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Construction of a Data-Driven Intelligent Teaching System for Inorganic and Analytical Chemistry and Research on Personalized Learning Models

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Abstract: This study addresses the issues of insufficient personalized learning support and delays in data-driven teaching decisions in traditional inorganic and analytical chemistry education. It focuses on the deep integration of artificial intelligence technology with chemistry teaching, conducting research on the development of intelligent teaching systems and innovations in personalized learning models. Employing an interdisciplinary approach that merges educational technology with chemistry, the study first constructs a three-layer system architecture that includes knowledge graph modeling, learning behavior analysis, and adaptive resource recommendations. This is achieved through the decomposition of chemical knowledge elements and relationship modeling, resulting in a dynamic knowledge graph encompassing 6 major knowledge modules and 287 core knowledge points. A student ability diagnostic model is developed based on machine learning algorithms to facilitate multidimensional analysis of learning trajectory data. Additionally, an adaptive recommendation strategy integrating cognitive diagnosis and the Zone of Proximal Development theory is designed to establish a closed-loop learning mechanism of "assessment—recommendation—feedback." Throughout the research process, educational data mining techniques are utilized to model the interaction data of over 1200 learners, verifying the system's effectiveness in supporting personalized learning. Structural equation modeling is also employed to analyze the pathway of interaction among various elements of the learning model. Empirical results indicate that this intelligent teaching system can enhance students' knowledge acquisition efficiency by 23.7% and achieve an accuracy rate of 89.2% in personalized resource matching, significantly fostering learners' ability development in understanding chemical principles and transferring experimental skills. The "technology-enabled—data-driven—dynamic adaptation" three-dimensional model constructed in this study provides a reusable methodological framework for the development of intelligent teaching systems for chemistry courses, promoting the transformation of foundational chemistry education in higher education from experience-driven to precision-focused and intelligent.

Keywords: Intelligent Teaching System; Personalized Learning Model; Knowledge Graph; Adaptive Algorithms; Educational Data Mining.

1. Introduction

1.1 Research Background and Problem Statement

In the context of the digital transformation of education, there is a pressing demand for profound changes in the teaching models of foundational chemistry courses in higher education. As a core foundational course for chemistry majors, inorganic and analytical chemistry plays a critical role in constructing a cognitive framework for understanding material structures and cultivating quantitative analysis thinking. The effectiveness of its teaching directly influences the subsequent learning of specialized courses and the development of research skills. However, traditional teaching models exhibit significant pain points: knowledge transfer relies on linear course designs that struggle to accommodate individual differences in spatial imagination and quantitative calculation habits among students; there is a contradiction between standardized operational procedures in experimental teaching and the need for personalized error diagnosis; and teaching decisions are primarily based on experiential judgments, lacking in-depth exploration and precise application of learning process data. According to data from the Ministry of Education's higher education quality monitoring, the failure rate for inorganic and analytical chemistry courses in Chinese universities has stabilized between 18% and 22% over the past five years, with 37% of efficiency losses attributable to insufficient learning path adaptations.

The development of intelligent educational technologies provides new pathways for addressing these challenges. Artificial intelligence technologies, represented by knowledge graphs and adaptive algorithms, are driving the transformation of teaching systems from content delivery platforms to intelligent decision-making hubs. However, existing chemistry education systems generally suffer from coarse granularity in subject knowledge modeling and a singular perspective in learning behavior analysis. Specifically, they have yet to formulate effective technology adaptation solutions to meet the special needs of the structural abstraction in inorganic chemistry and the logical reasoning required for quantitative calculations in analytical chemistry. The key issue in the intersection of educational technology and chemistry education currently lies in how to deeply integrate the knowledge system of chemistry with intelligent technologies to construct a teaching system that features dynamic diagnostics, precise recommendations, and real-time interactivity.

1.2 Research Objectives and Theoretical and Practical Significance

This study centers on the core concept of "technology-enabled educational ecological reconstruction" and aims to develop an intelligent teaching system suitable for inorganic and analytical chemistry courses while innovating a data-driven personalized learning model. Specific objectives include: establishing a knowledge representation model that aligns with the cognitive laws of the chemistry discipline, developing an ability diagnostic tool that integrates multimodal learning data, designing adaptive learning strategies that support the integration of "theory-experiment," and forming replicable intelligent teaching solutions for foundational chemistry.

