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Expanding content and integrating digital and artificial intelligence technologies into a smart petrology course: A research-informed approach to teaching

Chenlin Hu[1,2,*], Xin Li[1,2,*], Shuo Feng[1,2], Jonathan A. Quaye[3], Dongmei Qi[1,2], Xiaomei Zhang[1,2]

[1]*School of Geology and Mining Engineering, Xinjiang University, Urumqi, 830017, China*
[2]*Xinjiang Key Laboratory of Coalbed Methane Exploration and Development, Xinjiang Yaxin Coalbed Methane Investment and Development (Group) Co., Ltd, Urumqi, 830002, China*
[3]*Department of Petroleum Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, 451001, Ghana*

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Abstract: Advances in Emerging Engineering Education and the digital transformation of geoscience education are placing new demands on petrology courses, including the development of data literacy, systematic thinking, and adaptability to engineering practices. Conventional instruction still centers on memorization and classification, while constraints involving time, location, and safety restrict fieldwork and laboratory activities. Digital tools remain supplementary rather than being integrated into course content and instructional designs. Research findings are difficult to translate into teaching, leaving students familiar with rocks but unable to distinguish them reliably or apply their knowledge in practice. To address these problems, this study developed a research-informed model that combined curriculum restructuring with digital and AI-enabled instruction. Its three-tier framework of "core streamlining, cross-disciplinary supplementation, and frontier transformation" reorganizes petrological knowledge. It incorporated engineering case studies and converted advances in AI-based rock and mineral identification and digital rock mechanics into teachable modules. An integrated "six-in-one" collection of smart teaching resources supported human–machine collaboration in the classroom and a data-driven feedback loop throughout the teaching process. The model was evaluated in terms of knowledge acquisition, integrative thinking, and replicability using evidence from comparable international educational reforms and first-class courses at Xinjiang University that have been recognized at the provincial and ministerial levels. The findings indicate that the approach improves students' practical ability to identify rocks and minerals, promotes evidence-based geological systems thinking, and strengthens the connection between theoretical knowledge and engineering practices. This approach, implemented at Xinjiang University, offers a transferable model for digital and AI-enabled petrology instruction under comparable conditions, pending multi-institutional validation.

1. Introduction

The global development of Emerging Engineering Education and the adoption of digital and Artificial Intelligence (AI) technologies in geoscience are reshaping the education of Earth science students (Niedoba et al., 2025). As a foundational subject that connects microscopic mineral crystallization with large-scale plate tectonics, petrology has followed a linear teaching process involving theoretical lectures, hand-specimen identification, microscopic observation, and field description (King, 2006; Bicudo et al., 2026). Although this approach develops basic observational skills, three structural limitations have become increasingly apparent. First, its emphasis on static descriptions and classification leaves little room for applying petrological data to practical problems in resource exploration and engineering geology. Consequently, students may understand rocks in theory but struggle to distinguish or use them in practice. Second, limited specimen representativeness, time and location constraints, and safety concerns restrict laboratory and field work. As a result, instruction cannot encompass the full natural variability of the three major rock types, and students often become familiar with "typical samples" without understanding actual geological bodies. Third, there is a time lag and discrepancy between the frontiers of the discipline and classroom teaching, and research findings are rarely incorporated systematically into instruction (Bethune, 2020; Jedlicková et al., 2024). Collectively, these limitations disconnect petrology instruction from the data literacy, systems

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*Corresponding author.
E-mail address: huchenlin@xju.edu.cn (C. Hu); lixinwaxj@xju.edu.cn (X. Li).
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thinking, and engineering adaptability needed for interdisciplinary education, ultimately constraining the quality of geoscience education.

