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RESEARCH ARTICLE

Student Portraits and Their Applications in Personalized Learning: Theoretical Foundations and Practical Exploration

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Abstract As a data-driven analysis and decision-making tool, student portraits have gained significant attention in education management and personalized instruction. This research systematically explores the construction process of student portraits by integrating knowledge graph technology with advanced data analytics, including clustering, predictive modelling, and natural language processing. It then examines the portraits' applications in personalized learning, such as student-centric adaptation of content and paths, and personalized teaching, especially the educator-driven instructional adjustments. Through case studies and quantitative analysis of multimodal datasets, including structured academic records, unstructured behavioural logs, and socio-emotional assessments, the research demonstrates how student portraits enable academic early warnings, adaptive learning path design, and equitable resource allocation. The findings provide actionable insights and technical frameworks for implementing precision education.

Keywords student portraits, personalized teaching and learning, knowledge graph, learning analytics, academic risk prediction

1 Introduction

The wave of global digitalization and intelligent transformation has positioned education innovation as a cornerstone of national competitiveness. In China's pursuit of a modern socialist society, the triad of education, technology, and talent development forms an interdependent ecosystem that requires dynamic alignment with evolving industrial demands. Student portrait modelling has emerged as a critical driver in this context and offered data-driven insights to bridge educational practices with personalized learning needs.

Recent advances in educational technology have demonstrated both optimizations and limitations. Shoaib et al. (2024) developed an AI-based prediction system using a convolutional neural network–support vector machine hybrid. However, they restricted their analysis to structured academic metrics. Meanwhile, Zheng et al. (2023) enhanced course recommendations through evolutionary deep belief network (DBN) optimization. The DBN model's generalizability remained constrained by limited dataset diversity (Zheng et al., 2023). Static characterization persists in massive open online course-based studies despite attempts to incorporate multimodal fusion into behavioural monitoring (Li, 2022; Wang et al., 2022; Yu et al., 2020). Three critical limitations inhibit research progress, including overreliance on single-modal data sources, inflexible static modelling frameworks, and superficial behavioural metrics lacking temporal depth.

To address these limitations, a dynamic student portrait framework has been proposed in this research, integrating three key innovations: first, a multimodal fusion architecture combining academic, behavioural, and affective data streams; second, adaptive updating mechanisms through lightweight long short-term

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memory (LSTM) networks and real-time processing; third, deep behavioural analytics employing social network metrics and causal pattern mining. This framework advances beyond frequency-based metrics to enable responsive and resource-efficient educational interventions aligned with modern pedagogical requirements.

2 Policy Evolution in Educational Digitalization

The core task of education is about cultivating talent. Educational digitalization is critical in bridging the gap between talent supplies and industry demands in the digital age. The systems and mechanisms have been reformed and integrated education, science, research, and talent effectively. The systems and mechanisms create a stronger synergistic effect between research and teaching and foster closer collaboration between universities and businesses through industry–education partnerships. Addressing bottlenecks in the education, science, research, and talent cycle is essential and enables seamless collaboration. This kind of collaboration drives high-quality education, cultivates talents, promotes innovation, and ensures that all elements work together smoothly and effectively. In recent years, the Chinese government and related ministries have introduced policies to address the evolving needs of talent development in the digital and intelligent era. These policies prioritize educational digitalization as a key strategy and outline initiatives that harness new digital technologies seamlessly to connect education, talent, innovation, and industrial chains, as shown in Table 1. By focusing on these critical areas, these policies aim to create a balanced and forward-looking way to cultivate talent in an increasingly digital world.

Government policies emphasize the need for universities to transform their talent cultivation models through digitalization, intelligent technologies, and practical applications, focusing on interdisciplinary, technology-integrated, and skill-driven education to develop versatile, application-oriented, and innovative talent that aligns with market demands. This transformation requires integrating digital and intelligent knowledge systems into curricula to foster interdisciplinary thinking, enabling students to bridge disciplines, leverage “Big Data +” and AI, and solve complex problems collaboratively. Moreover, universities are expected to blend diverse resources which incorporate foundational interdisciplinary education, research fostering technological innovation, and industry–education collaboration. By adopting a “Big Data +” approach, universities can implement personalized talent cultivation models through comprehensive student portraits, improve education quality, optimize resource allocation, and analyze data across teaching, research, student life, and employment systematically to provide real-time insights. The integration can be used to balance talent supply and demand and ensure alignment with workforce needs.

3 Theoretical Framework for Student Portraits

3.1 | Theoretical Framework

Student portraits, a central concept in educational data mining and learning analytics, are theoretically rooted at the intersection of user profiling and learner modelling. The concept of user personas, first introduced by Cooper (2004), was applied widely in the commercial sector to describe and categorize user behavioural characteristics. In the educational context, this concept has been redefined to capture and analyze the multidimensional attributes of students within the learning process and provide data-driven support for personalized instruction and precision education (Gašević & Siemens, 2015; Siemens, 2013).

Existing research has predominantly focused on explicit features, such as academic performance, classroom behaviour, and learning motivation, resulting in the construction of largely superficial student portraits. These models often lack an in-depth exploration of implicit dimensions, including cognitive development, emotional states, and social interactions (Holmes et al., 2020). For instance, Baker et al. (2016) highlighted that, despite the widespread application of learning analytics in tracking students’ academic progress, the analysis of students’ emotional and social dynamics remains in its infancy.

From a social interaction perspective, students’ academic performance is not determined by individual effort solely. Moreover, interaction patterns within social networks also play a crucial role in influencing learning outcomes. How individuals interact within a group can affect knowledge acquisition and integration. Constructing interaction networks within learning communities can reveal the relational structures among students, peers, and teachers. The interaction networks allow a better understanding of how the learning environment impacts academic performance through social support, collaboration, and competition. The frequency, quality, and positioning of interactions among students within these networks reflect the roles learners assume within the group and their potential influence on academic success (Dawson, 2008).

