Integration of Ideological and Political Elements in Natural Fiber Teaching and Evaluation of Online Learning Effects

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ABSTRACT Natural-fiber courses in textile education often integrate ideological and political elements in fragmented ways, with limited structured organization for themes such as sustainable manufacturing ethics and insufficient quantitative evaluation in online environments. This study presents a system for integrating ideological and political elements into natural-fiber courses within an online learning environment. The knowledge-graph-driven instructional design embeds four core themes: craftsmanship, green development, national culture, and social responsibility. The same knowledgeorganization and learning-analytics framework can also support engineering education in smart textiles, electromagnetic-compatible materials, and antenna-integrated wearable systems, where professional knowledge and value-oriented design constraints must be taught together. The platform collects posts, assignments, and test data, and applies a multidimensional learning-analytics model based on clustering and association-rule mining. The evaluation system covers knowledge mastery, interactive activity, and ideological and political identification, defined as an observable behavior-oriented indicator of value-related semantic expression in online learning outcomes. Experimental results show that ideological and political identification in the silk-fiber course reaches 89.7 in the craftsmanship dimension, while the cotton-fiber course scores 87.2 in the green-development dimension. Typical error rates remain below 20%, and correct response rates exceed 80% across instructional tasks. The study validates structured integration and quantitative feedback for natural-fiber education and provides a transferable model for engineering-oriented materials curricula.

INDEX TERMS natural fiber teaching,knowledge graph,learning analytics,smart textile education,electromagnetic material literacy

I. INTRODUCTION

As an important foundation of the textile major, the natural fiber course not only carries the task of imparting professional knowledge, but also shoulders the mission of educating people with values. In the context of the "Double First-Class" construction and the ideological and political education of the new era, integrating the spirit of craftsmanship, the green development concept, the inheritance of national culture and social responsibility into the teaching of natural fiber [1,2] not only helps students form a complete professional cognition, but also subtly strengthens the value orientation. However, in actual teaching, how to achieve a systematic combination of ideological and political elements with professional knowledge and scientifically evaluate their effectiveness in an online learning environment remains an important issue that needs to be solved [3,4].

The difficulties in current teaching practice are mainly reflected in three aspects. First, the way of integrating ideological and political elements is fragmented, often remaining in the form of verbal prompts or case embellishments in classroom segments, lacking a path to form a stable logical connection with professional knowledge [5]. Second, in the online learning context, students' learning behaviors are complex and diverse, and how to capture and analyze these behavioral data to accurately reflect the learning status is a great challenge [6,7]. Third, the evaluation methods for teaching effectiveness are relatively simple, making it difficult to take into account both knowledge acquisition and value identification, resulting in insufficient accuracy and pertinence in teaching feedback [8,9].

To overcome these difficulties, existing studies have attempted to propose solutions from various perspectives. For example, some studies have embedded ideological and political content into course chapters based on topic modularization, but they are often limited to the addition of knowledge points and lack overall structural support [10]. Other studies have applied interactive records of online learning platforms and used learning behavior data for statistical analysis, but they focus on knowledge achievement rates and pay less attention to value dimensions [11,12]. Other scholars have explored the construction of a hybrid teaching model to enhance students' comprehensive experience through the combination of online and offline teaching, but it is difficult to ensure the implementation of unified standards in large-scale applications [13]. Although these methods provide useful explorations, they still have deficiencies in the systematic organization of ideological and political elements, data-driven precise analysis, and multi-dimensional integration of evaluation indicators, making it difficult to form a complete solution that takes into account both professional depth and value orientation.

In response to the above problems, this study designs a teaching method centered on the systematic integration of ideological and political elements and the evaluation of online learning outcomes. To distinguish the instructional contribution of the proposed knowledge graph–driven integration model from conventional ideological and political embedding practices, the study adopts a comparative instructional design. A parallel teaching condition based on a traditional linear content organization and non-graph-based ideological and political integration is introduced as a control reference. Both instructional conditions follow identical course objectives, teaching duration, assessment structure, and platform environment, ensuring that observed differences in learning outcomes can be attributed to the instructional organization mechanism rather than external factors. This comparative perspective establishes the analytical foundation for evaluating not only overall teaching effectiveness but also the specific added value of the knowledge graph–driven integration approach.

In this process, knowledge graphs are applied to achieve content structuring and logical support. The spirit of craftsmanship, the concept of green development, the inheritance of national culture, and social responsibility are applied into the natural fiber knowledge graph to construct a two-layer semantic chain of knowledge and value. This chain is then mapped to the online platform to achieve structured push and logical recommendation of course resources. During the teaching process, behavioral data such as students' learning paths, homework, discussions, and tests are collected, and a three-dimensional evaluation system of knowledge mastery, ideological and political identification, and interactive activity is constructed through clustering and association rule mining.In this study, ideological and political identification is not treated as an internal belief structure or a stable value orientation at the psychological level. Instead, it is operationalized as an externally observable expression state manifested through students' learning interactions in the online environment. The indicator focuses on the extent to which value-oriented discourse associated with ideological and political elements is explicitly articulated, sustained, and aligned with course content during the learning process. This definition intentionally constrains the analytical scope of the indicator to the behavioral and discursive level, ensuring conceptual consistency with the data sources and analytical methods adopted in this research. This methodology achieves a systematic integration of professional textile manufacturing knowledge with ideological and political elements, providing a unified solution for structured implementation and quantitative feedback in natural fiber courses, and thus laying a practical foundation for coordinated professional education and value guidance.

II. IDEOLOGICAL AND POLITICAL ELEMENTS EMBEDDING AND LEARNING EVALUATION METHOD BASED ON KNOWLEDGE GRAPH

A. NATURAL FIBER KNOWLEDGE GRAPH CONSTRUCTION

The construction of the natural fiber knowledge graph focuses on semantic hierarchy and relational structuring [14,15]. First, a top-level semantic framework is established, defining natural fibers as a set F, where $F = \{f_1, f_2, f_3, f_4\}$, corresponding to cotton fiber, linen fiber, silk fiber, and wool fiber. Each fiber type f_i is further decomposed into specialized attribute nodes $A = \{a_1, a_2, \ldots, a_m\}$, covering dimensions such as source, molecular structure, micromorphology, mechanical properties, chemical stability, and processing technology. The relationship between nodes is defined as a triple, denoted by $R = (h, r, t)$: h is the starting node; t is the target node; r is the semantic relationship, such as "having", "derived from", and "applicable to". This approach enables the computability and logical expression of knowledge.