Digital and AI technologies (e.g., virtual microscopes, remote sensing, machine learning, 3D rock models, Virtual Reality (VR) field activities, and knowledge graphs) have demonstrated educational values in particular settings (Wang, 2020; Cai et al., 2026; Esmaeilzadeh et al., 2026). International studies have shown that combining physical and virtual learning environments can substantially improve rock and mineral identification, and interactive AI modules can partially bridge the cognitive gap between standard specimens and naturally variable materials (Guillaume et al., 2023; Petrelli, 2024; Mkhohlakali et al., 2026). Nevertheless, these technologies are commonly treated only as supplementary tools. Knowledge graphs may list isolated concepts without reorganizing the underlying content, AI identification assistants are frequently confined to after-class support, and VR scenarios are developed separately from the course's central concepts and most challenging topics (Bond and Cawood, 2021; Pugsley et al., 2022). Similarly, research findings tend to appear only as occasional case studies rather than as components of systematic instructional design informed by cognitive principles. Research questions, digital and AI tools, and teaching feedback may fail to create a coherent instructional cycle (Haroldson et al., 2024; Giotopoulos et al., 2025). Therefore, the main challenge is to align technological integration with curriculum restructuring throughout the teaching process while preserving the established ways of thinking used in petrology (Yang, 2024; Tsangaratos et al., 2025; Sun and Liu, 2026).

Based on the principle of feeding research into teaching, this study presented a novel approach to expanding a smart petrology curriculum and supporting instruction with digital and AI technologies. This approach combined curriculum restructuring and the integration of digital and AI tools (Jeffery et al., 2021; Pashchenko et al., 2025). First, the traditional knowledge framework was streamlined and reinforced. Specifically, redundant crystallography chapters were removed; the instructions on the mineral composition, textures and structures, and modes of occurrence of the three major rock types were refined; and identification methods were integrated across theory, laboratory work, and field practice. Authentic engineering cases from areas (e.g., resource exploration and geological engineering) were incorporated, and advances in AI-based rock and mineral identification and digital rock mechanics were adapted into teaching modules (Apopei, 2025; Tsangaratos et al., 2025). Second, a "six-in-one" collection of smart teaching resources involved knowledge graphs, AI identification assistants, a virtual specimen library, VR/AR field practice, a human-machine collaborative classroom, and a data-driven feedback loop. These resources integrated digital and AI tools into each stage of "learning, practice, assessment, and evaluation" (Fang et al., 2024). Finally, the approach was assessed through comparative evaluation of teaching outcomes, tracking of integrated competency development, and analysis of its transferability across diverse institutional contexts. This study aims to provide a replicable model for transforming foundational geology courses through coordinated improvements in the content, technology, and assessment. It also explores institutional pathways for incorporating current research into teaching and supports the development of digital literacy and practical engineering competence among geoscience students in Emerging Engineering Education.

2. Expanding the curriculum

To reduce the traditional emphasis on theory at the expense of application, Xinjiang University's Petrology course draws on the geological advantages of the Central Asian Orogenic Belt and incorporates research directly into teaching. Its three-tier framework combines a streamlined core, interdisciplinary supplementation, and translation of current research into teaching. The framework progresses from consolidating foundational knowledge to broadening disciplinary boundaries and engaging with emerging frontiers while aligning course content with regional geological conditions and engineering accreditation requirements.

2.1 Refining and restructuring core knowledge

Xinjiang University redesigned its Petrology course around the Central Asian Orogenic Belt to reduce overemphasis on crystallographic theory and better integrate regional geology. To ensure transparency and reproducibility, a formal methodology was established. Decisions on crystallography content involved three stakeholder groups: the teaching team, external discipline experts, and industry representatives from the Xinjiang Oilfield Research Institute. Three criteria guided evaluation: relevance to rock identification, redundancy with prerequisite courses, and practical applicability in engineering geology. Consensus was reached via a modified Delphi process with two rounds of rating and deliberation, requiring $\geqslant$80% agreement. The revised module underwent three-stage review: disciplinary peer review, industry consultation, and accreditation alignment with university and national standards.

Following this methodology, redundant crystallography was reduced, and mineralogy was consolidated into a module on rapid identification of major rock-forming minerals. Practical hand-specimen training was strengthened early. Regionally specific cases were incorporated for igneous, sedimentary, and metamorphic rocks, drawing on local data and specimens (Geng et al., 2018). Collaboration with the oilfield institute provided representative cores for laboratory work.

Consistent with international reforms, the revised course focuses on mineral composition, textures, structures, and occurrence of the three rock types, linking hand-specimen, microscope, and outcrop scales. The original 10 chapters were consolidated into eight, reducing lecture time by about 20%. This improved systematic identification training and students' cross-scale observation skills, freeing time for interdisciplinary and digital/AI modules (Table 1).