Furthermore, applying knowledge graph

Table 1 Digital education policies in China

Published year	Issuing authority	Policy	Main content
2023	Ministry of Education (MOE) of the People's Republic of China (PRC), National Development and Reform Commission (NDRC) of the PRC, Ministry of Finance of the PRC	*Opinions on implementing the action plan for expanding and improving basic education in the new era*	Specifying the implementation of 8 major actions, such as the digitalization strategy action to empower high-quality development (MOE of the PRC et al., 2023)
2023	State Council of the PRC	*Overall layout plan for the construction of digital China*	Promoting inclusive digital public services, implementing the national education digitalization strategic action, improving the national smart education platform, advancing digital health, and regulating the development of Internet-based healthcare and Internet hospitals (State Council of the PRC, 2023)
2022	NDRC of the PRC	*Accelerating the development of a complete domestic demand system*	Accelerating the construction of Internet-based education, enhancing the "Internet + education" platform, and improving the supply capacity of educational resources and services (NDRC of the PRC, 2022)
2022	General Office of the Central Committee of the Communist Party of China and the General Office of the State Council	*Opinions on strengthening the construction of high-skill talent teams in the new era*	Focusing on building a digital China, enhancing digital literacy and skills, establishing pilot zones for digital skills training, building training bases, sharing digital education resources, and hosting activities to improve digital literacy (General Office of the Central Committee of the Communist Party of China & General Office of the State Council, 2022)
2022	Ministry of Civil Affairs of the PRC	*Strengthening the construction of digital government*	Establishing a unified and updating civil affairs governance data directory dynamically and enhancing data sharing across departments, such as public security, education, healthcare, and finance through the national e-government platform (Ministry of Civil Affairs of the PRC, 2022)
2022	Ministry of Science and Technology of the PRC, MOE of the PRC, Ministry of Industry and Information Technology of the PRC, Ministry of Transport of the PRC, Ministry of Agriculture and Rural Affairs of the PRC, and National Health Commission of the PRC	*The guiding opinions on accelerating scenario innovation to promote high-quality economic development with high-level application of AI*	Exploring applications in education, such as online and virtual classrooms, virtual training, research laboratories, new teaching materials, smart campus, and educational resource construction (Ministry of Science and Technology of the PRC et al., 2022)
2021	MOE of the PRC, Office of the Central Cyberspace Affairs Commission, NDRC of the PRC, Ministry of Industry, and Information Technology of the PRC	*The guiding opinions on constructing new educational infrastructure and a high-quality education support system*	Enhancing digital resource supply chain management, such as blockchain for intellectual property protection and AI for content review; supporting iterative updates of digital resources based on user feedback and third-party evaluations (MOE of the PRC et al., 2021)
2021	Ministry of Industry and Information Technology of the PRC, Office of the Central Cyberspace Affairs Commission, and NDRC of the PRC	*"Set sailing" action plan for 5G applications (2021–2023)*	Promoting 5G technology in education, including smart classrooms, holographic teaching, campus security, and digital education management; developing technical standards for online education; improving the informatization of teaching, research, and services (Ministry of Industry and Information Technology of the PRC et al., 2021)
2019	NDRC of the PRC, MOE of the PRC, Ministry of Industry and Information Technology of the PRC, Ministry of Finance of the PRC, Ministry of Human Resources and Social Security of the PRC, and State-Owned Assets Supervision, and Administration Commission of the State Council	*National pilot program for industry–education integration*	Deepening industry–education integration and promoting the seamless connection of education, talent, industry, and innovation chains (NDRC of the PRC et al., 2019)

technologies provides a more structured cognitive framework for constructing student portraits. Rooted in the theory of semantic networks, knowledge graphs establish semantic connections among students' behaviours, subject contents, and learning tasks, thereby unveiling how students acquire, integrate, and apply knowledge. This theoretical framework emphasizes the multidimensionality of student learning and extends beyond academic performance to focus on knowledge transfer and cognitive patterns across different subjects and contexts. Inference models are applied to understand students' performance and behaviours in identifying learning bottlenecks and strengths in activities (Shi et al., 2022). This framework integrates students' learning behaviours and contents organically and enables the dynamic tracking of students' knowledge construction and behavioural development.

Affective computing and natural language processing (NLP), grounded in psychological and emotional research, recognize the profound impact of students' emotional states on their learning outcomes. Students experience anxiety, confusion, and excitement in the learning process. These emotions influence their cognitive abilities, learning motivation, and information-processing capacities (Calvo & D'Mello, 2010). NLP analyzes the text's emotional content and helps educators track students' emotional states accurately by combining emotional analysis with students' linguistic expressions, such as assignments and classroom discussions. This allows for the timely detection of psychological stress, emotional difficulties, and mood fluctuations, which enables to implementation of appropriate interventions.

Building on these theoretical frameworks, this research proposes a dynamic and multidimensional framework for student portraits. This framework integrates knowledge graphs, machine learning, and real-time data analysis techniques. Moreover, it extends beyond academic performance to delve into students' cognitive abilities, emotional states, and social behaviours. By leveraging this framework, educators can access real-time and personalized data to design adaptive learning pathways, which fosters both educational equity and holistic student development. Furthermore, this framework signifies a shift in student portrait research from static description to dynamic prediction and personalized intervention. It offers both theoretical support and practical pathways for modern educational practices (Viberg et al., 2018). These advancements, however, necessitate corresponding technological innovations to overcome implementation barriers in real-world educational settings.

3.2 | Technological Innovation Framework

Although previous studies have made notable strides in the construction of student portraits, certain challenges persist. One area for improvement is data diversity, as many approaches tend to rely primarily on academic performance, often overlooking the potential insights offered by multimodal data sources, including behavioural logs, physiological signals, and emotional states (Siemens & Baker, 2012). For example, Hung et al. (2020) predominantly emphasized exam results and potentially missed out on a more holistic view of student's engagement in online platforms. Another improvement is the development of dynamic updating mechanisms. Many models tend to operate with fixed representations, which may not fully accommodate the evolving nature of student learning over time. A case in point is the model proposed by Chen et al. (2021), which, while useful, may not fully capture shifts in students' learning patterns across the semester.

In addition, the complexity of some models presents challenges for practical implementation. Deep learning architectures, such as the 12-layer neural network used by Lin et al. (2024), while sophisticated, often entail significant computational demands that may not justify the incremental improvements in accuracy. Moreover, a tendency toward shallow behavioural analysis persists, with many models focusing on simple frequency-based metrics, such as login times, rather than delving into more intricate temporal patterns and uncovering causal relationships (Baker et al., 2016).

To address these challenges, this research makes three distinctive contributions that advance the field of student portrait construction and its applications in personalized learning: first, a multimodal framework that integrates academic records, behavioural logs, and socio-emotional assessments, resolving single-modality limitations in existing profiling approaches; second, a synergistic architecture combining real-time adaptive engines, such as Apache Kafka and LSTM networks, with lightweight knowledge graph reasoning, enabling dynamic temporal updates while maintaining computational efficiency for scalable deployment; third, social network analysis (SNA) and affective computing techniques that decode causal–temporal interaction patterns and emotional dynamics, and transcend conventional frequency-based behavioural metrics. These advancements establish an adaptive technical infrastructure for precision education and bridge theoretical frameworks with empirical implementation challenges in personalized learning ecosystems. These advancing practices address the limitations of previous studies, provide a robust technical and theoretical foundation for precision education, and enable adaptive interventions, equitable resource allocation, and the cultivation of interdisciplinary talent in alignment with modern educational demands.

3.3 | Core Dimensions of Portraits

While the current construction of student portraits mainly focuses on academic performance and learning behaviours (Li & He, 2021; Pang et al., 2020), there are certain deficiencies in mental health, social behaviours, dynamics, multimodal data fusion, and individual difference adaptation. This research divides the core dimensions of student portraits into the six areas shown in Figure 1, including academic performance, social behaviour and interactive patterns, learning behaviour and engagement, learning interest and motivation, mental health and emotional states, and background and socio-economic status. These core dimensions aim to provide more comprehensive data support for educational decision-making.