To ensure semantic consistency between different knowledge nodes, standardization is required, mapping all attribute values to a unified ontology vocabulary [16,17]. Assuming the attribute value set is $V = \{v_1, v_2, \ldots, v_k\}$, the mapping function $\phi : V \to C$ is used to complete the correspondence with the standard concept set C to eliminate redundancy and ambiguity. The weight distribution between nodes is obtained by calculating the semantic relevance, and the cosine similarity model S is defined as:

$$S(h,t) = \frac{\sum_{j=1}^{d} h_j \cdot t_j}{\sqrt{\sum_{j=1}^{d} h_j^2} \cdot \sqrt{\sum_{j=1}^{d} t_j^2}} \tag{1}$$

In Formula (1), h_j and t_j are the semantic vector components of nodes h and t in the j-th dimension, respectively, and d is the vector dimension. The weight result is used to mark the strength of the edge in the knowledge graph to facilitate the logical push and automatic retrieval of subsequent teaching content. At the graph visualization level, all nodes are stored in the form of multidimensional tensors. It is assumed that the overall knowledge graph is $G = (N, E, W)$, where N is the node set; E is the edge set; W is the weight matrix. The relationship between nodes is defined by the adjacency matrix M. $M_{ij} = 1$ indicates that nodes n_i and n_j are associated, otherwise $M_{ij} = 0$. The final generated graph structure is presented as a visual graph structure in the course platform, which not only ensures the hierarchical display of fiber type knowledge, but also realizes the docking conditions with the subsequent ideological and political elements embedding [18,19].

B. SEMANTIC EMBEDDING MECHANISM OF IDEOLOGICAL AND POLITICAL EDUCATION ELEMENTS

The semantic embedding mechanism of ideological and political education elements relies on the structured framework of the natural fiber knowledge graph to form a two-layer semantic chain between value-oriented information and professional knowledge nodes [20,21]. The four core elements of ideological and political education are expanded on this structure and defined as a set $P = \{p_1, p_2, p_3, p_4\}$, which represent craftsman spirit, green development concept, national cultural heritage, and social responsibility, respectively. Each element p_k establishes a corresponding relationship with the professional knowledge node through the semantic mapping function $\psi : N \to P$, forming a cross-level semantic mapping edge.

In the logical fusion layer, a two-layer semantic chain $L = (N, P, E')$ is constructed, where E' is an extended relationship set containing links between knowledge nodes and ideological and political element nodes [22,23]. The relationship weight is also calculated by Formula (1), which represents the semantic matching degree between knowledge nodes and ideological and political element nodes. The matching value obtained by this function is directly attached to E' as the edge weight, thereby ensuring that the embedding between value information and professional knowledge has a quantifiable structural constraint. After generating a complete embedding, the two-layer semantic chain and the original knowledge graph are integrated into an extended graph $\hat{G} = (N \cup P, E \cup E', W \cup M)$ through a union operation. This extended graph supports content organization and push logic in the course implementation platform, enabling seamless structural coupling of professional knowledge and ideological and political education elements, ensuring that knowledge and value orientation can be simultaneously accessed and presented during online teaching [24,25].

C. MAPPING OF TEACHING CONTENT AND NETWORK PLATFORM

The mapping of teaching content and network platform is based on the extended knowledge graph $\hat{G}$, establishing a multi-level index structure based on the correspondence between nodes and course resources [26,27]. Let the course resource set be $R = \{r_1, r_2, \ldots, r_q\}$, where each element r_i represents a teaching resource file, and resource types include text, images, videos, and interactive modules. To achieve precise matching between graph nodes and resources, a resource mapping function $\eta : (N \cup P) \to R$ is defined. This function associates each knowledge node or ideological and political element node with a unique course resource, achieving a unified mapping of content between the structure and the platform. At the presentation layer of the online platform, the priority of teaching resource push is determined by a weighted function Θ, and the formula is:

$$\Theta(x) = \alpha \sum_{y \in \mathrm{Adj}(x)} W(x, y) + \beta \sum_{z \in \mathrm{Adj}(x)} M(x, z) \quad (2)$$

In Formula (2), x represents an arbitrary node; $\mathrm{Adj}(x)$ represents the set of nodes adjacent to node x; $W(x, y)$ represents the weight of node x and knowledge node y; $M(x, z)$ represents the degree of match between node x and ideological and political node z; α and β are empirically calibrated adjustment parameters that regulate the relative contribution of professional knowledge relevance and ideological and political semantic alignment in the resource push process. The result of this function serves as the ranking basis, determining the display order of teaching resources on the learning platform interface.

The values of α and β are not arbitrarily assigned. Their determination is grounded in an empirical calibration process conducted prior to the formal teaching experiment. During the pilot phase of the course platform deployment, multiple combinations of α and β were systematically tested under identical instructional content and learner cohorts. The evaluation criterion for parameter selection was defined by the stability of resource recommendation sequences and the consistency of learning behavior distribution across professional knowledge nodes and ideological and political element nodes. The selected parameter configuration corresponds to the condition under which the variance of recommendation ranking outcomes reached a minimum while maintaining balanced exposure frequency between professional knowledge resources and value-oriented resources. This process ensures that the weighting mechanism reflects the structural characteristics of learner interaction data rather than subjective preference, thereby providing an empirically grounded basis for the resource push logic.

In its operational mechanism, the platform uses an adjacency matrix structure for real-time retrieval and scheduling. When a student accesses a node, the system calls the corresponding course resources based on the value of $\Theta(x)$ and generates a recommended path by expanding the relationship between adjacent nodes in the graph, thereby ensuring the progressive nature of learning content and the consistency of value orientation [28,29]. Ultimately, the mapping mechanism achieves the dynamic matching and linked push of natural fiber professional knowledge and ideological and political elements on the online platform, enabling the learning process to form a logical chain that unfolds synchronously at the professional and value levels.

D. MULTI-DIMENSIONAL LEARNING BEHAVIOR COLLECTION AND PROCESSING

Learning behavior data is collected based on the interaction logs of the course platform. All behaviors are formalized as event tuples $E = (u, s, \hat{r}, a, \hat{t}, m)$. Here, u is the user identifier; s is the session identifier; $\hat{r}$ is the resource identifier; a is the action type; $\hat{t}$ is the timestamp; m is the behavior-related metadata. Events are submitted by the client in JSON (JavaScript Object Notation) format and written to the log database on the server. Real-time distribution and caching are achieved through a streaming processing framework [30,31]. Sessions are divided based on a time threshold $\tau = 1800$ seconds. A new session is generated when the time difference between adjacent events exceeds τ. When the time interval is less than 5 seconds and the resource and action are consistent, subsequent events are considered duplicates and discarded to ensure the uniqueness and validity of the sequence.

Click behaviors are combined into a path sequence $\pi = (r_1, r_2, \ldots, r_k)$ in order of access, and the resource identifier $\hat{r}$ is converted into a knowledge graph node v through a mapping function. Based on this, a transition matrix $T = (t_{ij})$ is defined, where t_{ij} represents the normalized frequency of nodes v_i and v_j appearing adjacently in the user path. This matrix is used to characterize the knowledge transfer trajectory during the learning process.

Homework submission records and test scores are stored in a structured form. Homework records are triples $(u, \hat{r}, \delta)$, where δ is the submission time difference, reflecting the learning rhythm; test scores are (u, q, s_q), where q is the test question number, and s_q is the score, normalized to the interval $[0, 1]$. Discussion posting behavior is recorded as $(u, \hat{r}, \zeta)$, where ζ is the text vector, which is calculated by the word embedding model and used for subsequent content similarity analysis.

