Research on Personalized Management of Student Cadres in Private Universities Based on Knowledge Graphs

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Abstract. Traditional student cadre management faces prominent issues such as data silos, subjective evaluation, homogenized training, and low person-post matching, making it difficult to adapt to the digital era and the demands of students' personalized development. This study aims to introduce knowledge graphs, a cutting-edge artificial intelligence technology, to construct an integrated and intelligent personalized management model for student cadres. This research provides a new theoretical perspective for the application of knowledge graphs in educational management and offers a forward-looking, operable solution for the digital transformation of student affairs in private universities.

Keywords: Knowledge Graph; Student Cadre Management; Personalized Cultivation; Intelligentization

1 Introduction

University student cadres play crucial roles in student self-management, self-service, and self-education, serving as a bridge and bond between the university and its students[1]. Their comprehensive qualities, capability structures, and development status directly affect the quality of campus culture, the efficiency of student affairs management, and the overall effectiveness of talent cultivation. However, examining the current practical state of student cadre management in private universities reveals a continued reliance on experience-driven, extensive traditional models, facing numerous pressing challenges.

2 The Specificity, Current Situation, and Challenges of Student Cadre Management in Private Universities

2.1 Single Data Dimension, Manifesting as Fragmentation and Siloing

Information related to student cadres (e.g., academic performance, personality traits, skill certifications, social practice, records of rewards and punishments, interpersonal

C. F. Peng et al. (eds.), *Proceedings of the 2026 5th International Conference on Humanities, Wisdom Education and Service Management (HWESM 2026)*, Advances in Social Science, Education and Humanities Research 1024,
https://doi.org/10.2991/978-2-38476-593-5_44

relationships) is typically scattered across multiple independent information platforms such as academic affairs, student affairs, the Youth League Committee, and psychological counseling centers. These systems have inconsistent data standards and are isolated from each other, forming severe "data silos." This prevents the effective aggregation of information to form a complete, multi-dimensional panoramic view of student cadres, leaving management decisions lacking comprehensive and objective data support.

2.2 Lagging Evaluation Mechanism, Prominent Subjectivity and One-sidedness

Current evaluation systems largely rely on subjective methods such as qualitative assessments by counselors and Youth League Committee secretaries, end-of-term defense reports, and democratic peer reviews. These methods struggle to quantitatively evaluate intrinsic qualities like organizational coordination, innovative thinking, stress tolerance, and sense of service. They are susceptible to interference from subjective factors like the "primacy effect" and "halo effect," leading to low reliability and validity of evaluation results, thus failing to accurately reflect the contributions, growth, and development potential of student cadres.

2.3 Homogenized Training Model, Neglecting Personalization and Differences

Training content and methods often adopt a one-size-fits-all approach, lacking precise identification and diagnosis of individual capabilities, interests, career plans, and areas for improvement. This "uniform" training model struggles to meet the diverse and personalized growth needs of student cadres, constraining the full realization of their strengths and effective improvement of their weaknesses, thereby reducing the targeting and effectiveness of training efforts.

2.4 Inaccurate Selection and Allocation, Person-Post Matching Needs Improvement

In cadre selection, team formation, and task assignment, decisions often rely on limited experiential judgment and superficial impressions, lacking a scientific competency model and job requirement model for precise matching. This can easily lead to an imbalance where the capable are overworked while others are underutilized, or a structural mismatch where the person does not fit the post. This not only affects organizational operational efficiency but also dampens the enthusiasm of some students.

3 The Connotation and Compatibility of Knowledge Graphs and Personalized Student Cadre Management

With the development of digital intelligence technologies, the emergence of intelligent agents and their educational applications offer possibilities to overcome the persistent challenges of personalized instruction in traditional digital technologies[2]. Among these, knowledge graphs, as the latest technology in the development of knowledge visualization within artificial intelligence, consist of a series of knowledge elements. Each knowledge element includes not only knowledge content but also related learning resources, activities, etc. Their fine-grained structure can meet students' personalized needs[3]. Introducing this technology into the vertical domain of student cadre management, by constructing a knowledge graph specific to this field, enables deep integration and semantic association of multi-source heterogeneous data, thereby forming dynamic, multi-dimensional, and computable individual and group "digital portraits." Based on this, management decisions can be driven to shift from "experience-driven" to "data-driven" and "intelligence-driven" paradigms, ultimately achieving personalized management throughout the entire lifecycle of student cadres—"selection, cultivation, management, and evaluation"—improving management efficiency and promoting their comprehensive development.