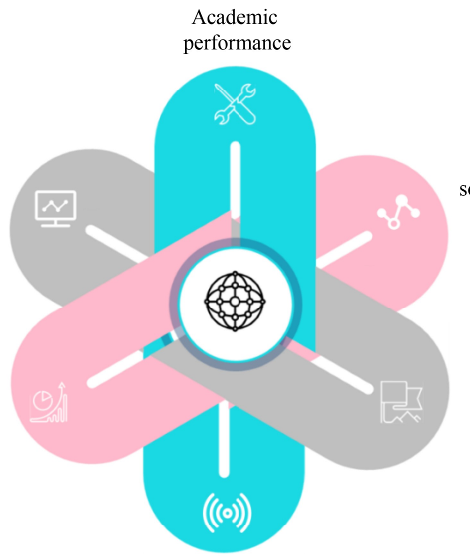

Figure 1 Six core dimensions of student portrait.

3.3.1 Academic Performance

Academic performance is the most basic and intuitive dimension of student portraits, mainly covering indicators such as students' homework completion, test scores, and grade point average. These data reflect students' learning ability, knowledge mastery, and academic potential to form the core of student's learning effectiveness assessment. Through academic performance, educators can assess students' academic progress and develop appropriate learning paths, as well as provide the quantitative data needed to optimize personalized teaching programs.

3.3.2 Social Behaviour and Interactive Patterns

The social behaviour and interaction patterns dimension focuses on how students behave in groups, including interactions with peers, faculty, and other members in their social networks (Sibanda et al., 2021). Student's social skills, cooperative competency, and relationships play an important role in their personal growth and academic success. By analyzing student's interactive behaviours in classroom discussions, extracurricular activities, and social platforms, educators can identify students' social needs, help them build good social networks, and promote the development of their teamwork skills and leadership potential. This dimension expands the scope of personalized education, especially in terms of providing emotional support and encouraging social adaptation.

To analyze social behaviour effectively, data should be sourced from multiple channels, such as social media interactions, campus forums, and records of participation in offline activities. These diverse data sources provide a comprehensive view of student's social engagement. Moreover, applying SNA methods allows for a quantifiable understanding of student's position within their social networks (Kim & Hastak, 2018). Centrality as indicating influence within a group, connectivity as representing the degree of integration into a network, and clustering coefficients as measuring group cohesion, can be used to identify key influencers, socially isolated individuals, and required additional supports.

3.3.3 Learning Behaviour and Engagement

The learning behaviour and engagement dimension focuses on student's motivation and engagement, including data on class attendance, homework submission, and use of online learning platforms. These behavioural data can reflect students' learning attitudes, learning habits, and independent learning abilities comprehensively. They also provide important support for the design of personalized learning paths (Arizmendi et al., 2023). Especially in the digital learning environment, online learning recording, such as course access time and completion degree, can reveal students' motivation and interest in learning. These data help teachers identify students' learning difficulties and challenges promptly, and provide a data basis for adjusting teaching content and resource allocation.

3.3.4 Learning Interest and Motivation

The learning interest and motivation dimension focuses on student's academic interests, their motivation to learn, and cognitive styles. Student's learning interests and motivation are important factors that influence their learning behaviours and outcomes. Personalized teaching is emphasized in this dimension on the design of differentiated learning paths based on student's interest preferences and learning motivation to stimulate their intrinsic motivation and enhance learning outcomes (Kong et al., 2018). Educators provide open-ended tasks, exploratory opportunities, and creative challenges for intrinsically motivated learners to nurture their natural curiosity. For extrinsically motivated students, goal-oriented strategies, such as milestone rewards and clear benchmarks, can enhance engagement and performance effectively. Through data analysis, student's learning interests and motivation can provide educators with valuable information and guidance, especially in cultivating innovative talents. This dimension enables educators to provide students with customized learning content and challenges according to their individual needs and innovative potential, thus promoting their all-round development.

3.3.5 Mental Health and Emotional States

The mental health and emotional states dimension focuses on students' psychological development and emotional changes. It is mainly assessed through data, such as psychological assessments, emotional analyses, and work and rest patterns. Students' mood swings, psychological stress, and learning anxiety have a direct impact on learning efficiency and academic performance (Yadegaridehkordi et al., 2019). Therefore, monitoring and intervening promptly in students' mental health issues is crucial for personalized teaching. Through a comprehensive analysis of mental health data, educational institutions provide personalized counselling and support to help students cope with the psychological challenges of the learning process.

3.3.6 Background and Socio-Economic Status

The background and socio-economic status dimension include student's family background, economic status, and parents' education levels, which help analyze their growth environment and external support. The research has shown that family economic background and parents' education levels have a significant impact on student's academic achievement and learning attitudes. Through analysis of such socio-economic data, educators can formulate fairer and more targeted policies to provide assistance to students from economically disadvantaged families and provide data support for the rational allocation and optimization of educational resources. Moreover, social background data helps educators better understand students' living environments and social support, which promotes equity and inclusion in education.

4 Student Portraits Based on Knowledge Graphs

4.1 | Data Acquisition and Preprocessing

Data acquisition is the core aspect of constructing student portraits, which is realized by automated acquisition, sensor acquisition, and questionnaires and surveys. This research utilizes an application programming interface (API) and crawler technology to automate student learning behaviour data acquisition from an online learning platform (Ai et al., 2024). These data record student's interactive behaviour in the digital learning environment in real-time, and provide high-frequency and dynamic behavioural data support for subsequent analysis. Sensor collection acquires data about students' activities at school through sensors in the campus environment, such as library checkout records, and provides multidimensional perspective support for analyzing learning resource use and social interaction patterns (Fu, 2020). Moreover, this research applies regular questionnaires, surveys, and psychological status assessments to collect subjective data, including information on study habits, mental health, and emotional tendencies. These subjective data are crucial for revealing students' learning motivation and psychological needs and complement objective behavioural data.

Data preprocessing, encompassing data cleaning, integration, and conversion, is important to ensure data quality and analysis effectiveness. In the data cleaning stage, duplicates, errors, and missing data are removed, while abnormal data such as unreasonable learning hours records are corrected and processed to ensure accuracy and reliability. Data integration standardizes the data structure by unifying the data formats from different sources, thus realizing the integration and analysis of diverse data. Subsequently, the data conversion and statute link use numerical and vectorized techniques to convert data formats and feature selection techniques to carry out dimensional statute to reduce the amount of redundant information and improve analysis efficiency. Moreover, privacy and security issues in data processing are especially critical. In this research, encryption technology, anonymization, and strict access control are adopted to ensure the security of students' sensitive information and effectively avoid the risk of data leakage or misuse. The overall process of data collection and preprocessing is illustrated in Figure 2.

4.2 | Knowledge Graph Modelling

The knowledge graph integrates the multidimensional feature information of students by defining the semantic relationship between domain ontology and annotated data to form a dynamic semantic network in Figure 3, which provides technical support for accurate modelling of student's features.