The word embedding model employed to generate the discussion text vector ζ is a transformer-based contextual semantic representation model pretrained on large-scale academic and educational corpora and subsequently adapted to the instructional discourse domain. The model maps each discussion post into a fixed-dimensional dense semantic space by encoding the full sentence-level context rather than isolated tokens, thereby preserving syntactic dependency and semantic coherence across the learning discourse. The training corpus used for domain adaptation consists of textual materials collected from historical online course discussions, instructional descriptions, assignment explanations, and value-oriented teaching resources within the same learning platform, forming a domain-consistent corpus with sufficient coverage of both professional textile terminology and ideological and political discourse. All discussion posts are tokenized and processed through the embedding model to obtain sentence-level semantic vectors, which are normalized to ensure comparability across learners and learning units. This processing pipeline ensures that ζ represents a stable and reproducible semantic abstraction of students' observable discursive behavior in the online learning environment.

In the behavior processing stage, all events are arranged in time series to form a learning trajectory $\Gamma_u = (\epsilon_1, \epsilon_2, \ldots, \epsilon_n)$ and projected to the knowledge graph path $\Lambda_u = (v_1, v_2, \ldots, v_n)$ through the mapping function ψ. The participation of each node is calculated by the function:

$$\eta(v, t) = \sum_{\epsilon \in \Gamma_u, \psi(\hat{r}) = v} \exp(-\lambda_t \cdot (\tau_c - t)) \tag{3}$$

In Formula (3), τ_c is the current time, and λ_t is the time decay coefficient. This function ensures that recent behavior contributes more to the participation accumulation, reflecting the dynamic learning state. Through the above processing, users' clicks, homework, discussions and test scores are uniformly mapped to the knowledge graph node space, achieving precise correspondence between behavior sequences and knowledge content, and providing data support for subsequent multi-dimensional learning analysis and effectiveness evaluation [32,33].

E. DESIGN OF LEARNING EFFECTIVENESS EVALUATION MODEL

The evaluation of learning effectiveness is based on the three core indicators of knowledge mastery, ideological and political identification, and interactive activity.

Although the three indicators are mathematically represented as independent dimensions, their roles in the learning process are not conceptually isolated. Knowledge mastery, ideological and political identification, and interactive activity jointly constitute an integrated learning system in which cognitive acquisition, value-oriented expression, and behavioral engagement are mutually reinforcing. The synergistic effect emphasized in this study refers to the coordinated manifestation of these dimensions at the level of observable learning outcomes rather than to a latent nonlinear psychological coupling. From an analytical perspective, the objective of the evaluation model is to synthesize heterogeneous behavioral evidence into a unified quantitative scale while preserving interpretability and comparability across learners. Under this constraint, a weighted aggregation framework is adopted to represent synergy as a structured co-contribution of multiple dimensions within the same evaluative space, rather than as an implicit interaction term that would obscure the attribution of learning effects.

Through unified mathematical modeling, the quantitative characterization of students' learning process and results is achieved [34,35]. The construction of knowledge mastery is based on test scores and homework records. It is assumed that the student set is $U = \{u_1, u_2, \ldots, u_m\}$; the test set is $Q = \{q_1, q_2, \ldots, q_n\}$; the score of student u_i on test question q_j is recorded as s_{ij}, and normalized to the interval $[0, 1]$. Its overall knowledge mastery is defined as:

$$K_i = \frac{1}{n} \sum_{j=1}^{n} s_{ij} \tag{4}$$

In Formula (4), K_i ranges from [0, 1]. The larger the value, the higher the degree of professional knowledge mastery.

The quantification of ideological and political identification is constructed at the level of learning behavior semantics rather than internal value orientation. The model captures students' explicit engagement with ideological and political elements through their discursive expressions in the discussion environment, treating posted texts as behavioral traces generated under the instructional context. The semantic similarity calculation does not assume the internalization of values or the formation of stable beliefs. Instead, it measures the degree to which students' learning discourse remains semantically aligned with predefined ideological and political elements during the learning process. Within this framework, higher similarity values indicate a stronger and more sustained presence of value-oriented expressions in students' interactions, reflecting the observable responsiveness of learning behavior to ideological and political content embedded in the course design. This operational definition ensures that the indicator functions as a behavior-based representation of value-related expression, maintaining methodological coherence between data sources, analytical techniques, and theoretical interpretation. According to the ideological and political element set P defined in Section "Semantic Embedding Mechanism of Ideological and Political Education Elements", the identification of student u_i on element P_k is calculated by the text semantic similarity function ϕ:

$$R_{ik} = \frac{1}{|T_i|} \sum_{t \in T_i} \phi(t, P_k) \tag{5}$$

In Formula (5), T_i represents the post set of student u_i, and $\phi(t, P_k) \in [0, 1]$ represents the matching degree between the post text vector and the ideological and political element semantic vector. The semantic vector of each latent ideological and political element P_k is constructed within the same embedding space as the discussion text vectors to ensure metric consistency. For each element P_k, its semantic representation is derived by encoding a curated textual description that operationally defines the element within the instructional context, reflecting its value orientation as it is explicitly presented in the course design rather than as an abstract ideological construct. These textual descriptions are processed using the identical word embedding model and preprocessing pipeline applied to student discussion posts, yielding normalized semantic vectors that function as stable anchors in the shared semantic space. By enforcing a unified embedding mechanism for both learner-generated discourse and predefined ideological and political elements, the semantic similarity function ϕ computes alignment scores that are mathematically coherent and reproducible across different datasets and experimental settings.

The overall ideological and political identification of students is recorded as:

$$R_i = \frac{1}{|P|} \sum_{k=1}^{|P|} R_{ik} \tag{6}$$

The interactive activity is modeled by three types of behaviors: clicks, homework, and discussion. It is assumed that the three types of behavior sets are A^{click}, A^{task}, A^{disc}, respectively, and the frequency of student u_i in behavior a is recorded as $f_i(a)$. After normalization, its interactive activity is defined as:

$$I_i = \alpha \cdot \frac{\sum_{a \in A^{\text{click}}} f_i(a)}{\max_j \sum_{a \in A^{\text{click}}} f_j(a)} + \beta \cdot \frac{\sum_{a \in A^{\text{task}}} f_i(a)}{\max_j \sum_{a \in A^{\text{task}}} f_j(a)} + \gamma \cdot \frac{\sum_{a \in A^{\text{disc}}} f_i(a)}{\max_j \sum_{a \in A^{\text{disc}}} f_j(a)} \tag{7}$$

The adjustment parameter α+β+γ=1 in Formula (7) is used to balance the contribution of the three types of behaviors in the evaluation process.