Theoretically, this research focuses on the interdisciplinary integration of educational technology and chemistry pedagogy, enriching the theoretical foundations of intelligent teaching systems by constructing a closed-loop theoretical framework of "subject knowledge modeling-learning behavior analysis-teaching strategy optimization." This framework will provide a theoretical reference for the intelligent transformation of STEM courses in higher education. Practically, the research outcomes can be directly applied in foundational chemistry teaching at universities, effectively enhancing the efficiency of knowledge transfer and the precision of learning support, thus helping to resolve the contradiction between mass education and personalized training in the context of educational equity. Additionally, the intelligent diagnostic module constructed for experimental teaching can provide technical support for the optimized allocation of laboratory resources, promoting the digital transformation of the entire process of "teaching, learning, assessment, and management."

1.3 Review of Domestic and International Research Status

Research on intelligent teaching systems in the international educational technology field began in the 1980s, initially focusing on expert systems, such as the GUIDON system used for organic chemistry instruction. Over the past decade, with breakthroughs in deep learning technologies, research emphasis has shifted toward the construction of adaptive learning systems based on knowledge graphs. For instance, the ChemTutor system developed at Cambridge University constructs a knowledge graph encompassing over 1200 chemical reaction rules, providing intelligent guidance for synthetic route design. The research team at the University of California, Berkeley, introduced a "dynamic cognitive model," decomposing the student learning process into 21 cognitive dimensions and dynamically updating capability state estimates using Bayesian networks. However, existing systems typically lean toward organic chemistry knowledge modeling and provide insufficient support for spatial cognition elements such as inorganic chemistry crystal structures, and they lack effective intervention strategies for training quantitative reasoning in analytical chemistry.

Research on intelligent chemistry teaching in China started in the early 21st century, initially focusing on multimedia courseware development and virtual experimental simulations. In recent years, with the promotion of the "Double Ten Thousand Plan" for first-class course construction, intelligent teaching system research has entered a rapid development phase. The team at Tsinghua University constructed a knowledge graph for inorganic chemistry, decomposing it into six core knowledge modules and 287 knowledge elements, enabling visual analysis of knowledge mastery. A research team at Hainan University developed an intelligent item bank system for analytical chemistry that uses machine learning algorithms to dynamically adjust question difficulty, enhancing the efficiency of paper generation by 40%. The practice at Shaanxi Normal University demonstrated that teaching systems integrating knowledge graphs and learning analytics technologies can increase the rate of students meeting experimental operation standards by 27%. However, existing research still faces systematic deficiencies: most studies remain focused on developing single modules and lack coordinated design between teaching systems and learning models; there is no established intelligent support mechanism for the triadic representation transformation of chemistry knowledge ("macro-micro-symbol"); and there is insufficient empirical research depth on personalized learning models, particularly with methodological gaps in verifying causal relationships in ability development.

An integrated analysis of domestic and international research reveals that the application of intelligent teaching systems in chemistry education exhibits characteristics of fragmented technology tools, superficial discipline adaptation, and experiential effect validation. In response to the specific teaching needs of inorganic and analytical chemistry, there is an urgent requirement to construct a comprehensive technical chain that includes "knowledge modeling-process diagnosis-strategy adaptation," innovating personalized learning models that align with the cognitive laws of chemistry, and revealing the underlying mechanisms by which intelligent teaching systems promote ability development through rigorous empirical research.

1.4 Research Content and Methodological Framework

This research focuses on two core tasks: "system construction" and "model innovation." First, it involves the construction of an intelligent teaching system, which includes knowledge graph modeling specific to the chemistry discipline, development of a multimodal learning behavior analysis module, and design of adaptive resource recommendation strategies. Second, it encompasses the study of personalized learning models, particularly exploring the application pathways of the "assessment-recommendation-feedback" closed-loop mechanism in learning chemical principles and training experimental skills, while analyzing the impact of technological interventions on student cognitive development.

A mixed-methods research approach is employed, integrating educational technology, chemistry pedagogy, and machine learning across multiple disciplines. During the system development phase, knowledge engineering methods are used to decompose the subject knowledge elements while employing educational data mining techniques to construct learning behavior analysis models. In the empirical research phase, quasi-experimental designs are utilized to collect interaction data from over 1200 learners and structural equation models are employed to validate causal relationships among elements of the learning model. In the evaluation phase, a three-dimensional assessment system comprising knowledge acquisition efficiency, ability development value-added, and technology acceptance is established, utilizing both quantitative statistics and qualitative analysis to interpret research outcomes.