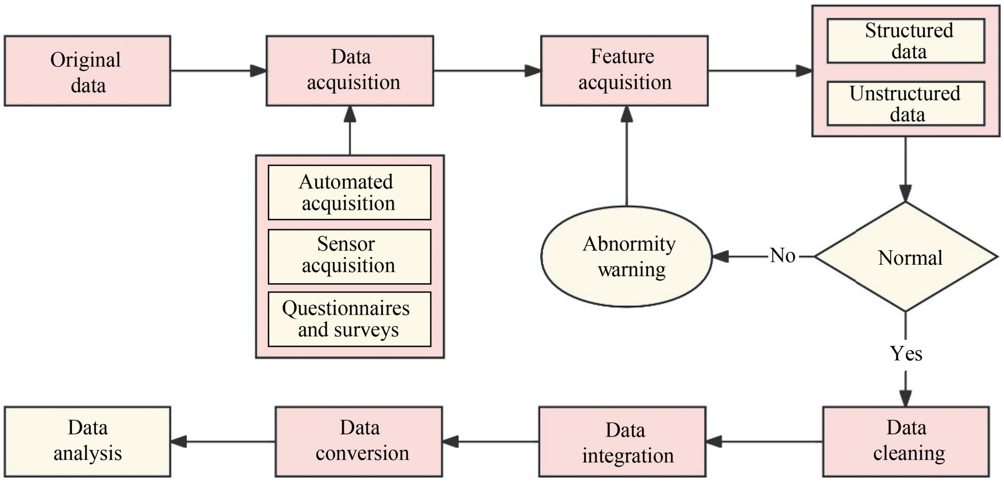

Figure 2 Data collection and preprocessing flowchart.

Figure 3 Knowledge graph modelling of student's features. GPA: grade point average, ID: identification.

4.2.1 Ontology Construction

The construction of domain ontology is the starting point of knowledge graph modelling, which is used to specify the core concepts, entity types, and attribute relationships covered in the graph (Li et al., 2024). For example, in an educational scenario, the ontology involves course content, student's behavioural characteristics, and teacher–student interactions. This process ensures a semantic description of student's learning data and lays the foundation for subsequent analysis.

4.2.2 Semantic Annotation of Data

Through NLP techniques and knowledge extraction tools, entities, and relationships are extracted from multi-source data, while the data is semantized using manual annotation or automated mapping techniques to conform to the standards of the domain ontology.

4.2.3 Knowledge Storage and Management

In terms of data storage, semantic web standards, such as the resource description framework (RDF) and the web ontology language (OWL) are used to organize the data and store it efficiently in graph databases, such as Neo4j, to support complex querying and reasoning operations (Uifălean, 2023). The knowledge graph modelling process is illustrated in Figure 4.

4.3 | Student Portrait Generation

A student portrait is a comprehensive multidimensional description of a student's individual characteristics, learning behaviour, and needs, which provides support for personalized teaching and learning path optimization by analyzing Big Data such as student's learning behaviour, knowledge mastery, and interests.

4.3.1 Data Preprocessing and Normalization

Data preprocessing is the basis for ensuring the quality of the portrait. Duplicate, incomplete, or abnormal data are removed through cleaning and filtering, and data transformation and normalization methods are used to transform data from different sources into a uniform scale, providing consistency for subsequent analysis.

4.3.2 Model Selection and Construction

Appropriate modelling techniques are selected to construct the portrait model according to the goal of the portrait. Cluster analysis, such as k-means clustering and density-based spatial clustering of applications with noise, identifies natural groupings in the student population and reveals students' common and individual characteristics (Li et al., 2019). Classification and regression models, such as decision trees and random forests, are used to predict students' behaviours and learning outcomes, support the personalized generation of portraits, and combine Bayesian inference and probabilistic graphical models with knowledge graphs to further realize uncertainty inference and enhance the dynamic adaptability of portraits.

4.3.3 Multidimensional Feature Integration

Multidimensional feature integration is the core aspect of generating a comprehensive student portrait. In this process, semantic information in the knowledge graph is combined with raw data features, while data such as course participation, classroom performance, and social interaction are integrated into a unified portrait framework through cross-featured analyses and association rule-mining techniques. This reveals the deep relationships between student's features and portrays student's learning habits, aptitude, and interest

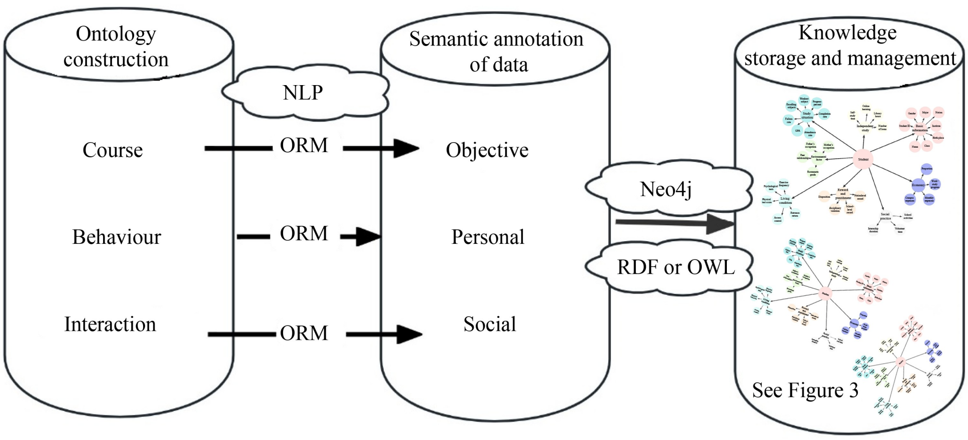

Figure 4 Knowledge graph modelling process. NLP: natural language processing, ORM: object relational mapping, RDF: resource description framework, OWL: web ontology language.

preferences from multiple dimensions comprehensively.

Cross-feature analysis and association rule mining in this framework are pivotal for merging data on course participation, classroom performance, and social interaction into a unified portrait structure. Through these methods, the framework can uncover deep and meaningful relationships among student's characteristics, which reveals how various dimensions influence each other. For example, the interplay between academic engagement and social network centrality can shed light on how collaboration impacts learning outcomes.

The integration process uses graph-based algorithms to model and analyze student's features dynamically. Graph embedding enables the transformation of high-dimensional and heterogeneous data into a compact and analyzable format to preserve the relationships and dependencies between features. This approach enhances the system's ability to capture temporal and contextual changes in student's behaviour, which supports real-time updates and personalized interventions.

4.4 | Dynamic and Personalized Portrait Presentation

Dynamic generation and updating mechanisms ensure the timeliness of the portrait. Relying on real-time data processing frameworks, such as Apache Kafka, the student portrait system integrates the latest information from multiple data sources quickly and updates the portrait instantly (Mager, 2023). For example, when a student completes a new learning task, the relevant data is incorporated into the portrait model in real time, which reflects the student's latest status and provides teachers with an efficient and accurate overview of the student's academic performance.

The personalized presentation of the portrait is made possible by data visualization techniques that transform complex data into an intuitive and understandable form. For example, interactive dashboards show an overall picture of a student's key learning metrics. The dynamic trend charts track changes in specific metrics over time and enable educators to analyze student's trends visually. Moreover, tools such as Tableau and D3.js allow educators to customize the portraits' content to suit different teaching needs, which increases the value of the portraits in actual educational decision-making.