Finally, the comprehensive learning effect is achieved by weighted integration of the above three indicators, and the weight parameters are set to $\lambda_1, \lambda_2, \lambda_3$, satisfying $\lambda_1 + \lambda_2 + \lambda_3 = 1$. The selection of a linear weighted integration form for the comprehensive evaluation does not imply an assumption of independence among the three indicators. Instead, it reflects a modeling decision aligned with the data structure and analytical objectives of this study. All three indicators are derived from behavior-level observations collected within the same online learning environment and projected onto a common normalized scale. Introducing nonlinear interaction terms at this stage would increase model complexity without providing additional explanatory power under the current data granularity. Moreover, a linear formulation ensures transparency in the contribution of each dimension, allowing the synergistic learning effect to be interpreted as the simultaneous elevation of cognitive performance, value-related expression, and interaction intensity within a unified evaluative framework. The comprehensive evaluation value of the student u_i is recorded as:

$$E_i = \lambda_1 K_i + \lambda_2 R_i + \lambda_3 I_i \tag{8}$$

The weighting parameters λ_1, λ_2, and λ_3 are determined through an empirical calibration procedure rather than subjective assignment. Prior to the final evaluation, a parameter sensitivity analysis was conducted using historical learning behavior data from the same platform environment. The calibration objective was defined as minimizing the variance of the comprehensive evaluation score across equivalent performance strata while maintaining discriminative power among learners with distinct behavioral profiles. By iteratively adjusting the weight configuration and examining the stability of ranking outcomes and inter-indicator correlation consistency, the selected parameter set reflects a balanced contribution of knowledge mastery, ideological and political identification, and interactive activity. This data-driven determination ensures that the comprehensive evaluation value captures the coordinated influence of the three dimensions in a stable and interpretable manner, thereby operationalizing the synergistic learning effect within a measurable framework. This model not only ensures the balanced reflection of the three dimensions of knowledge, ideological and political education, and interaction in the results, but also provides a unified quantitative scale for subsequent empirical analysis, so that the online teaching effect of the natural fiber course can be systematically evaluated under the dual goals of professional education and value guidance.

III. EXPERIMENTAL PROCEDURE

The experimental procedure was conducted within a fully online natural fiber course implemented on the university learning management platform. The participants consisted of 300 undergraduate students majoring in textile engineering, all of whom were enrolled in the same compulsory natural fiber course during a single academic semester. The course covered four instructional units corresponding to cotton fiber, hemp fiber, silk fiber, and wool fiber, and each unit was delivered using the same knowledge graph– driven instructional framework described in Section "Ideological and political elements embedding and learning evaluation method based on knowledge graph". The intervention spanned sixteen consecutive teaching weeks, aligning with the standard semester schedule, and all learning activities, assessments, and interactions took place exclusively within the online platform environment to ensure consistency of data collection conditions. This study was approved by the Ethics Committee of Haikou University of Economics, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

Prior to the commencement of the formal teaching intervention, all enrolled students were informed of the course structure and evaluation mechanism, and baseline access to learning resources was provided uniformly. The instructional implementation adopted a quasi-experimental comparative design. The participant cohort was divided into an experimental group and a control group prior to the commencement of teaching. The experimental group received instruction through the proposed knowledge graph–driven integration framework, in which professional knowledge nodes and ideological and political elements were structurally embedded and dynamically recommended. The control group followed a conventional online teaching approach based on linear chapter organization, instructor-curated resource sequencing, and explicit but non-structured ideological and political content insertion aligned with standard curriculum practice. Both groups were taught by the same instructional team, used the same learning platform, followed the same syllabus schedule, and completed identical assessments, thereby controlling for instructional time, content scope, and evaluation criteria.Learning behavior data were continuously recorded from the first week to the final week of the course, covering the complete learning cycle from initial exposure to final assessment.

For the purpose of learning behavior analysis and result visualization, students were divided into ten groups labeled G1 through G10 during the data analysis stage rather than during instruction. The grouping was performed by random assignment after data collection was completed, with each group containing an equal number of students. This grouping strategy was adopted to control for individual variability while preserving the overall statistical distribution of learning behaviors. No grouping variable related to prior academic performance, learning ability, or demographic characteristics was used in the grouping process, ensuring that the group-level comparisons reflected emergent behavioral patterns rather than predefined learner attributes.

The evaluation of knowledge mastery was based on unit tests and assignment questions embedded within each fiber module. The typical error rate reported in the results section was calculated using a predefined subset of test questions that consistently exhibited higher incorrect response frequencies across the student cohort. These questions were identified through post-test statistical analysis by ranking all objective test items according to their incorrect response proportions and selecting those that exceeded the cohort-level mean error rate by a stable margin. The selected questions primarily reflected conceptual misunderstandings or application-level difficulties within the corresponding fiber knowledge domain, and their aggregated incorrect response ratio was defined as the typical error rate for that fiber unit. All experimental data used for Figures 1 through 5 were derived from the same cohort, course duration, and platform environment described above. The consistency of instructional content, evaluation criteria, and data collection mechanisms ensures that the reported results are directly attributable to the proposed knowledge graph–based instructional and evaluation framework, thereby supporting the reproducibility and interpretability of the experimental findings.

IV. EXPERIMENT AND DISCUSSION OF RESULTS

A. PARAMETER CALIBRATION AND VALIDATION OF THE RESOURCE PUSH MECHANISM

To verify the effectiveness and rationality of the weighting parameters α and β in the resource push mechanism, an internal validation analysis was conducted based on learning behavior logs collected during the experimental period. The analysis examined the distribution of accessed resources and the corresponding engagement intensity across professional knowledge nodes and ideological and political element nodes. The calibrated parameter setting demonstrates a stable balance in learner exposure, preventing the dominance of either purely technical content or value-oriented content in the recommendation sequence. The observed learning trajectories show coherent transitions between knowledge acquisition activities and value-related discourse participation, indicating that the weighting mechanism effectively supports the intended dual-objective instructional design. This validation confirms that the parameter configuration functions as an operational control mechanism aligned with the pedagogical goals of synchronized professional education and ideological and political guidance.

B. KNOWLEDGE MASTERY EVALUATION RESULTS

In a systematic assessment of students' mastery of natural fiber knowledge, this study analyzes four dimensions: compliance rate, excellent performance rate, correct answer rate, and typical error rate. In this study, the compliance rate refers to the proportion of students whose overall test performance for a given fiber unit reaches or exceeds the predefined instructional requirement threshold, indicating task completion and attainment of basic learning objectives. The correct answer rate, by contrast, is calculated as the aggregated proportion of correctly answered objective test items across all students within the same fiber unit, reflecting item-level response accuracy rather than learner-level qualification. These two indicators therefore capture different aspects of knowledge mastery, with compliance rate emphasizing whether learners meet the expected competency standard for the unit, and correct answer rate focusing on the correctness of responses at the question level.

This analysis reveals differences in learning outcomes across different fiber types. By comparing the mastery of cotton, linen, silk, and wool fibers, the distribution of students' knowledge between basic mastery and advanced performance is revealed, further highlighting gaps and weaknesses in the teaching process. Based on this approach, Figure 1 shows a comparison of knowledge mastery across different fiber types.