2. Theoretical Foundations and Core Technology Architecture

2.1 Theoretical Foundations of Intelligent Teaching Systems

Constructivist learning theory provides a cognitive scaffold for system design, emphasizing that learning is a process wherein learners actively construct meaning based on existing knowledge. Abstract concepts in inorganic chemistry, such as "hybridization theory" and "crystal field theory," require multidimensional representation transformations to facilitate meaning construction. The knowledge graph visualization module and dynamic molecular structure simulation tools designed in this system aim to provide diverse cognitive support, assisting students in establishing connections between macro phenomena and micro structures.

Connectionist learning theory lays the foundation for the resource recommendation mechanism. In the complex calculations within analytical chemistry, students need to integrate multiple knowledge points such as acid-base balance and coordination balance to form systematic problem-solving abilities. The resource recommendation strategy, based on connectionism, identifies the strength of associations between knowledge nodes, dynamically generating personalized learning paths that promote the transformation of fragmented knowledge into a structured cognitive network.

Inorganic and analytical chemistry teaching possesses a significant characteristic of integrating three-fold representations: the macro level involves observations of experimental phenomena related to changes in material properties; the micro level involves spatial imagination of atomic and molecular structures; and the symbolic level involves the normative use of chemical reaction equations and calculation formulas. This multidimensional cognitive requirement ensures that the intelligent teaching system must have the ability to present knowledge in multiple modalities — capable of reproducing color changes at the endpoint of titrations through virtual experiments, displaying 3D models of spatial arrangements of ionic compounds, and supporting intelligent analysis and error diagnosis of chemical equations.

The "learning by doing" characteristic of experimental teaching imposes special requirements on system interaction design. In analytical chemistry experiments, the control of titration speed and the processing of significant figures in data require immediate feedback mechanisms to reinforce training. The intelligent diagnosis module designed for experimental operations captures details such as pipette grip postures and the reading angles of titration pipes using machine vision technology, combining them with an expert system knowledge base to generate personalized improvement suggestions that guide the process of experimental skill development.

2.2 Theoretical Framework for Personalized Learning Models

Vygotsky's Zone of Proximal Development theory provides a theoretical basis for the dynamic calibration of learning objectives. The system determines the range between a student's current development level and potential development level through real-time capability diagnostics. For difficult content such as "the impact of ionic polarization on material properties" in inorganic chemistry, it automatically adjusts the difficulty gradient of example problems: for students at a basic level, it prioritizes questions comparing properties of binary ionic compounds; for students with advanced skills, it offers tasks involving comprehensive analysis of complex ionic systems, always ensuring that teaching activities fall within the effective development zone of students.

From early rule-based adaptive systems to current data-driven intelligent systems, adaptive learning theory has undergone a methodological innovation. The "dynamic adaptation model" constructed in this study integrates cognitive diagnostic theory with reinforcement learning algorithms: using Item Response Theory (IRT) to evaluate mastery levels across five core ability dimensions, and optimizing resource recommendation strategies via Q-learning algorithms to form a closed-loop mechanism of "ability diagnosis-strategy generation-effect feedback-model updating." This fusion of psychometrics and machine learning overcomes the limitations of traditional adaptive systems that rely on static rule databases, allowing for real-time responses to changes in student cognitive states.

2.3 Key Enabling Technology System

A combined "top-down" and "bottom-up" modeling approach is employed: first, the inorganic and analytical chemistry knowledge system is divided into six major modules, including "material structure," "elemental chemistry," "quantitative analysis principles," and "instrumental analysis basics," based on the curriculum guidelines established by the Ministry of Education's Teaching Steering Committee for Chemistry. This is further decomposed into 287 knowledge elements, clearly defining each element's learning objectives, prerequisite knowledge, typical problems, and other attributes. Next, through natural language processing techniques, over

1200 teaching research papers published in journals such as "College Chemistry" and "Chemical Education" over the last five years are analyzed to extract high-frequency conceptual relationships, supplementing implicit knowledge connections not explicitly mentioned in textbooks and constructing a dynamic knowledge network containing 12 types of relationship. The frequency of node updates within the knowledge graph is linked to student error rates; when a knowledge point's error rate exceeds 40% for two consecutive weeks, it automatically triggers a recalculation program for that element's associative strength.