These dynamic and personalized visualization techniques not only improve the accessibility of student portrait data but also support more informed and targeted educational interventions, ultimately fostering a more adaptive and effective teaching environment. Figure 5 illustrates the entire procedural framework.

5 AI-Driven Student Portrait for Personalized Education and Talent Development

5.1 | Analysis of Student Portrait

Focusing on each student's unique characteristics, personalized portraits aim to provide insights into

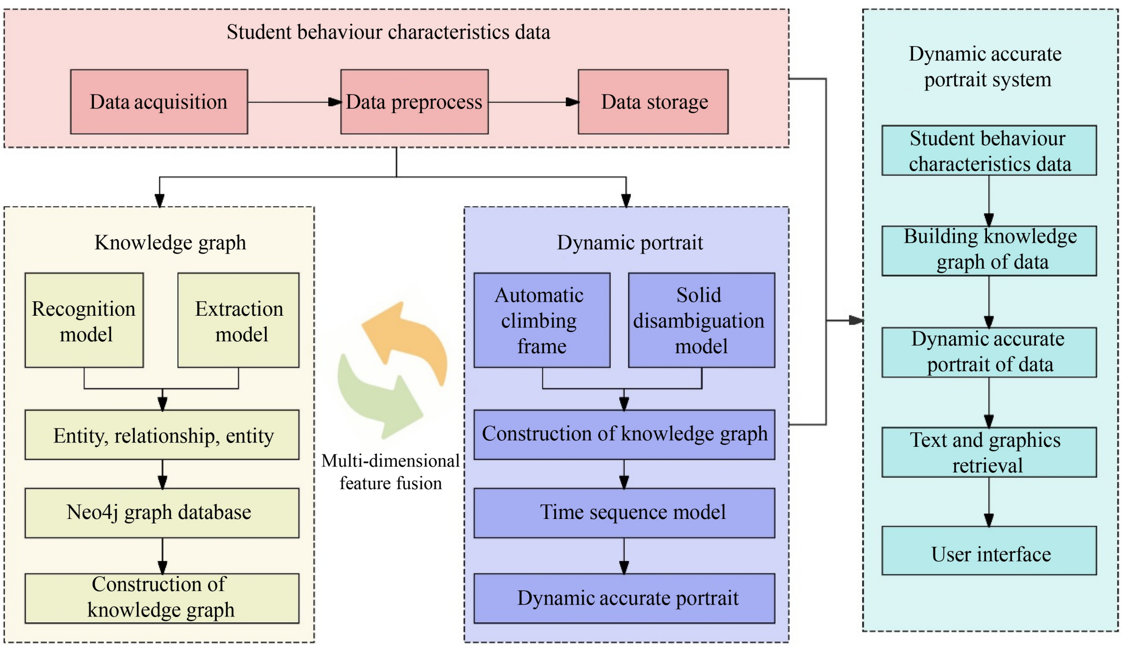

Figure 5 Framework of the student portrait system based on knowledge graphs.

students' learning habits, interests, and academic performance to support personalized instruction. To build the portrait, we combine machine learning and deep learning technologies to analyze students' behavioural data and interest information.

Student's learning behaviour data, including access records from online learning platforms, homework submissions, and classroom interaction data, can reflect student's learning habits, level of engagement, and knowledge mastery. This research utilizes an LSTM model to process these time-series data (Shi et al., 2015). LSTM is suitable for capturing the long-term dependencies in student's learning process. By training LSTM, the student's future learning behaviours, such as the learning progress and achievement trend of a certain subject, can be predicted. Therefore, the model can help teachers tailor their teaching strategies to student's personalized learning needs.

To further enrich the student's personalized portrait, NLP techniques to analyze text data are applied (Vinyals et al., 2015). Using TextBlob for sentiment analysis, the positive and negative sentiments in students' comments are categorized, which helped teachers identify student's learning sentiment problems in time and intervene accordingly. Meanwhile, using word vector models, such as Word2Vec, student's interest vocabulary is extracted, student's interests in different subjects are identified, and data is provided to support the generation of personalized learning content recommendations (Zhang et al., 2015).

After analyzing student's learning behaviours and affective states, collaborative filtering algorithms are utilized to provide personalized learning resource recommendations. The user-based collaborative filtering model implemented using Surprise Public Library can recommend relevant learning resources based on student's interests and historical behaviours, such as course materials and textbooks. The algorithm generates accurate learning resource recommendations by identifying behavioural similarities between students to enhance the personalized learning experience. The design process of the personalized student portrait system is illustrated in Figure 6.

5.2 | Practical Applications of Student Portrait

Practical applications of the student portrait system in education fully embody the fusion of big data and AI technology. Combining data stream processing, knowledge graph reasoning, and machine learning models, the personalized student portrait system uses Streamlit as the core visualization framework to present student's multidimensional characteristics and analysis results intuitively, which provides strong support for

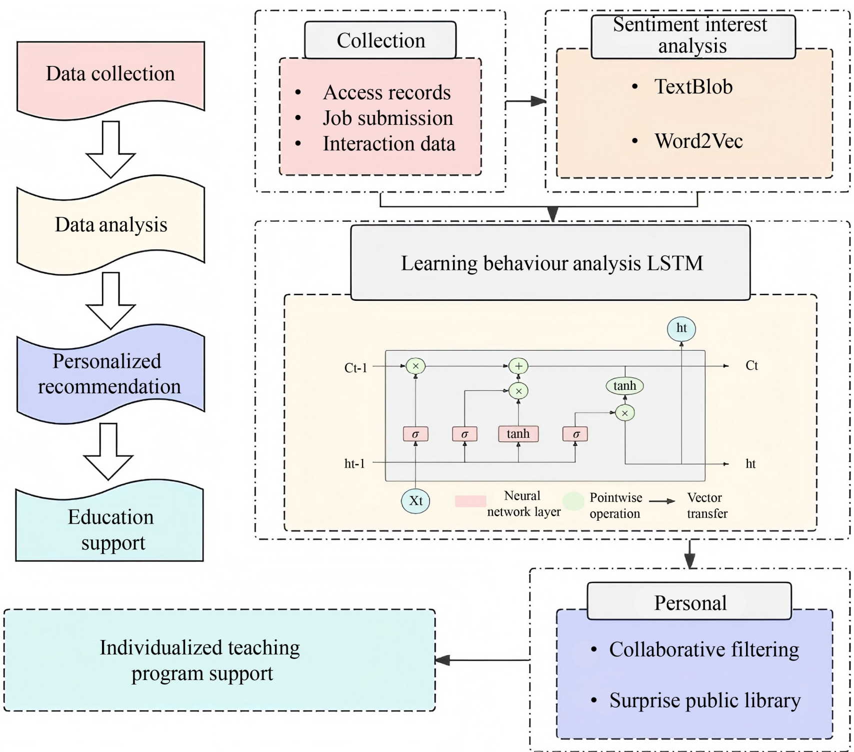

Figure 6 Personalized student portrait system design process. LSTM: long short-term memory, Ct: computed tomography, ht: hyper transfer, tanh: hyperbolic tangent function.

personalized teaching and optimization of educational resources.