As shown in Figure 1, silk fiber achieves a compliance rate of 95.6% and an excellent performance rate of 74.1%, demonstrating a high overall mastery level. This is directly related to its systematic content structure and comprehensive learning resources. Cotton fiber also performs well, with a compliance rate of 92.4% and a correct answer rate of 88.5%, demonstrating a high level of student acceptance and familiarity. In contrast, students' mastery of hemp and wool fibers is relatively limited, with an 85.2% compliance rate for hemp fiber and a mere 49.5% excellent performance rate for wool fiber. This reflects the relative difficulty of these two knowledge points, and the resulting obstacles in students' understanding and application. The distribution of typical error rates further confirms this: the error rate for wool fiber is 17.6%, higher than the 11.5% for cotton fiber and 9.3% for silk fiber, indicating a tendency for misconceptions in conceptual understanding and application. Overall, significant differences in mastery levels are observed across fiber types, necessitating the design of more targeted instructional strategies for hemp and wool fiber content. When comparing the experimental group with the control group, a consistent performance gap is observed across all fiber categories. The experimental group demonstrates higher compliance rates, excellent performance rates, and correct answer rates, accompanied by lower typical error rates. This contrast indicates that the observed high mastery levels are not merely the result of effective teaching execution, but are associated with the structured content organization and semantic linkage enabled by the knowledge graph–driven instructional design. In the absence of such structural support, the control group exhibits greater dispersion in performance and a higher incidence of conceptual errors, particularly in fiber categories with complex structural properties.

C. IDEOLOGICAL AND POLITICAL IDENTIFICATION EVALUATION RESULTS

It should be emphasized that the ideological and political identification scores reported in this section represent the intensity and stability of value-oriented expression within students' learning discourse, rather than direct evidence of internal belief formation or value internalization. The analysis focuses on how frequently and consistently ideological and political themes emerge in students' interactions with course content, reflecting the extent to which the instructional design guides learning behavior toward value-related semantic spaces during the online learning process.

Applying ideological and political elements into natural fiber instruction, through the organic integration of subject knowledge and value guidance, examines students' acceptance of value dimensions within different knowledge blocks. The study focuses on four key areas: craftsmanship, green development, national cultural heritage, and social responsibility. The study incorporates these elements into the teaching of cotton, hemp, silk, and wool fibers. Furthermore, students' post-learning scores are collected to analyze the overall impact of the integration of ideological and political elements into the natural fiber curriculum. Figure 2 shows that students' discussion discourse in the silk fiber course exhibits a high degree of semantic alignment with ideological and political elements, with scores of 89.7 in the craftsmanship dimension and 88.6 in the social responsibility dimension. This pattern is associated with the structured organization of course content and the coherence of teaching resources, which guide students' learning interactions toward sustained value-oriented semantic expression. Cotton fiber performs well in terms of green development concepts and national cultural heritage, scoring 87.2 and 88.0, respectively. This is related to its strong thematic linkage with sustainable development in the industrial chain and its prominent cultural positioning, which promotes consistent value-related discourse within students' learning interactions. Wool fiber falls in the middle range across all dimensions, scoring 83.1 in green development concepts and 84.1 in social responsibility, indicating that value-oriented semantic content is present in students' discussions, but the intensity and stability of such expression remain moderate. Hemp fiber scores the lowest in all four dimensions, with craftsmanship at only 81.8 and national cultural heritage at 80.9. This phenomenon indicates that the lower identification scores observed for hemp and wool fibers are not merely the result of learner motivation or engagement differences, but are closely related to the structural characteristics of the knowledge graph–based embedding

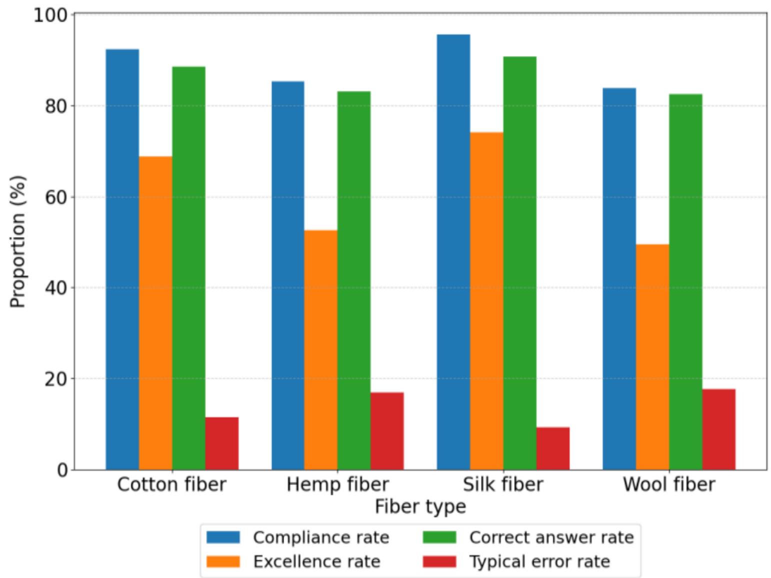

FIGURE 1. Comparison of knowledge mastery across different fiber types, where compliance rate represents the proportion of students meeting the unit-level instructional requirement and correct answer rate represents the aggregated accuracy of objective test responses

mechanism itself. In the proposed system, ideological and political elements are embedded through semantic alignment between value nodes and professional knowledge nodes. However, for hemp and wool fibers, the corresponding professional knowledge nodes exhibit higher abstraction levels, denser terminological dependency, and weaker direct semantic correspondence with value-oriented concepts. As a result, the semantic matching weights generated in the two-layer chain tend to be lower and more dispersed, reducing the probability that value-related nodes are activated during learners' interaction trajectories. Consequently, students' discussion discourse is less consistently guided toward explicit value-oriented semantic spaces, which is directly reflected in the reduced ideological and political identification scores. This is primarily due to the difficulty of learning and the relatively implicit cultural symbols associated with it, which constrains the extent to which value-related themes are explicitly articulated in students' learning discourse. Overall, the integration of ideological and political elements into different fiber courses reveals a hierarchical pattern of engagement. This variation highlights the importance of targeted guidance in instructional design.

A comparative analysis between the experimental group and the control group reveals a marked difference in the stability and intensity of value-oriented semantic expression. While the control group demonstrates sporadic alignment with ideological and political elements, such expressions tend to remain fragmented and weakly connected to professional knowledge discourse. In contrast, the experimental group exhibits sustained semantic alignment across learning units, reflecting the effect of the two-layer semantic chain that continuously activates ideological and political nodes during learning path progression. This comparison supports the interpretation that the proposed knowledge graph–driven integration model contributes specifically to the coherence and persistence of value-related expression, rather than merely increasing the frequency of student discussions.

D. INTERACTIVE ACTIVITY EVALUATION RESULTS

After quantifying student learning behaviors, the study focuses on three types of interactive data recorded in online platform logs: discussion forum exchanges, assignment submissions, and participation in stage tests. To mitigate the potential for random bias due to individual differences, the data is normalized and divided into 10 groups of equal size, with the group mean serving as the unit of analysis. This approach not only highlights the differences in interactive behavior among different learning groups but also lays the foundation for subsequent exploration of patterns. It should be noted that the 10 groups shown in Figure 3 are active student groups, and therefore have relatively high overall activity levels. This more clearly reflects the interactive status of active participants in the online learning platform and, overall, reflects the interactive engagement of students within the online learning platform.