3.1 Knowledge Graph Technology and Its Applications

A knowledge graph is a technology that uses graph structures to model and represent knowledge. It is a knowledge base that connects entities, concepts, attributes, etc., through relationships, representing entities (concepts, people, things) and their interrelations in the objective world in the form of a graph[4]. Its basic unit is the "entity-relationship-entity" triple, forming a vast semantic association network through nodes (entities) and edges (relationships). Its construction typically involves two main steps: Schema Layer design (defining ontologies and rules) and Data Layer population.

This new intelligent technology, characterized by richer semantic relationships, stronger reasoning capabilities, and more intuitive visualization, can empower personalized learning research. However, research on personalized learning based on knowledge graphs is still in its infancy, primarily focusing on knowledge graph construction and learning path recommendation methods, and is often used as a diagnostic educational method[5]. Applications in the education field have gradually emerged in recent years, such as constructing subject knowledge graphs for adaptive learning and building academic resource graphs for researcher recommendations. However, the specific application of knowledge graphs to student management, particularly the refined governance of the student cadre subgroup, remains an underexplored research frontier with significant innovative potential.

3.2 Student Cadre Management Theory and the Concept of Personalization

Traditional student cadre management theories focus on applying organizational behavior and leadership theories, emphasizing institutional construction, functional division, and macro-level incentives. Many student cadres have an unclear understanding of their own abilities and underestimate difficulties, which can easily lead to tasks not being completed as desired or on schedule, thereby affecting their own work enthusiasm[6]. UNESCO included the "student-centered" educational philosophy in the *World

Declaration on Higher Education for the Twenty-First Century: Vision and Action*. With the deepening of the "student-centered" concept, "student-centered" student affairs management in universities is gradually moving into practice [7]. Personalized management theory posits that management is not simply about control and constraint, but about identifying, motivating, and empowering each unique individual. It requires managers to deeply understand an individual's capability structure, motivation sources, learning styles, and development aspirations, and to provide differentiated resource support, task challenges, and growth paths. Combining knowledge graph technology with this provides the technical feasibility to realize this concept. The Student Cadre Knowledge Graph (SCKG) acts as a "digital twin" middleware connecting macro-level management objectives with micro-level individual characteristics, making abstract principles like "teaching according to aptitude" and "matching person to post" computable and operable.

4 Construction Model of the Student Cadre Knowledge Graph (SCKG)

4.1 Overall Architecture Design

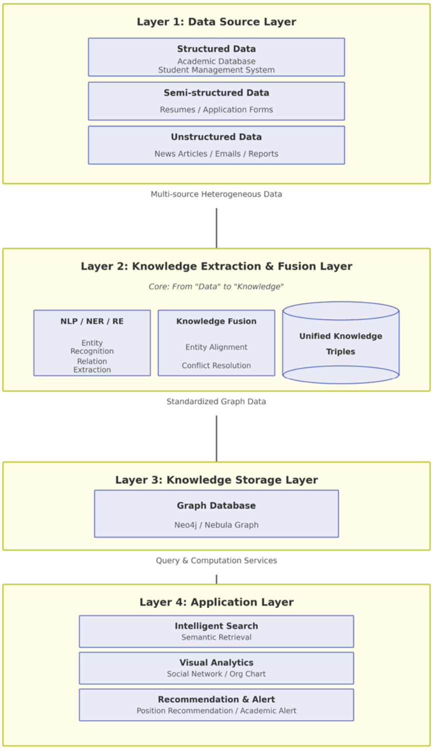

Fig. 1. Overall Architecture Design

The SCKG construction adopts a combination of top-down (defining ontologies) and bottom-up (extracting data) approaches. Its overall architecture can be divided into four layers (see Figure 1).

4.2 Ontology Design

The ontology is the schema of the SCKG, defining the concepts, attributes, and relationship types within it, serving as its semantic cornerstone. The design of the SCKG's core ontology is divided into Core Entity Classes (Table 1) and Core Relationship Classes (Table 2).