At the data level, the student portrait system collects multi-source data, such as students' behavioural data, classroom participation, and family background, from the online learning platform by integrating API interfaces with real-time data stream processing technology such as Apache Kafka. High-quality and structured input data are formed through data preprocessing modules, including denoising, format unification, and normalization. Meanwhile, the semantic representation of the student's knowledge state and behavioural pattern is realized with the RDF and OWL storage framework by combining the construction and reasoning capabilities of the knowledge graph.

At the analysis level, the student portrait system adopts cluster analysis to realize student group feature mining. It combines classification and regression models to predict academic risks and behavioural trends. Moreover, NLP technology is used to analyze text data for sentiment analysis and keyword extraction to capture potential psychological problems and learning needs effectively. The system also embeds collaborative filtering algorithms to recommend learning resources based on historical behaviours and interests. At the visualization level, Streamlit is used to develop an interactive dashboard that displays student portraits and group characteristics through radar charts, heat maps, line graphs, and other charts. It also supports real-time dynamic updating to enhance the refinement of education management. In practical applications, the system identifies students with weak academic performance through academic warnings and pushes personalized learning plans to reduce the risk of dropouts (Li et al., 2019). By optimizing educational resources and combining them with the portrait of poor students, the system provides accurate financial assistance solutions for students with financial difficulties.

This system's effectiveness is demonstrated through various compelling use cases. Figure 7 illustrates one student portrait, showcasing the student's academic performance, extracurricular capabilities, and comprehensive multidimensional traits. The system's academic risk prediction functionality is depicted in Figure 8.

Moreover, Figure 9 presents the passing rates for key skill-based exams using bar charts, such as the National College English Test Band 4 (CET-4), CET-6, and National Computer Rank Examination Band 2, which provides actionable insights into students' foundational skill levels, and informs targeted supplementary training programs. Furthermore, Figure 10 highlights poverty prediction results using radar charts and analyzes disadvantaged students' socio-economic conditions comprehensively. This supports targeted financial aid allocation and reinforces the system's commitment to promoting equity and inclusivity in education.

In summary, integrating robust data collection, advanced analytical methods, and intuitive visualizations into the student portrait system highlights its potential to enhance personalized learning, support early interventions, and optimize resource allocation. By addressing diverse students' needs through

Basic information

Name	Bin Qiu	Gender	Male	Contact number	131*****122
Ethnicity	Han	Hobby	Basketball	Politics status	Party member
Native place	Zhanjiang, Guangdong	GPA	4	Overall ranking	1
Graduate institutions	Beijing Institute of Technology, Zhuhai		Major	Applied statistics	
College entrance exam score	500		Email	2********@qq.com	
Industry	Finance			Work location	Zhuhai

Student comprehensive performance

	Entry level	Learning outcomes	Extracurricular development ability	School performance	Student rating
Bin Qiu	Low	Low	High	Low	Pass

Bin Qiu's personal radar chart

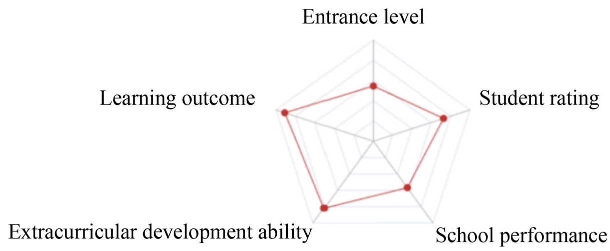

Figure 7 Radar chart of individual's abilities and basic information overview. GPA: grade point average. The asterisks "*" here were deliberately removed to conceal students' privacy.

Academic warning system

The list of students who are expected to receive academic warnings is as follows. Please pay more attention to the following students' academic status!

	26	27	28	28	30	31
Name	Hao Wang	Shi Wang	Jian Qiu	Hai Zhang	Li Wu	Weilai Lin

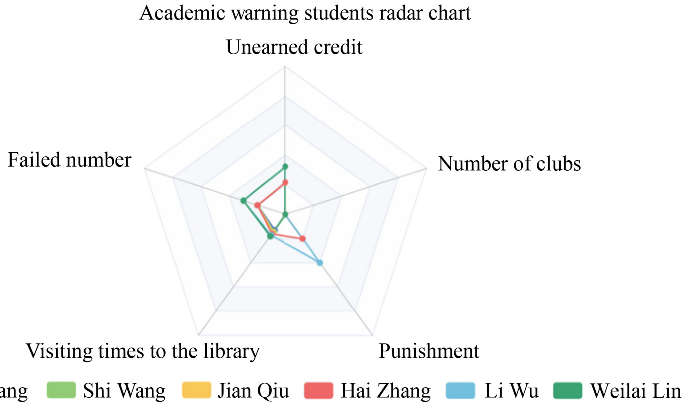

Figure 8 Academic warning system.

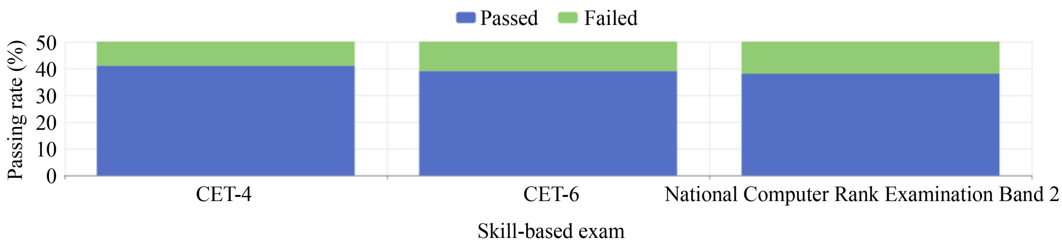

Figure 9 Passing rates for key skill-based exam. CET-4: National College English Test Band 4, CET-6: National College English Test Band 6.

Poverty prediction results

The following students are poor students whose family situation is inferred by the algorithm. Please pay attention to their economic situation and give help!

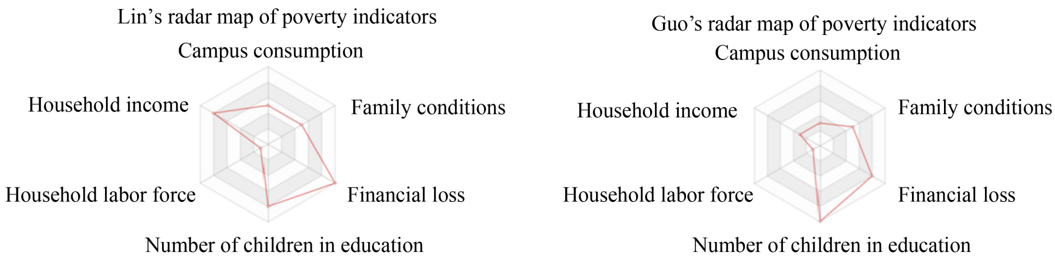

Figure 10 Poverty prediction results.

multidimensional analysis of academic performance, behavioural patterns, and socio-economic backgrounds, the system tailors educational resources, identifies at-risk students, and fosters equity and inclusivity. Moreover, the system plays a pivotal role in recognizing students with exceptional talents and supporting their specialized development, which aligns with the demands of cutting-edge fields, such as AI and life sciences. By providing tailored pathways and targeted resources, the system accelerates the cultivation of high-calibre talent, bridging educational opportunities and resource allocation while contributing to more effective, inclusive, and innovative educational outcomes.