Figure 3 shows a high overall activity level, with a mean of approximately 0.82, indicating that most groups maintain a relatively active attitude towards participation in the online learning environment. Some groups perform exceptionally well. G10's activity levels in discussion and testing reach 0.91 and 0.92, respectively. This high engagement suggests this group has developed strong learning motivation and task-driven thinking in the online environment. In contrast, G5's activity levels in discussion are 0.72, and in assignments and tests are 0.75 and 0.73, respectively. These overall levels are relatively low, likely due to the group's instability

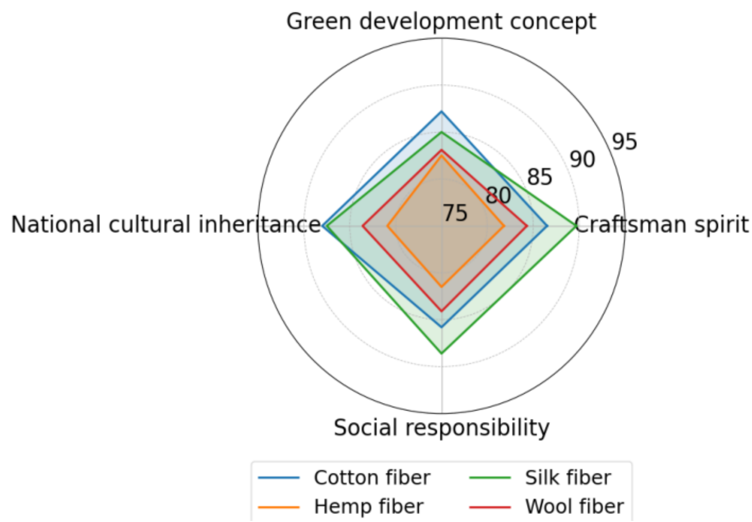

FIGURE 2. Identification of ideological and political elements in natural fiber teaching

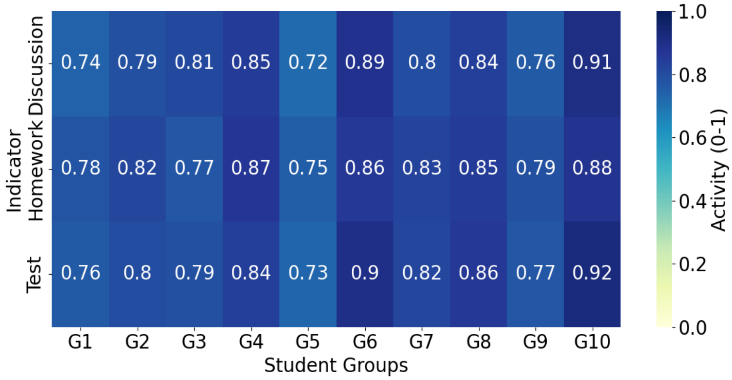

FIGURE 3. Interactive activity of students by group on the online learning platform

in learning habits or a lack of autonomy in the online environment. The remaining groups range from 0.74 to 0.90, with slight variations but generally stable, reflecting the strong support provided by the online platform's resource delivery and interactive design for student engagement. In behavioral research on online learning, it's necessary to combine data from different dimensions to reveal patterns in student interaction on the platform. Based on online platform log data, this study chronologically processes the learning behaviors of all students. By normalizing discussion, homework, and test activity across different time periods throughout the day, the dynamic distribution of group learning activities can be captured. This method provides a holistic view of the changing trends in interactive participation throughout the day, avoiding biases caused by single indicators or individual differences. Figure 4 illustrates the performance of three types of learning behaviors over different time periods.

Figure 4 shows that the distribution of the three types of learning behaviors varies significantly throughout the day. Discussion activity reaches 0.57 between 10:00 AM and 12:00 PM and rises to 0.77 between 8:00 PM and 10:00 PM, indicating that classroom interaction and free exchange at night drive peak discussion activity. Homework activity remains relatively low, at only 0.40, between 8:00 AM and 10:00 AM, but rises to 0.74 between 10:00 PM and 12:00 AM, reflecting that students generally complete homework after class and at night. Test activity peaks at 0.62 between 10:00 AM and 12:00 PM and then gradually declines to 0.44 late at night, reflecting that teachers primarily assign tests during the day. The distribution of the three indicators across different time periods reveals that students' learning behaviors exhibit distinct circadian patterns, with nighttime homework and discussion being key drivers of overall activity.

E. COMPREHENSIVE EFFECTIVENESS EVALUATION

In teaching evaluation research, it is often necessary to statistically summarize the learning performance of grouped students to examine the differences in knowledge mastery, value identification, and learning participation among different groups. This study randomly selects 300 students from

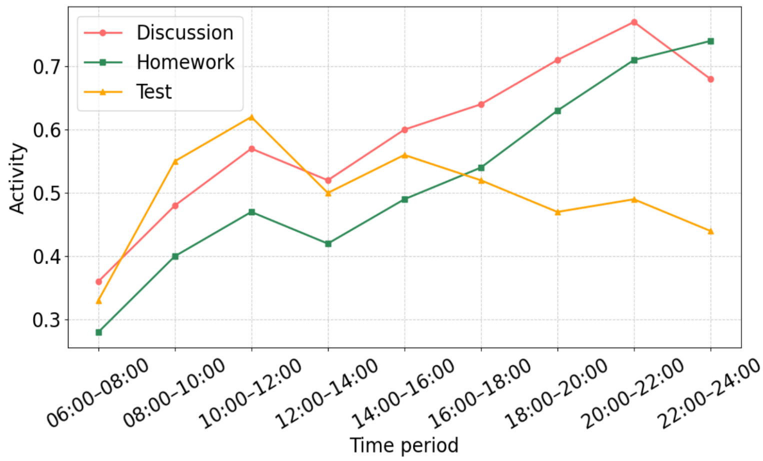

FIGURE 4. Time series line chart of learning behavior activity

all students and divides them into 10 groups of equal size. Then, the distribution characteristics of the three dimensions of knowledge mastery, ideological and political identification, and interactive activity are analyzed. The discreteness and centralization trend of each group of data are presented in the form of a box plot, providing a visual reference for the subsequent comprehensive effectiveness evaluation. Figure 5 shows the statistical distribution of the three dimensions.

During the experimental phase, participating students were organized into ten learning groups labeled G1 through G10. Each group engaged with identical instructional content and learning tasks under the same intervention conditions, allowing group-level performance distributions to be examined within each fiber category. Figure 5 visualizes these distributions using box plots, thereby illustrating both consistency and variability in learning outcomes across groups. From the results in Figure 5, the overall knowledge mastery remains at a high level. The maximum value of some groups reaches 100 points, while the minimum value of G8 is only 42.7 points, indicating that there are significant differences within them, indicating that students have hierarchical levels in learning adaptability and knowledge structure mastery. The overall fluctuation in ideological and political identification is greater than that in knowledge mastery. While G3 and G4 reach a maximum of 100 points, G6 has a minimum of 42.2 points, reflecting a weakening of value-oriented acceptance among some students. This is closely related to differences in the depth of understanding of ideological and political elements and course participation among different groups. Interactive activity varies significantly, with G2 and G8 reaching a maximum of 100 points, while G9 has a minimum of only 28.8 points. The median for some groups falls below 66 points, indicating significant divergence among students in terms of class participation and learning motivation. Overall, the results of the three indicators reveal a relatively balanced knowledge mastery, while ideological and political identification and interactive activity are more influenced by individual learning habits and value perceptions.