2.2 Integrating engineering applications and case studies

Regionally focused engineering cases connect Xinjiang University's Petrology course with the distinctive resources and engineering needs of Xinjiang and Central Asia. In the solid mineral exploration module, students use representative copper-nickel sulfide deposits, including Kalatongke and Huangshan, to practice "lithofacies

Table 1 Comparison of core content optimization in conventional and smart petrology courses

Representative topics	Conventional course content	Smart course content	Key curricular changes
Fundamentals of mineral identification	Instruction in the theory of crystal optics and optical mineralogy	Consolidated into "Physical properties and rapid identification of major rock-forming minerals"; more hands-on practice with specimens	Reduce optical theory; incorporate actual mineral images from the Tarim Basin
Classification and occurrence of igneous rocks	Systematic classification using chemical composition and SiO_2 content	Focus on porphyritic texture, vesicular structure, and intrusive/extrusive occurrence; use case studies of representative Tianshan plutons	Link texture, structure, and occurrence to avoid repetition
Analysis of igneous petrogenesis	Emphasis on theories of magma differentiation, assimilation, and contamination	Use research data on magmatic rocks from the Central Asian Orogenic Belt to examine their relationship with tectonic setting	Incorporate regional tectonic context and strengthen petrogenetic reasoning
Composition of sedimentary rocks	Emphasis on descriptive classification of clastic and carbonate rocks	Improve interpretation of texture, structure, and sedimentary-facies development; use thin-section data from the Tarim Basin	Improve field recognition of facies indicators; introduce measured research data
Sedimentary facies and sequence	Instruction based primarily on classical facies models	Use actual drilling-core data from Xinjiang and nearby areas to practice sedimentary-microfacies analysis	Connect observations across thin sections, cores, and outcrops
Textures and structures of metamorphic rocks	Systematic instruction in crystalloblastic textures and types of schistosity	Compare spatial variations among metamorphic-facies belts using specimens from the Tianshan Orogenic Belt	Emphasize the relationship between regional metamorphism and tectonic setting
Metamorphic facies and engineering properties	Limited to the theory of metamorphic-facies equilibrium	Use engineering cases from representative metamorphic belts to assess the stability of surrounding rock masses	Connect metamorphic petrology with applications in engineering geology
Integrated training in rock identification	Laboratory reports distributed across separate chapters	Use project-based tasks to link hand-specimen, microscope, and outcrop identification	Progress from concise theoretical lectures to indoor experiments and field training

identification, alteration logging, and mineralization potential assessment". The Rock and Engineering Geology module is built around a water-diversion tunnel on the northern slope of the Tianshan Mountains and the Tianshan Shengli Tunnel. Students examine the engineering-geological characteristics of mylonite and tectonic breccia in deep and major fault zones and assess rock mass quality using field survey data collected by the research team. In the rock-physical-properties module, representative drilling cores from the Junggar and Tarim Basins were used to relate lithology to petrophysical measurements, such as density and magnetic susceptibility. Across all modules, project-based tasks followed "feature description, problem identification, and mechanism interpretation", helping students transfer knowledge and skills between contexts.

Case-based teaching in the Petrology course is designed to be systematic and broad enough to serve several degree programs. For students in Resource Exploration Engineering, Geological Engineering, Exploration Technology and Engineering, and Gemology and Materials Science, the curriculum offers four general modules: "Solid Mineral Exploration", "Rock and Engineering Geology", "Rock Physical Properties and Geophysical Exploration", and "Gemstone Identification". Each includes 2–3 authentic engineering cases from professional practice (Gao et al., 2025). In "Solid Mineral Exploration", students identify potassic–sericitic alteration zones in granodiorite porphyry during porphyry copper exploration (Li et al., 2025). "Rock and Engineering Geology" examines the classification of rocks surrounding deeply buried tunnels and the stability of bedding plane rock slopes, including how water-induced mudstone softening controls the stability of the surrounding rock. "Rock Physical Properties and Geophysical Exploration" relates the resistivity and magnetic susceptibility of rocks and ores to their mineral composition, texture, and structure (Jin et al., 2024). "Gemstone Identification" uses representative materials, including jadeite and Hetian jade, to explain the petrological basis of gemstone nomenclature and the criteria used for commercial evaluation. These general modules and Xinjiang-specific case studies form a coherent framework for applying petrology in diverse engineering applications (Figure 1).