5.3 | Significance of Student Portrait Applications

The student portrait technology provides solid technical support for the implementation of personalized education. Through the dynamic analysis of student's learning behaviours, psychological states, and interest preferences, educators can develop a comprehensive understanding of differences among students and formulate more targeted teaching programs. Personalized learning path design realizes accurate assessment of student's learning progress and abilities with the help of student portraits and recommends differentiated learning contents and paths for students to improve learning efficiency (Baker et al., 2016). Moreover, with the help of sentiment analysis technology, the student portrait system can capture student's psychological dynamics promptly, provide early academic warnings and scientific interventions for potential emotional problems, and further guarantee student's learning quality and sense of well-being. Meanwhile, based on advanced technologies such as LSTM, the student portrait generates dynamic predictions of academic performance that provide educators with a scientific basis for adjusting teaching strategies, which ensures a high degree of compatibility between educational activities and student's needs.

In addition, as a Big Data-driven path of talent cultivation, student portrait technology provides key support for the cultivation of composite and innovative talents in a data-driven manner. By integrating student's multidisciplinary abilities and personalized characteristics, institutions can more accurately identify and explore student's potential and promote the integration of interdisciplinary knowledge and the enhancement of innovative capabilities. Especially in the industry–education integration, the student portrait provides a scientific basis for enterprise–university collaboration by analyzing student's abilities, interests, and career development tendencies, which helps to cultivate high-quality talents with practical ability and innovative spirit. Moreover, by analyzing socio-economic background and academic performance, the student portrait system provides an important reference for the fair distribution of educational resources, helps disadvantaged groups obtain better educational opportunities, and promotes educational equity and social inclusion effectively.

As an important part of the digital education ecosystem, the student portrait technology plays a significant role in promoting education's modernization and intelligent development. The student portrait system can generate personalized student-characteristic models dynamically based on real-time data processing and knowledge graph inference technology. It provides education administrators with more refined decision-making support, captures student's psychological dynamics promptly, offers early academic warnings and scientific interventions for potential emotional problems, and guarantees optimized and dynamic allocation of educational resources to students. It improves the efficiency and effectiveness of the education system by matching student's demands with resource supply accurately. On a broader level, the student portrait promotes the deep connections between education, talents, and industry chains through the industry–teaching–research mechanism, which not only meets the demand for high-quality talent cultivation in the era of digitization but also provides a new solution path for the synergistic development of education, science and technology, and industry.

For example, compacting and improving the digital base of talent cultivation in science and technology disciplines is necessary for many current science and technology colleges to build composite and applied talent cultivation systems. The talent cultivation model of the School of Future Technology at Harbin Institute of Technology (HIT) is a typical case in which student portrait technology represents a significant opportunity for practical application. The college aims to explore the cutting-edge cross-cutting fields of AI, intelligent manufacturing, intelligent energy, and life and health. It has set up four special academic classes and top-notch future technology classes and carries out teaching and cultivation according to the core principle of "one student, one policy." Under such a principle, the school can maximize the student's potential and cultivate them into the talents with the most application value. At all stages of cultivation, supporting the "one student, one policy" personalized cultivation plan will require a data-driven solution that provides rich application scenarios for student portrait technology. As Figure 11 shows, the technology would develop and aggregate student's data and build an effective bridge between student's potential, syllabus design, and enterprise practice to realize the "one student, one policy" principle and help students develop valuable talents. The technology also enables teachers to understand the modulable direction of students earlier and more comprehensively and to intervene in different stages of student's training promptly so that students can clarify their career development plans for engaging in academics or technology at an earlier stage.

Student portrait technology can increase efficiency by matching universities' talent supply with enterprises' talent demand. For example, the purpose of the university–enterprise partnership between HIT and a large-scale aerospace company is not only to realize the students' needs for enterprise practice but also to meet the real demand of enterprises to understand the basic situation of talents earlier, find out the potential shortcomings of talents earlier, and reshape student's competence system according to the needs of the enterprises before joining the workforce. Such demands are met through student portrait technology. This technology realizes the convergence program for senior early entry talent training that enterprises want so that they can design the key training contents of student's entry training according to student portrait, save time cultivating talent, and reduce the structural contradiction between talent supply and demand in the long term. As shown in Figure 12, student portrait technology would help match talent supply to talent demand and provide the best talent–job matches for students and enterprises.

6 Policy Implications

Although China has made commendable progress in digital education, significant disparities and challenges persist, particularly in teacher training, resource development, and data security. To address these issues, the government needs to prioritize expanding digital infrastructure and maintaining sustainable input into

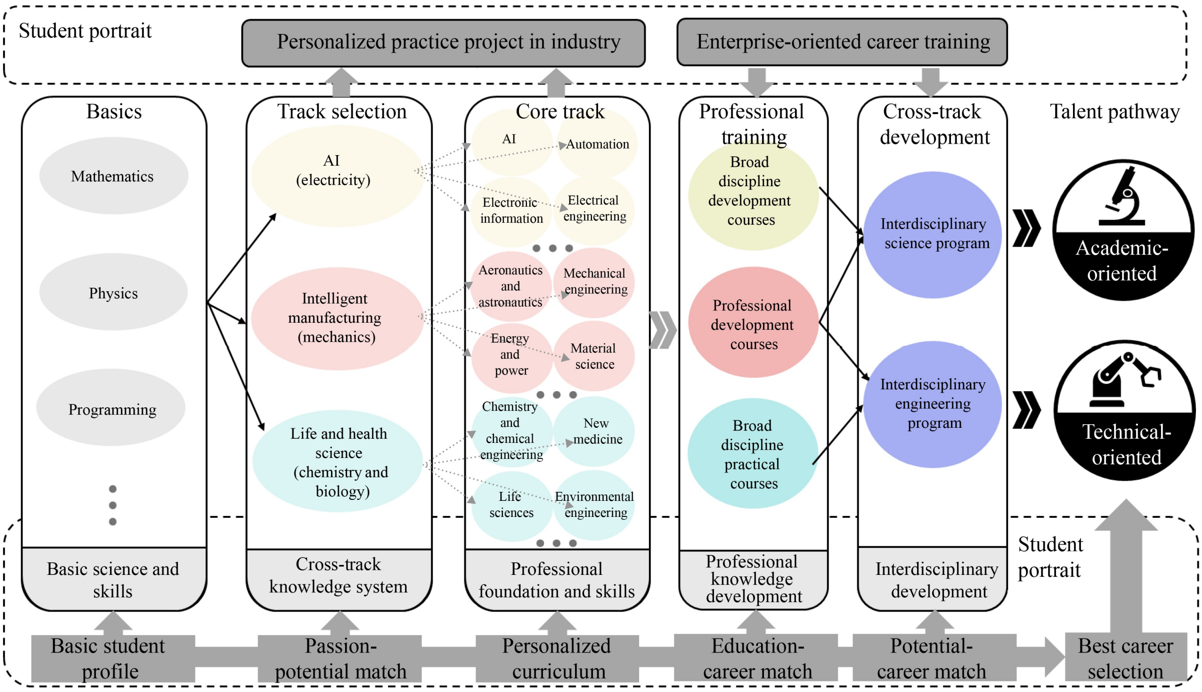

Figure 11 Potential applications of student portrait technology in talent cultivation at Harbin Institute of Technology.