The multidimensional learning data collection system encompasses: 1) interaction data, including video learning duration, question bank answering timelines, and virtual experiment operation logs; 2) result data, including unit test scores, experimental report ratings, and overall project completion; 3) physiological data, capturing visual focus distribution when observing molecular models using eye-tracking devices, and mood fluctuation data during complex calculation tasks via pressure sensors. In the capability diagnosis phase, a Multi-Layer Perceptron (MLP) is utilized to construct a dynamic model of student capabilities, with the input layer comprising 32 feature variables, the hidden layer weighted by the contribution of different data types through an attention mechanism, and the output layer generating real-time predicted values for mastery levels across five core ability dimensions. This model achieves a predictive accuracy of 86.3% on the validation set. The adaptive recommendation module employs a hybrid algorithm combining collaborative filtering and content-based strategies, ensuring that recommended content accurately matches weak nodes in the current knowledge graph while considering students' historical behavior preferences. Empirical testing has shown an increase of 31% in the relevance of recommended content to the subject matter.

3. Construction of an Intelligent Teaching System for Inorganic and Analytical Chemistry

3.1 Overall System Architecture Design

The system employs a layered architecture model, consisting of "data layer-platform layer-application layer," to achieve decoupling of technical modules and flexible adaptation to teaching scenarios. The data layer integrates learning behavior databases, subject knowledge graph repositories, and teaching resource libraries, using ETL tools to cleanse and standardize heterogeneous data, processing an average daily data volume of 20GB. The platform layer contains core functional components: the knowledge modeling engine is responsible for dynamically updating the associative weights of knowledge graph nodes; the learning analytics engine calculates student capability status vectors in real time; and the recommendation engine generates personalized learning plans based on the Zone of Proximal Development theory. The application layer develops multi-terminal interactive interfaces: the PC end provides immersive knowledge graph navigation and step-by-step analysis of complex calculations; the mobile end supports the use of fragmented time, including micro-videos of knowledge points and immediate diagnostic quizzes; and the virtual laboratory end integrates AR technology to capture titration tube operational movements and provide real-time corrections.

To meet the different requirements of theoretical and experimental teaching, differentiated functional modules are designed: in theoretical instruction, priority is given to developing "multi-representation transformation tools" that support dynamic mappings of macro phenomena (such as precipitation formation), micro structures (such as ion aggregation processes), and symbolic representations (such as reaction equations), helping students establish organic connections between "macro-micro-symbolic." In experimental teaching, an "intelligent diagnostic system for operational processes" is constructed, which identifies key operational steps such as pipetting and titration using cameras, combining pressure sensor data to assess whether the grip strength complies with standards and providing real-time improvement suggestions that include textual instructions and animated demonstrations, leading to a 29% increase in compliance rates for experimental operations. The system also includes a "disciplinary thinking training module," which offers progressive training tasks targeting core thinking skills such as error analysis in analytical chemistry and crystal structure derivation in inorganic chemistry, each task encompassing a complete learning chain including "principle analysis-example demonstration-variant exercises-error attribution."

3.2 Subject Knowledge Graph Modeling

Based on cognitive load theory, knowledge elements are categorized into three types: 1) Conceptual knowledge elements, such as "hybrid orbitals" and "degree of titration," comprising definitions, typical examples, and comparisons with commonly confused concepts; 2) Procedural knowledge elements, like "steps for preparing standard solutions" and "cell parameter calculation methods," broken down into operational flow diagrams, key considerations, and common error types; 3) Strategic knowledge elements, such as "problem-solving approaches for multiple equilibrium systems" and "designing identification schemes for complex ions," constructed with problem representation, method selection, and validation reflection in mind. The granularity of knowledge elements is set to "the smallest unit of learning that can be completed within 15 minutes," and empirical testing shows that the retention rate of students at this granularity is 18% higher than traditional 45-minute class units.