Table 1. Core Entity Classes

Entity Class	Description	Key Attributes
Student Cadre	Core entity of the knowledge graph	Student ID, Name, Grade, Major
Organization	Organization the student belongs to	Name, Type, Function Description
Position	Position held by the student	Position Name, Responsibility Requirements, Capability Requirements
Activity	Activities participated in by the student	Activity Name, Time, Scale, Content
Skill	Skills mastered by the student	Skill Name, Proficiency Level
Course Grade	Student's course performance	Course Name, Score, Type
Award/Disciplinary Record	Rewards or disciplinary actions received by the student	Award Name, Level, Time

Table 2. Core Relationship Classes

Relationship Type	Relationship Direction	Description	Optional Attributes
Holds a Position	Student—Position	Student holds a certain position	Start time, End time
Belongs to	Student/Position—Organization	Student or position belongs to an organization	—
Participates in	Student—Activity	Student participates in an activity	Role (organizer/participant), Performance evaluation
Has Skill	Student—Skill	Student masters a certain skill	Proficiency level, Certification source
Excels at	Student—Course	Student excels in a certain course	—
Received	Student—Award	Student receives a certain award	—
Collaborates with	Student—Student	Collaborative relationship between students	Relationship strength, Collaboration count, Collaboration time

4.3 Knowledge Extraction, Fusion, and Storage

Knowledge Extraction: For structured data, direct mapping via ETL tools is used. For unstructured text (e.g., work summaries), an NLP pipeline is employed: first, text preprocessing, then using NER models to identify entities such as person names, organization names, and activity names, followed by relation classification models to determine relationships between entities, finally extracting triples.

Knowledge Fusion: Addresses issues like synonymy (two students with the same name) and polysemy (e.g., "Student Union" and "Student Council" referring to the same organization). By calculating the similarity of entity attributes and conducting manual verification, different representations pointing to the same entity are merged.

Knowledge Storage: The cleaned and fused triples are stored in a graph database. Graph databases support efficient associative queries (e.g., "find all second-year students proficient in 'copywriting' who have participated in organizing the 'welcome event'"), which traditional relational databases struggle to handle effectively.

5 Application Scenarios of SCKG in Personalized Management

The ultimate value of constructing SCKG lies in its application. Four core application scenarios are detailed below.

5.1 Scenario 1: Precise Selection and Recommendation

Application Mechanism: When a position (e.g., "Publicity Department Head") becomes vacant, the system can perform intelligent matching and searching within the SCKG based on the competency requirement model for that position (defined in the Position entity, e.g., requiring skills like "photography and videography," "press release editing," "team management").

Implementation Path:

(1) The system parses the job requirements, transforming them into one or more skill nodes/relationship query conditions.

(2) A graph traversal algorithm is executed in the graph database to find candidates who simultaneously meet these skill criteria and have supporting activity experience and award records.

(3) The system not only returns a list of matches but also generates a personalized recommendation report for each candidate, visually displaying their capability radar chart and the degree of fit with the job requirements, providing an evidence chain (e.g., "This student possesses 'photography and videography' skills, evidenced by winning second prize in a certain 'Photography Contest'").

Value: Transforms "talent identification" into "talent competition," achieves precise person-post matching, and improves selection efficiency and credibility.

5.2 Scenario 2: Personalized Cultivation and Empowerment

Application Mechanism: Generates a dynamic "capability profile" for each student cadre based on the SCKG, identifying their "strengths" and "areas for improvement," thereby recommending personalized learning resources and development opportunities.

Implementation Path:

(1) Profile Generation: The system aggregates all relevant nodes related to a student, such as skills, courses, and activity performance, using weighted calculations to form their multi-dimensional capability profile.

(2) Gap Analysis: Compares their capability profile with the requirements of their current position or their personal development goals, automatically identifying competency gaps (e.g., a certain vice-chairperson is weak in "financial budgeting").

(3) Intelligent Empowerment: The system automatically recommends relevant resources, such as online courses (How to Create a Project Budget*), internal training workshops, recommends a mentor (another student strong in financial ability), or suggests participating in the next activity project requiring budget preparation.

Value: Achieves precise, "one-policy-per-person" empowerment, transforming "passive participation" into "active growth," significantly enhancing training effectiveness.

5.3 Scenario 3: Comprehensive Evaluation and Feedback

Application Mechanism: Shifts from a single subjective evaluation to constructing a multi-dimensional comprehensive evaluation model that integrates objective behavioral data (relationships and attributes in the graph) and subjective assessments.

Implementation Path:

(1) Data Quantification: Converts relationships in the graph into calculable indicators. For example, the frequency and role of `participatesIn` relationships reflect "proactiveness" and "leadership"; the breadth and intensity of `collaboratesWith` relationships reflect "interpersonal collaboration" ability.