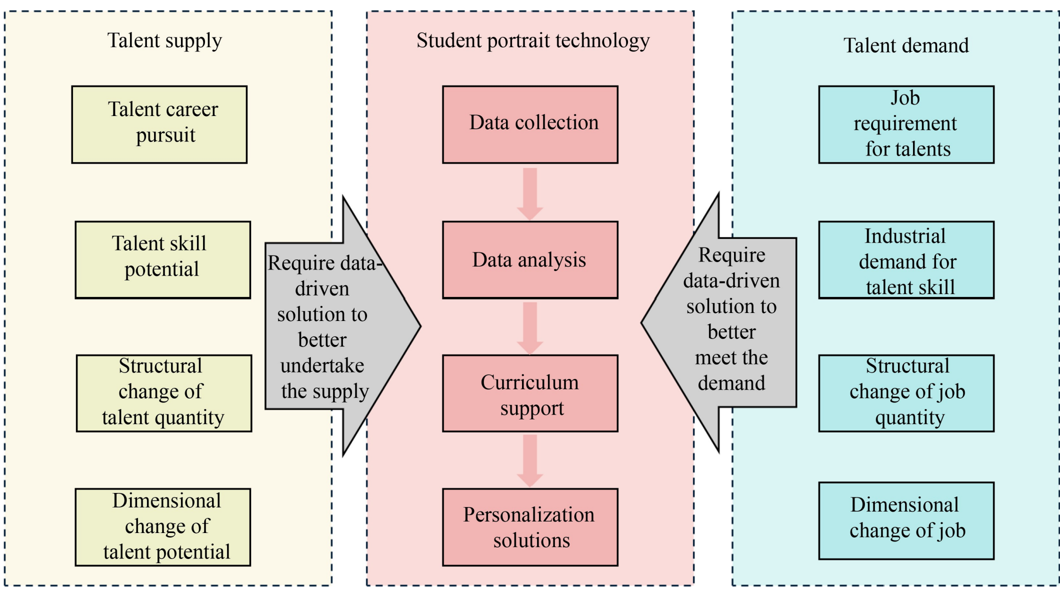

Figure 12 Potential application of student portrait technology in dynamically matching talent supply and demand.

digital education.

The first step is to improve teachers' digital literacy. A survey by the China Association for Educational Technology in 2023 revealed that only 37% of educators felt confident using digital tools. Nationwide professional development programs tailored to digital skill building should be made mandatory. If even 10% of China's 17.3 million teachers improved their digital competencies, this could positively impact the education of over 200 million students. The government could collaborate with leading educational technology companies, leverage their expertise to design training platforms and workshops, and ensure that educators are equipped to create engaging digital content and manage virtual classrooms effectively.

The second step is to further encourage public–private partnerships to enhance broader applications of new technology and digital education initiatives. With China's education technology market valued at 70 billion USD in 2023, collaborations with leading companies could scale digital resource development and deployment, particularly tracking students in science, technology, engineering, and mathematics.

The third step is to monitor and evaluate mechanisms for new technology applications. A 2023 national statistical bulletin on education reported by the MOE of the PRC showed that nearly 45% of digital education projects lacked adequate evaluation (MOE of the PRC, 2024). Building a robust monitoring system to track progress and outcomes will optimize resource allocation and policy adjustments. Scaling such initiatives nationwide ensures effectiveness and accountability in digital education policies.

By adopting these strategies, the Chinese government can transform its digital education landscape into a more efficient system. With concerted efforts and strategic investments, China positions itself as a global leader in digital education and prepares its young talents for the demands of the 21st-century knowledge economy.

7 Conclusions

Student portraits have become vital in advancing personalized education and ensuring equitable resource allocation. This research focuses on developing a comprehensive framework for constructing dynamic and multidimensional student portraits using knowledge graphs and advanced data analytics. The system provides a holistic understanding of student's characteristics and needs by integrating diverse data sources, including academic performance, learning behaviours, social interactions, and socio-economic backgrounds. Dynamic data collection, preprocessing techniques, and knowledge graph modelling enable semantic representation of student's knowledge states and behavioural patterns, which ensures adaptability and real-time responsiveness.

The methodology employs real-time data processing and machine learning models, such as LSTM networks, to analyze time-series learning behaviours and predict academic trends. These predictive capabilities allow educators to implement timely interventions and optimize personalized teaching strategies. Moreover, SNA metrics quantify students' roles in social interactions, such as centrality and connectivity, enhancing the system's ability to address their interpersonal and collaborative needs. Advanced visualization tools, including radar charts and trend graphs, further facilitate the intuitive presentation of portrait results, enabling educators to analyze and respond to student's dynamic needs effectively.

The results demonstrate the system's effectiveness across various educational applications, including academic risk prediction, exam pass rate analysis, subject preference identification, and resource recommendation. For example, the system identifies students at risk of academic underperformance accurately, supports the optimization of exam preparation resources, and provides targeted financial aid recommendations for disadvantaged students, which promotes inclusivity and equity.

In conclusion, the proposed framework offers significant potential to support personalized learning paths, refine teaching strategies, and advance educational equity. Future developments will focus on integrating emotion recognition, adaptive algorithms, and privacy-preserving mechanisms to enhance system capabilities. Expanding the system's application to lifelong learning and cross-cultural educational contexts will increase its global relevance, offering a transformative approach to data-driven education in the digital age.

Based on knowledge graph and data analysis methods, this research proposes a multidimensional process for constructing student portraits, which provides an innovative solution for personalized education and educational equity practices. By comprehensively constructing multidimensional information on student's academic performance, behavioural characteristics, and social background, this research demonstrates the great potential of student portrait technology in personalized learning path design, academic warning, and educational resource optimization. Student portrait technology can help educators understand each students' needs and development and provide accurate data support for educational decision-making, thus promoting educational equity and inclusiveness.

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Conflicts of Interest The authors declare that they have no conflicts of interest.

Ethics Statements The authors declare that their Institutional Ethics Committee confirmed that no ethical review was required for this study. Written informed consent for participation was not required because all participants' data was anonymized before the statistical analyses were conducted.

Data Availability Statements The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Authors Contributions Yawen Li made substantial contributions to the conception and design of the work, participated in the acquisition and analysis of data, and critically revised the manuscript for important intellectual content; Zongxuan Chai contributed to data interpretation, created graphical visualizations, and provided substantial technical translation support; Shuai You conducted critical analysis of policy implications and potential technology applications, performed manuscript translation, and led the final revision process; Guanhua Ye and Qi Liu jointly drafted the initial work and participated in its critical revision through iterative intellectual refinement. All authors approved the version to be published and agree 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.

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