2.3 Translating research findings into teaching

At Xinjiang University, the findings of the Petrology teaching team's research are systematically converted into course materials. Its case database is updated annually with geochemical data from Carboniferous-Permian volcanic rocks in the Junggar Basin, carbonate-microfacies data from the Tarim Basin, P-T-t paths for high-pressure metamorphic rocks from the Tianshan Orogenic Belt, and other relevant datasets. These materials support inquiry-based tasks that

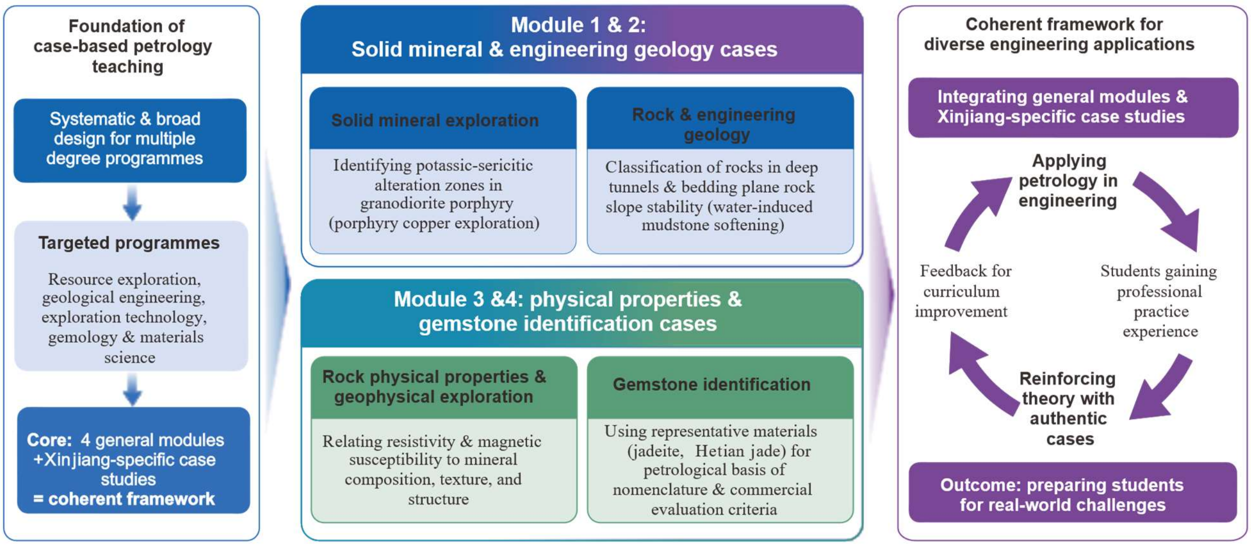

Figure 1 Petrology application modules and a project-based learning framework across diverse engineering fields

progress through "data acquisition-independent observation-interpretation and verification". Students use the team's measured data to identify tectonic settings, interpret sedimentary microfacies, and compare their conclusions with published findings, thereby completing their inquiry cycle. Additional projects contribute authentic activities, including carbonate microfacies analysis and studies of reservoir diagenesis, for integrated practical training. Moreover, research from the Dabasong Uplift in the Junggar Basin provides the basis for a dedicated module on "Application of Sedimentary Petrology in Petroleum Exploration", which helps students connect theoretical knowledge with engineering practice.

Beyond incorporating its own research outputs, the course draws on the university's expertise in AI-based rock and mineral identification and digital rock mechanics to develop two advanced topics. In the first topic, "AI-based Intelligent Identification of Rocks and Minerals", a convolutional neural network for classifying mineral images becomes a classroom case study. Practical identification tasks on an open-source platform follow the sequence "data acquisition-feature extraction-model training-result interpretation". Students compare misclassified specimens with correct identifications, encouraging a closer examination of the details used in identification. The "Digital Rock Mechanics" topic introduces recent research on micro-CT scanning and three-dimensional pore-network reconstruction through a virtual "digital core analysis" experiment (Liu et al., 2024; Khimulia and Karev, 2026). Students rotate and section three-dimensional core models to examine how microscopic pore structures in sandstone and carbonate rocks influence macroscopic properties, such as permeability and strength (Liu et al., 2023; Makarian et al., 2025). These observations clarify how the microstructure controls the engineering behavior (Al Balushi and Taleghani, 2022). Collectively, the research findings and advanced technological topics form a two-way "research-teaching-research" cycle (Figure 2). Current research has moved beyond published papers and become a teaching resource through which students can engage with developments in their discipline.