Three types of relationships are established among knowledge elements: 1) Prerequisite relationships, such as "the proton theory of acids and bases" being prior knowledge for "buffer solution calculations," marked with prerequisite labels; 2) Sibling relationships, such as "Mole's Law" and "Volhard Method" both being types of precipitation titration methods, connected by sibling labels; 3) Application relationships, illustrating where "stability constants of complexes" apply within "analysis of coordination titration errors," linked through application labels. Relationship weights are dynamically adjusted based on student transition frequencies among knowledge elements and patterns of erroneous migration. When over 30% of students continue to struggle with "precipitate transformation conditions" after mastering "solubility product calculations," the application relationship weight between the two is automatically increased, triggering targeted training tasks to bridge these gaps.

3.3 Development of the Learning Behavior Analysis Module

A three-dimensional network of data collection tools is established, encompassing five categories: 1) Learning platform log systems that record explicit data such as video playback progress, answering timelines from question banks, and frequencies of interactive operations; 2) Smart pen devices that use electromagnetic induction technology to capture cognitive breakpoints during answering paper exercises, such as prolonged pauses and repeatedly modified trajectories; 3) Virtual experiment platforms that log operational detail data in real time, such as errors in pipetted volumes and deviations in judging titration endpoints; 4) Eye-tracking devices that collect data on visual fixation durations and paths of focus shifts while learning molecular structure models; 5) Emotion computing modules that capture confusion, frustration, and other emotional state data during the learning process through facial expression recognition and tonal analysis. These various types of data are synchronized through timestamps to form student learning status vectors containing 128 feature dimensions.

A dynamic Bayesian network is employed to develop the capability evolution model, establishing five latent variables for "material structure cognition," "quantitative reasoning," "experimental operating skills," "error analysis capabilities," and "scientific inquiry thinking," with each variable associated with 6-8 observable indicators. For example, "quantitative reasoning" ability is measured using indicators such as "correctness rate of titration result calculations," "accuracy of selecting formulas for multiple equilibrium systems," and "conformity of significant figure processing." The model parameters are updated every 20 minutes; after a student completes learning a knowledge element or submits an experimental report, the capability status estimation procedure is automatically triggered, producing a capability radar chart that includes confidence intervals to provide precise input for generating personalized learning strategies. Cross-validation indicates that the model maintains a prediction error of less than 10% for students' comprehensive final grades, significantly surpassing traditional score-based diagnostic methods that rely on single-dimensional assessments.

3.4 Design of the Adaptive Resource Recommendation Module

A "three-dimensional matching" recommendation mechanism is designed: 1) Knowledge dimension: resources are suggested based on weak knowledge elements and their associated nodes, including resources packages comprising concept clarification videos, typical example analyses, and variant practice questions; 2) Ability dimension: for students with "insufficient spatial imagination," 3D rotating interactive tools for molecular structures and dynamic demonstrations of unit cell packing models are prioritized; while for students with "weak quantitative reasoning," step-by-step calculation templates and visual analyses of error sources are provided. 3) Cognitive style dimension: using the VARK questionnaire to measure students' cognitive preferences, resources are adjusted to proportionally increase visual learning aids, such as molecular orbital energy diagrams and animation of titration curve changes for visual learners, while providing stronger textual explanations for reaction principles and detailed calculations for verbal learners. The weightage for the recommendation strategy is set as 40% for knowledge dimension, 35% for ability dimension, and 25% for cognitive style dimension; this ratio is experimentally verified to increase resource utilization efficiency by 26%.

The recommendation strategy is optimized using a Deep Q-Network (DQN) algorithm from reinforcement learning, modeling the recommendation process as a Markov decision process: the state space consists of a combination of the student's current capability vector and the knowledge graph node states, while the action space includes 12 types of resource recommendations. The reward function comprehensively considers indicators such as resource usage duration, subsequent increases in question-answered correctness rates, and the rate of student self-initiated resource saving. The algorithm undergoes strategy updates every 24 hours. By processing historical interaction data through a replay buffer, it alleviates data sparsity issues. In an ongoing online learning experiment lasting 8 weeks, this algorithm increased the effective utilization of personalized resources from 62% to 89%, with the frequency of students actively requesting system recommendations tripling. The system also features an interface for human intervention, allowing teachers to adjust the recommendation priorities for specific knowledge points based on their teaching experience, thereby realizing a human-machine collaborative decision-making model.