(2) Model Construction: Establishes an evaluation indicator system, assigning weights to different indicators (e.g., task completion rate 40%, peer collaboration evaluation 30%, innovation performance 30%).

(3) Dynamic Report: The system periodically (e.g., each semester) automatically generates a personalized development report, using charts to display the student's growth trajectory, capability changes, contribution hotspots during their tenure, and providing data-driven improvement suggestions (e.g., "You led few independent projects this semester; it is recommended you proactively apply for a project leader role next semester").

Value: Evaluation results are more comprehensive, objective, and persuasive, and can be translated into specific, actionable growth guidance.

5.4 Scenario 4: Optimal Team Formation and Configuration

Application Mechanism: When forming a new project team, the system can recommend the optimal team composition with complementary capabilities, personalities, and experiences based on project goals.

Implementation Path:

(1) The manager inputs project requirements (e.g., need for four roles: "planning," "personnel," "aesthetics," "copywriting").

(2) The system first screens a candidate pool possessing the corresponding skills.

(3) Using graph algorithms (e.g., community discovery, influence analysis) and optimization models, it considers the historical collaboration rapport among members (`collaboratesWith` relationship strength), avoids combining members with a history of conflict, and ultimately recommends several optimal or suboptimal team configuration solutions.

Value: Enhances overall team effectiveness and collaboration smoothness, achieving a "1+1>2" effect.

6 Challenges, Prospects, and Conclusion

6.1 Practical Challenges and Countermeasures

Data Privacy and Security: Student data is highly sensitive. The "principle of minimum necessity" must be followed for data collection, strict hierarchical data access controls implemented, and data anonymized and desensitized. All operations must comply with laws and regulations such as the Cybersecurity Law and the Personal Information Protection Law.

Algorithm Fairness and Ethics: Vigilance is needed against algorithmic bias. For example, if historical data shows more males in leadership positions, the model might develop gender bias. Algorithmic fairness needs regular auditing, debiasing techniques should be employed, and channels for manual review and intervention must be preserved.

Technical Implementation Hurdles: Building and maintaining SCKG requires expertise in NLP, graph databases, etc. A countermeasure is to collaborate with university information technology centers and computer science departments for development, or to adopt mature commercial middleware products.

Data Quality and Continuous Updates: Initial data quality may be low, and the graph needs continuous updating. A long-term data governance mechanism needs establishment, convenient data entry and update interfaces designed, and students could be encouraged to maintain some personal information through mechanisms like point incentives.

6.2 Future Prospect

Future research can delve into the following directions:

Integration with Generative AI (AIGC). Combine with Large Language Models (LLM) to create a more intelligent "digital mentor" assistant. For example, student cadres could ask directly in natural language: "System, based on my situation, how should I develop next?" The LLM would call upon the SCKG data to generate fluent, personalized advice reports.

Dynamic Prediction and Early Warning. Utilize temporal graph neural networks to analyze trends in student cadre behavior changes, predict potential risks such as "burnout," "intention to leave," or "psychological stress" in advance, and issue warnings to supervising instructors for proactive intervention.

Cross-Institutional Knowledge Graph Interconnection. Explore establishing inter-university alliances to conduct anonymized data comparisons and analyses, providing support for macro-level educational decision-making, while ensuring privacy.

7 Conclusion

This study systematically proposes a personalized management framework for student cadres based on knowledge graphs. The research indicates that knowledge graph technology can effectively address the core pain points in current student cadre management, such as data fragmentation, subjective evaluation, and homogenized training. It provides powerful technical support for achieving the transformation from "one-size-fits-all" to "personalized" management. By constructing the SCKG and applying it to core scenarios like selection, cultivation, evaluation, and team configuration, the scientific nature, precision, and foresight of management decisions can be significantly enhanced. This not only helps optimize the operational efficiency of student organizations but also empowers the comprehensive development of individual student cadres. Although challenges such as data security and algorithm ethics exist, with the continuous maturation of technology and refinement of governance systems, intelligent management based on knowledge graphs is poised to become a new trend in the future development of university student affairs, contributing significantly to fulfilling the fundamental task of "fostering virtue through education."

Acknowledgments

Fund Project: Xi’an Eurasia University key project “Design and Application of a Personalized Learning Recommendation Platform Based on Knowledge Graphs” (Project No.: 2025ZD010)

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