V. CONCLUSIONS

Based on the textile industry's focus on ethical and skilled practitioners, this study anchors the natural fiber course content in a knowledge graph, embedding craftsmanship, green development, national cultural heritage, and social responsibility as a two-layer semantic chain to enable dynamic online teaching and learning trajectory mapping. Comparative experimental results indicate that the proposed knowledge graph–driven integration model yields superior learning outcomes relative to a conventional non-graph-based instructional approach under equivalent teaching conditions. The observed advantages manifest not only in higher levels of professional knowledge mastery, but also in the structural coherence and persistence of ideological and political expression within students' learning behaviors. This comparative evidence substantiates the specific instructional contribution of the proposed model beyond general teaching effectiveness. The average student interaction activity remains at 0.82, demonstrating the comprehensive advantages of this model in strengthening professional knowledge mastery, enhancing the explicit articulation and sustained presence of value-oriented content within students' learning behaviors, and promoting active participation. The study concludes that semantic fusion based on the knowledge graph can effectively support the integrated development of structured instruction and ideological and political education in the natural fiber course, providing a feasible path for the systematic evaluation of online teaching effectiveness. However, the mastery and identification rates for hemp and wool fibers are relatively low, reflecting the need for improvement in the adaptability of complex knowledge points and implicit cultural connotations to teaching. A deeper examination of this limitation reveals that the knowledge graph–driven ideological and political embedding mechanism does not uniformly function across all content blocks. For fiber categories characterized by complex material structures and less

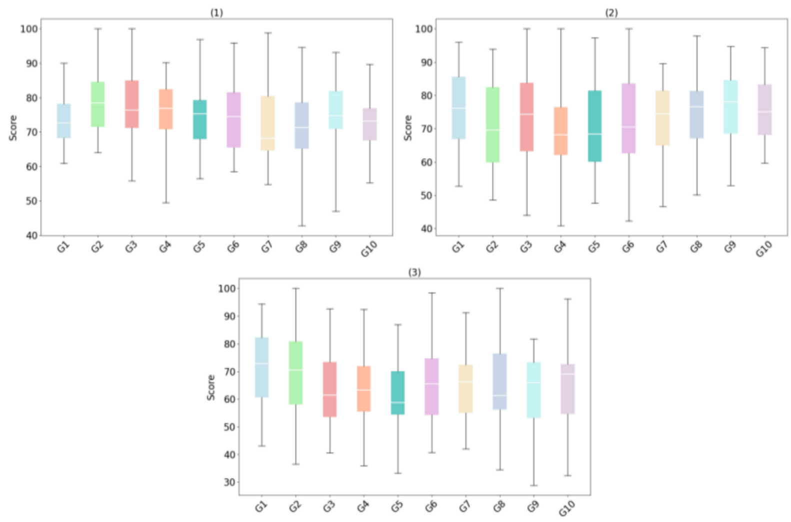

FIGURE 5. Box plot distributions of student performance across learning groups for different fiber categories. Subfigure (1) corresponds to Cotton fiber, subfigure (2) corresponds to Silk fiber, and subfigure (3) corresponds to Wool fiber

explicit cultural narratives, the current semantic embedding relies heavily on surface-level co-occurrence and predefined value mappings. This leads to insufficient activation of ideological and political nodes within the extended graph during learning path expansion, thereby weakening the system's capacity to provide consistent value guidance. In this sense, the observed lower performance for hemp and wool fibers should be interpreted as a structural boundary of the present model rather than an accidental deviation. This finding highlights that systematic support provided by knowledge graphs is conditional upon the semantic transparency and relational richness of the underlying professional knowledge domain. Future research should focus on optimizing resource delivery for weaker textile specialization areas, integrating multimodal data and cross-curricular applications to bolster the method's universality and dissemination value in textile technology education.

AUTHOR CONTRIBUTIONS

Jingyuan Sun designed, collected and analyzed the data, and drafted the manuscript. Jingyuan Sun conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jingyuan Sun participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Haikou University of Economics, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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REFERENCES

[1] J. Wood, J. Redfern, and J. Verran, "Developing textile sustainability education in the curriculum: Pedagogical approaches to material innovation in fashion," International Journal of Fashion Design. Technology and Education, vol. 16, no. 2, pp. 141-151, 2023, doi: 10.1080/17543266.2022.2131913.

[2] R. Masina, "Integration of Sustainable Development Goals in the Textile Science, Apparel Design, and Technology programs in Zimbabwean universities," Journal of Adult and Continuing Education, vol. 31, no. 1, pp. 265-284, 2025, doi: 10.1177/14779714241264972.

[3] B. Cao, "Research on the innovation of online and offline mixed teaching reform of ideological and political courses in universities in the new era," Journal of Theory and Practice of Management Science, vol. 3, no. 5, pp. 10-12, 2023, doi: 10.53469/jerp.2023.05(10).19.

[4] J. Shi, Y. Song, L. Li, T. Chen, and B. Huang, "Research on the Teaching Quality Evaluation System and Improvement Path of Ideological and Political for Online and Offline Blended Learning in Universities," International Journal of New Developments in Education, vol. 5, no. 24, pp. 64-73, 2023, doi: 10.25236/IJNDE.2023.052410.

[5] X. Wu and C. Jun, "The construction of curriculum-based ideological and political education mechanism for foreign language majors in Chinese universities," Front. Educ. Res, vol. 20, pp. 42-49, 2023.

[6] C. J. Arizmendi, M. L. Bernacki, M. Raković, R. D. Plumley, C. J. Urban, A. T. Panter, et al., "Predicting student outcomes using digital logs of learning behaviors: Review, current standards, and suggestions for future work," Behavior Research Methods, vol. 55, no. 6, pp. 3026-3054, 2023, doi: 10.3758/s13428-022-01939-9.

[7] Y. Qi, L. Zhuang, H. Chen, X. Han, and A. Liang, "Evaluation of students' learning engagement in online classes based on multimodal vision perspective," Electronics, vol. 13, no. 1, pp. 149, 2023, doi: 10.3390/electronics13010149.