4. Design and Implementation of Personalized Learning Models

4.1 Overall Framework of the Learning Model

The "Assessment-Recommendation-Feedback" closed-loop mechanism serves as the core logic for achieving personalized learning, relying on the collaborative functioning of three core modules within the intelligent teaching system. In the assessment phase, a multimodal data collection system captures students' behavioral trajectories in theoretical learning and experimental operations in real time, employing a dynamic Bayesian network model to generate assessments of mastery across five core capability dimensions, achieving an accuracy rate of 86.3%. The recommendation phase utilizes the node association weights from the knowledge graph and the student's capability status vector, employing a hybrid recommendation algorithm fused with cognitive diagnosis to generate personalized plans that include resource packages for knowledge analysis, skill training tasks, and cognitive guidance tools, with a single recommendation response time maintained under 200 ms. The feedback phase establishes a three-tier response system: immediate feedback addresses errors in experimental operations, such as automatically halting operations and highlighting standard action points when the pipetted volume error exceeds ±0.02 mL; formative feedback is based on unit test results, generating a knowledge mastery radar chart and suggestions for capability enhancement; and summative feedback is provided at the end of course modules, containing learning efficiency analyses, diagnostics of cognitive weaknesses, and planning for future learning pathways. This closed-loop mechanism optimizes through 20 iterations, resulting in a 23.7% increase in average student learning efficiency and a 19% decrease in the peak of the forgetting curve for key knowledge points.

Addressing the unique characteristics of inorganic and analytical chemistry, the learning model design emphasizes three adaptation strategies: 1) Knowledge Representation Adaptation: Developing tools for "macro-micro-symbolic" transformations that synchronously present videos of solution turbidity, microscopic animations of ion aggregation, and the derivation process for equilibrium constant expressions when explaining precipitation reactions, enhancing students' ability to correlate these three representations by 34%; 2) Cognitive Load Adaptation: Employing eye-tracking-based attention analysis technology, the system automatically breaks down complex molecular structure models into basic structural units when it detects that students' gaze duration exceeds a threshold with rising error rates, reducing spatial cognitive load by 28%; 3) Experimental Skill Adaptation: Constructing an operational action capture system within a virtual laboratory that integrates pressure sensor and camera data to identify in real time 12 types of operational problems such as unstable titration speeds and reading angle deviations, producing improvement plans with 3D animated demonstrations which increase the compliance rate for experimental operations from 62% to 89%.

4.2 Construction of Layered Progressive Learning Pathways

The basic theory learning module employs a three-tier framework of “Concept Construction-Principle Derivation-Application Transfer.” During the concept construction phase, core concepts such as “hybrid orbitals” and “titration jumps” are integrated with textbook definitions, visual models, and real-life examples (e.g., analogies between hybrid orbitals and the framework of an umbrella), creating multimodal concept packages that enhance accurate concept comprehension by 41%. The principle derivation phase introduces a “backward chaining derivation method,” using “pH calculations for buffer solutions” as an example. The system presents real-world problem scenarios first, guiding students to deconstruct required principles (acid-base proton theory, conservation of mass, conservation of charge) and then construct the calculation process, shortening the mastery period for complex principles by 35%. In the application transfer phase, a “wrong answer attribution training system” is developed that automatically analyzes students' error types in problems relating to the application of stability constants of complexes (concept confusion, formula misuse, step omission) and offers three targeted training tasks: foundational exercises to reinforce core concept distinctions, variant problems to practice flexible application of formulas, and comprehensive exercises to simulate scientific problem-solving scenarios, resulting in a 29% improvement in knowledge transfer ability.

The design of experimental skill training integrates a workflow of “Virtual Pre-training-Practical Verification-Reflective Improvement.” During the virtual pre-training phase, AR technology creates a highly realistic laboratory environment where students complete procedures such as reagent retrieval and instrument assembly through gesture interactions. The system provides real-time feedback on operational compliance; for example, if the angle of the pipette deviates vertically by more than 5°, a vibration alert is triggered, reducing operational errors during the pre-training stage by 67%. In the practical verification phase, a “dual data comparison” mechanism is adopted to simultaneously collect virtual experiment operation logs and real laboratory instrument data (e.g., changes in titration volume, weighing precision), using dynamic time warping algorithms to analyze operational consistency and identify seven key discrepancies such as pipetting speed control and timing in endpoint judgment. The reflective improvement phase generates personalized experimental reports that include operational process heat maps, analysis of error source matrices, and lists of optimization suggestions; for instance, in response to issues with “standard solution concentration deviations,” the system automatically associates related knowledge elements, such as “checking for leaks in volumetric flasks” and “controlling solute dissolution temperatures,” and recommends specialized reinforcement training tasks.

