0.48
Senior (≥50 years)	Teacher Portraits+LSTM	0.42	0.55
	ARIMA	0.29	0.38
	SVR	0.33	0.42
	RF	0.34	0.44

5. Discussion

While we constructed a dynamic modeling framework integrating behavioral data, social network evolution, and neurodynamics, several limitations remain. First, the behavioral logs rely heavily on the depth of use of digital platforms in universities; data sparsity may arise from insufficient technical access or low platform activity among some teachers, potentially introducing selection bias. Second, the design of the competency dimension is based on the new liberal arts education policy orientation within the context of Chinese higher education; its indicator weights and collaboration patterns may be influenced by specific institutional cultures, requiring recalibration of semantic mapping rules when migrating to other educational systems or non-academic organizations.

Nevertheless, this framework possesses significant scalability potential. In organizational learning scenarios, “teaching innovation” can be replaced with “process improvement frequency”, “academic resilience” can be transformed into “project delivery stability”, and the collaboration network can correspond to a cross-departmental knowledge flow graph. In regional innovation systems, nodes can represent enterprises or R&D institutions; centrality dynamically reflects technology-diffusion capabilities; and the LSTM input sequence can integrate patent, collaboration, and financing behaviors to predict innovation trajectories.

Finally, we strictly adhered to research ethics guidelines: All behavioral data came from an authorized platform, were anonymized, and had their identities removed; the research protocol passed internal ethical review, and participants' informed consent clearly stated that the data would only be used for academic modeling, and that participants could withdraw at any time. Future deployments should incorporate differential privacy or federated learning mechanisms to balance predictive utility with individual privacy protection.

6. Conclusions

This research grapples with the inherent complexity and fluid dynamics of university faculty competency within the “New liberal arts” landscape, proposing an integrated analytical framework that bridges multi-source behavioral analytics, social network evolution, and deep temporal neural forecasting. By leveraging teacher profiling techniques, we convert disparate teaching, research, and collaborative footprints into quantifiable competency metrics. This transition represents a fundamental shift from traditional, often biased, subjective assessments toward a more rigorous, objective quantification of professional growth. To account for how social structures shape individual trajectories, we introduce the rate of change in temporal network topology. This enables the model to capture the “social capital” effect, the dynamic influence of peer interaction, on professional evolution. We further implement a hybrid clustering strategy that blends DBSCAN and K-means to balance isolating idiosyncratic “outlier” trajectories and identify dominant developmental archetypes. This dual-layered approach significantly bolsters the robustness and interpretability of our trajectory classifications.

At the core of the methodology is a LSTM architecture, engineered to fuse historical competency data with dynamic, cross-domain correlation features. This configuration does more than just enhance predictive precision; it illuminates the significance of neural network dynamics in deciphering the nonlinear nature of human learning. Empirical evidence confirms that this framework consistently outperforms traditional static or regression-based models in forecasting accuracy and pattern recognition, even in the face of data sparsity or across disciplinary contexts. Ultimately, we advance the field of teacher development by shifting the research paradigm from descriptive snapshots to mechanism-driven dynamic deduction. This alignment with the dynamics of ANNs offers a blueprint for modeling complex, human-centered systems. The methodological contributions extend well beyond the classroom, offering scalable insights for organizational learning, collaborative innovation, and socio-economic modeling, thereby broadening the interdisciplinary reach of neural-based dynamic analysis.

Looking ahead, we identify three critical avenues for expansion: First, integrating Explainable AI (XAI) tools, such as attention mechanisms or SHAP value analysis, to demystify the causal links within the neural architecture; second, developing real-time, adaptive learning interfaces that provide immediate feedback loops to support systems; and third, conducting transfer learning trials across educational sectors (e.g., vocational or international K-12) to evaluate the framework's cross-cultural adaptability and boundary conditions.

Use of Generative-AI tools declaration

The author declares she has not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The author declares no conflicts of interest in this paper.

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