[8] N. Davidovitch, A. Gerkerova, and O. Kyselyova, "Comparative Analysis of Knowledge Control and Evaluation Methods in Higher Education," Education Sciences, vol. 14, no. 5, pp. 505, 2024, doi: 10.3390/educsci14050505.
[9] F. Qi, Y. Gao, M. Wang, T. Jiang, and Z. Li, "Data mining of online teaching evaluation based on deep learning," Mathematics, vol. 12, no. 17, pp. 2692, 2024, doi: 10.3390/math12172692.
[10] W. Yizhou, "The construction of ideological and political education in curriculum under the background of new liberal arts: Significance, concept, and practical path," Journal of Sociology and Education, vol. 1, no. 1, pp. 36-43, 2025.
[11] H. Vo and H. Ho, "Online learning environment and student engagement: The mediating role of expectancy and task value beliefs," The Australian Educational Researcher, vol. 51, no. 5, pp. 2183-2207, 2024, doi: 10.1007/s13384-024-00689-1.
[12] S. N. Kew and Z. Tasir, "Learning analytics in online learning environment: A systematic review on the focuses and the types of student-related analytics data," Technology, Knowledge and Learning, vol. 27, no. 2, pp. 405-427, 2022, doi: 10.1007/s10758-021-09541-2.
[13] K. C. Li, B. T. M. Wong, R. Kwan, and H. Chan, "Evaluation of hybrid learning and teaching practices: The perspective of academics," Sustainability, vol. 15, no. 8, pp. 6780, 2023, doi: 10.3390/su15086780.
[14] M. Li, Z. Ni, L. Tian, Y. Hu, J. Shen, and Y. Wang, "Research on hierarchical knowledge graphs of data, information, and knowledge based on multiple data sources," Applied Sciences, vol. 13, no. 8, pp. 4783, 2023, doi: 10.3390/app13084783.
[15] K. Qu, K. C. Li, B. T. M. Wong, M. M. F. Wu, and M. Liu, "A survey of knowledge graph approaches and applications in education," Electronics, vol. 13, no. 13, pp. 2537, 2024, doi: 10.3390/electronics13132537.
[16] Y. Yang, S. Chen, Y. Zhu, H. Zhu, and Z. Chen, "Knowledge graph empowerment from knowledge learning to graduation requirements achievement," Plos One, vol. 18, no. 10, Art. no. e0292903, 2023, doi: 10.1371/journal.pone.0292903.
[17] G. Tamašauskaitė and P. Groth, "Defining a knowledge graph development process through a systematic review," ACM Transactions on Software Engineering and Methodology, vol. 32, no. 1, pp. 1-40, 2023, doi: 10.1145/3522586.
[18] S. Chen, Y. Ma, and W. Lian, "Fostering idealogical and polical education via knowledge graph and KNN model: An emphasis on positive psychology," BMC Psychology, vol. 12, no. 1, pp. 170, 2024, doi: 10.1186/s40359-024-01654-4.
[19] Q. Deng, C. Zhang, W. Yu, and X. Wang, "A teaching method of ideological and political education in colleges and universities based on knowledge graph," Advances in Educational Technology and Psychology, vol. 7, no. 6, pp. 15-19, 2023, doi: 10.23977/aetp.2023.070603.
[20] Z. Huang, R. Tian, and G. Fu, "Mining and Teaching Practice of Ideological and Political Course Elements Based on Text Extraction and Knowledge Graph," Journal of Combinatorial Mathematics and Combinatorial Computing, vol. 119, pp. 95-104, 2024, doi: 10.61091/jcmcc119-10.
[21] W. Wei, X. Zhang, W. Fang, J. Li, L. Zhang, P. Yu, et al., "A Preliminary Study on Integration of Ideological and Political into Course Data Mining," Frontiers in Educational Research, vol. 5, no. 19, pp. 38-41, 2022, doi: 10.25236/FER.2022.051908.
[22] L. Tian, "Research on Intelligent Organization and Management Method of Civic and Political Education Content Based on Knowledge Map," J. COMBIN. MATH. COMBIN. COMPUT, vol. 127, pp. 3479-3492, 2025, doi: 10.61091/jcmcc127b-194.
[23] B. Abu-Salih and S. Alotaibi, "A systematic literature review of knowledge graph construction and application in education," Heliyon, vol. 10, no. 3, Art. no. e25383, 2024, doi: 10.1016/j.heliyon.2024.e25383.
[24] X. Huang and W. Liu, "Exploring Approaches to Integrate Ideological and Political Education within Public Management Courses," Journal of Learning and Development Studies, vol. 4, no. 3, pp. 84-91, 2024, doi: 10.32996/jlds.2024.4.3.11.
[25] Y. Zeng, C. Zhao, and X. Qie, "Integrating Ideological-Political Education into Academic Foreign Language Teaching: Notion, Principles and Framework," Mediterranean Archaeology & Archaeometry, vol. 25, no. 1, pp. 302, 2025.
[26] T. P. Nichols and A. Garcia, "Platform studies in education," Harvard Educational Review, vol. 92, no. 2, pp. 209-230, 2022, doi: 10.17763/1943-5045-92.2.209.
[27] H. Yang, "E-learning platforms in ideological and political education at universities: Students' motivation and learning performance," BMC Medical Education, vol. 24, no. 1, pp. 628, 2024, doi: 10.1186/s12909-024-05572-2.
[28] D. Ma, H. Zhu, S. Liao, Y. Chen, J. Liu, F. Tian, et al., "Learning path recommendation with multi-behavior user modeling and cascading deep Q networks," Knowledge-Based Systems, vol. 294, Art. no. 111743, 2024, doi: 10.1016/j.knosys.2024.111743.
[29] N. S. Raj and V. G. Renumol, "An improved adaptive learning path recommendation model driven by real-time learning analytics," Journal of Computers in Education, vol. 11, no. 1, pp. 121-148, 2024, doi: 10.1007/s40692-022-00250-y.
[30] M. Dorier, A. Gueroudji, V. Hayot-Sasson, H. D. Nguyen, S. Ockerman, R. Souza, et al., "Toward a persistent event-streaming system for high-performance computing applications," Frontiers in High Performance Computing, vol. 3, Art. no. 1638203, 2025, doi: 10.3389/fhpcp.2025.1638203.
[31] M. Fragkoulis, P. Carbone, V. Kalavri, and A. Katsifodimos, "A survey on the evolution of stream processing systems," The VLDB Journal, vol. 33, no. 2, pp. 507-541, 2024, doi: 10.1007/s00778-023-00819-8.
[32] Z. Shou, Y. Li, D. Li, J. Mo, and H. Zhang, "Research on Knowledge Tracing-Based Classroom Network Characteristic Learning Engagement and Temporal-Spatial Feature Fusion," Electronics, vol. 13, no. 8, pp. 1454, 2024, doi: 10.3390/electronics13081454.
[33] J. Pan, Z. Dong, L. Yan, and X. Cai, "Knowledge graph and personalized answer sequences for programming knowledge tracing," Applied Sciences, vol. 14, no. 17, pp. 7952, 2024, doi: 10.3390/app14177952.
[34] X. Li, Y. Dong, Y. Jiang, and G. Ogunmola, "Analysis of the teaching quality of college ideological and political education based on deep learning," Journal of Interconnection Networks, vol. 22, no. Supp02, Art. no. 2143002, 2022, doi: 10.1142/S0219265921430027.
[35] G. Yun, R. V. Ravi, and A. K. Jumani, "Analysis of the teaching quality on deep learning-based innovative ideological political education platform," Progress in Artificial Intelligence, vol. 12, no. 2, pp. 175-186, 2023, doi: 10.1007/s13748-021-00272-0.