4.3 Intelligent Interaction and Dynamic Adjustment Mechanisms

The real-time feedback system integrates semantic analysis and image recognition technology to provide dual intelligent support in theoretical learning: on the textual interaction level, when students input chemical reaction equations, the system automatically detects balancing errors and issues related to symbol conventions; for example, if "CO_2" is written as "Co2," the system instantly marks the correct capitalized format of the element symbol and suggests similar practice problems. On the image interaction level, after students draw schematic diagrams of molecular structures, the convolutional neural network analyzes aspects such as bond length ratios and atomic connection sequences, generating comparison diagrams containing correction suggestions, resulting in a 52% increase in the correctness rate of structural representations. Cognitive scaffolding is dynamically constructed based on the Zone of Proximal Development theory; during difficult tasks, such as "calculating crystal structures," comprehensive formula derivation templates are provided initially, with intermediate steps gradually hidden as students' accuracy improves, ultimately transitioning to independent problem-solving, enhancing students' self-efficacy by 37%.

Calibration of learning goals is based on a three-dimensional matching model of "Capability Status-Knowledge Graph-Instructional Progress." Whenever learning data for every five knowledge elements are collected, the target calibration program is triggered: first, structural equation models analyze the deviations between current capability development and preset goals; if "error analysis capability" lags behind the pace of theoretical knowledge mastery, the system automatically increases the weight of experimental data processing tasks. Second, readiness checks on the mastery distribution of related nodes in the knowledge graph are performed; if the error rate for core knowledge elements in any chapter surpasses 30%, local goal adjustments are activated, downgrading mastery goals from "application" to "understanding" and reorganizing training resources. Lastly, in alignment with curricular progress requirements, global target calibration occurs at key milestones such as midterms and finals to ensure that personalized learning pathways stay consistent with overall course objectives. Empirical results reveal that this mechanism increases the goal achievement rate from 71% to 88%, with an average response time for goal adjustments kept under four hours.

5. Empirical Research and Effect Evaluation

5.1 Research Design and Data Collection

This study employs a quasi-experimental design, selecting second-year chemistry majors from three colleges of varying levels, resulting in a total of 1,276 participants divided into experimental (using the intelligent teaching system, n=652) and control groups (traditional teaching methods, n=624). The experimental period spans a semester, covering the teaching of two core modules: "Material Structure" and "Quantitative Analysis." Implementation contexts include: in theoretical classes, the experimental group completes the full process of pre-study, in-class interaction, and post-study review through the system; during lab classes, the experimental group engages in pre-training using a virtual simulation platform combined with real laboratory equipment for practical operations, while the control group relies on traditional textbooks, PPTs, and in-person experiments.

An evaluation system is established composed of three primary indicators and eleven secondary indicators: 1) Knowledge Mastery Efficiency, measuring unit test accuracy rates, average mastery times per knowledge element, and repeat error rates; 2) Ability Development Levels, assessed through standardized tests evaluating five core abilities such as material structure cognition and quantitative reasoning, using item response theory to calculate capability enhancement scores; 3) Technology Acceptance, measured by an adapted UTAUT scale for perceived ease of use, perceived usefulness, and intention to use, with a Cronbach's α coefficient of 0.92. Additionally, during the experiment, learning platform log data (2.3TB), experimental operation video data (480 hours), and eye-tracking data (1.2 million data points) are collected, forming a multi-source heterogeneous dataset.

5.2 Data Analysis Methods

In the data preprocessing phase, principal component analysis is applied to reduce dimensionality, compressing the 128-dimensional learning feature vector to 32 dimensions while retaining 92% of the information variance. In the model construction phase, a random forest algorithm identifies key factors influencing learning efficiency, revealing that the "accuracy of adaptive resource recommendations," "response speed of real-time feedback," and "frequency of knowledge graph navigation" are the top three influencing factors, explaining 68% of variability. For experimental skill data, a hidden Markov model is utilized to identify typical error patterns, successfully clustering five core issues, including "non-standard instrument operation," "logical errors in data processing," and "misjudgment of experimental phenomena," providing a basis for precise intervention.

A structural equation model of "Technology

Intervention-Learning Behavior-Capacity Development" is constructed to validate the hypothesized pathways: the intelligent teaching system indirectly promotes capability development by optimizing learning behaviors (resource usage efficiency, interaction depth, training intensity). Model fit results show: $\chi^2/df=1.89$, RMSEA=0.06, CFI=0.94, conforming to good fit standards. Path analysis indicates that the standardized path coefficient of system recommendation accuracy on resource usage efficiency is 0.72 ($p<0.001$), and the total effect of learning behavior on capability development is 0.58, where the mediating effect of "quantitative reasoning ability" holds the largest proportion (39%), confirming the core hypothesis that technology intervention facilitates ability development by enhancing learning behaviors.

5.3 Key Results and Discussion

The experimental group significantly outperformed the control group in knowledge mastery efficiency: the average accuracy rate in unit tests increased by 15.2% (82.3% vs 67.1%), the average mastery time per knowledge element decreased by 22.4% (45 minutes vs 58 minutes), and the repeat error rates fell by 31%. Capability development assessments reveal that the experimental group achieved significantly higher value-added scores in "material structure cognition" (+21.3%) and "experimental operation skills" (+29.7%), with the improvement in analysis chemistry error analysis abilities being the most notable, reaching 34.5%, directly related to the system's targeted intelligent diagnostic functionality for experimental data. Technology acceptance surveys indicate that 89.4% of students believe the system significantly enhances learning autonomy, while 76.3% express a willingness to continue using it in future courses, validating its practical value.

Hierarchical regression analysis indicates that different segments of the "Assessment-Recommendation-Feedback" closed-loop mechanism impact learning outcomes differently: every 10% increase in diagnostic accuracy within the assessment module correlates with an 18% improvement in recommendation effectiveness; each 5% increase in accuracy of recommended resources leads to an increase of 12 minutes/day in student voluntary learning hours; and the immediacy and specificity of feedback contribute 47% to the enhancement of experimental skills. Further moderation effect analysis shows that students' initial ability levels significantly moderate system effectiveness: low starting ability students demonstrate an improvement magnitude of +28.9% under system support, which is 2.27 times greater than that of high starting ability students (+12.7%), highlighting the significant value of the intelligent teaching system in bridging the learning foundation gap and promoting educational equity.

Qualitative analyses reveal that system effectiveness is influenced by three main subject characteristics: 1) Complexity of Knowledge Representation: for content involving three-dimensional spatial representations like "crystal field theory," the system's 3D model interactive tools led to a 42% increase in learning efficiency, significantly surpassing pure symbolic representation knowledge (+18%); 2) Procedural Nature of Experimental Skills: skills such as titration are effectively trained through the intelligent diagnostic module, while the enhancement of innovative experimental design capabilities relies heavily on deep teacher involvement, with the system's support showing limited effectiveness (+9%); 3) Logical Nature of Computational Thinking: using step-by-step deduction tools for multistage balance calculations in analytical chemistry reduced error rates from 41% to 17%, reflecting the system's advantages in facilitating logical reasoning training. These findings indicate directions for future system optimization: enhancing support for open-ended problem-solving abilities and improving the intelligence level of "macro-micro-symbolic" representation transformations.

6. Conclusion

This study has established a data-driven intelligent teaching system for inorganic and analytical chemistry and innovated a personalized learning model based on "technology empowerment-data-driven-dynamic adaptation," creating a complete research feedback loop through theoretical modeling, system development, and empirical validation. The main innovations include: 1) proposing a knowledge graph modeling method aligned with the cognitive laws of the chemistry discipline, achieving dynamic associations and intelligent navigation of 287 knowledge elements; 2) developing an ability diagnostic model that integrates multimodal data to accurately characterize students' developmental trajectories across five core ability dimensions; 3) constructing the "Assessment-Recommendation-Feedback" closed-loop mechanism which enhances knowledge mastery efficiency by 23.7% and achieves a resource matching accuracy of 89.2%. The research reveals the pathways through which intelligent teaching systems promote ability development by optimizing learning behaviors, providing a reusable methodological framework for the intelligentization of chemistry courses.

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