3. Pathways for digital and AI-enabled teaching

Digital and AI-supported petrology teaching requires the integration of various technologies. Coordinating teaching resources, classroom activities, and data-driven feedback enables systemic changes in the instructional model. It also redistributes cognitive responsibilities and moves students from memorization to evidence-based reasoning.

3.1 Six-in-one resource matrix

The curriculum organizes six interconnected teaching resources into four core petrological competencies: cognition, identification, interpretation, and application. These include a knowledge graph, an AI-assisted tool for identifying rocks and minerals, a virtual specimen library, VR/AR field practice, a smart teaching platform, and a data engine that integrates learning, practice, testing, and evaluation (Zhao et al., 2025; Zhou et al., 2026). Shared knowledge tags, specimen identifiers, and task standards connect the six resources into one system. Within this system, the knowledge graph organizes what students learn, AI and virtual simulation support interaction, the smart platform coordinates teaching, and the data engine records evidence of learning (Figure 3).

3.1.1 Hierarchical knowledge graph

Course concepts form the nodes of the knowledge graph, while five types of relationships define its edges: compositional, classificatory, genetic, spatiotemporal, and application-related. These edges connect minerals, textures and structures, rock types, diagenetic and metallogenic processes, tectonic settings, and engineering properties across multiple dimensions. At the foundational level, students differentiate between concepts and identify taxonomic groups. The progressive level focuses on process mechanisms and evidence-based reasoning, while the extended level incorporates case studies from regional geology, mineral

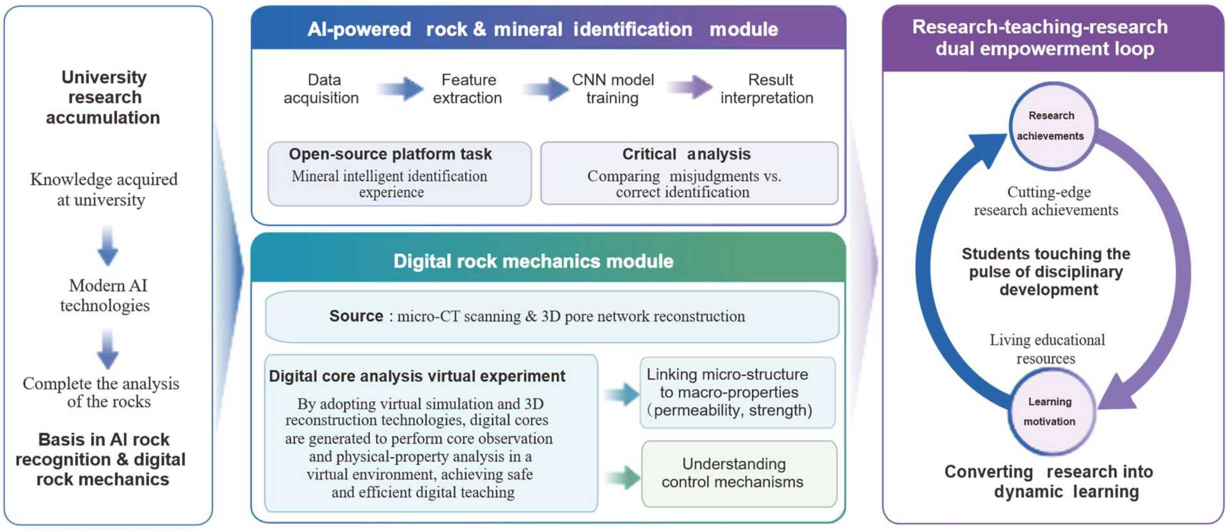

Figure 2 Pathway for translating research findings into teaching

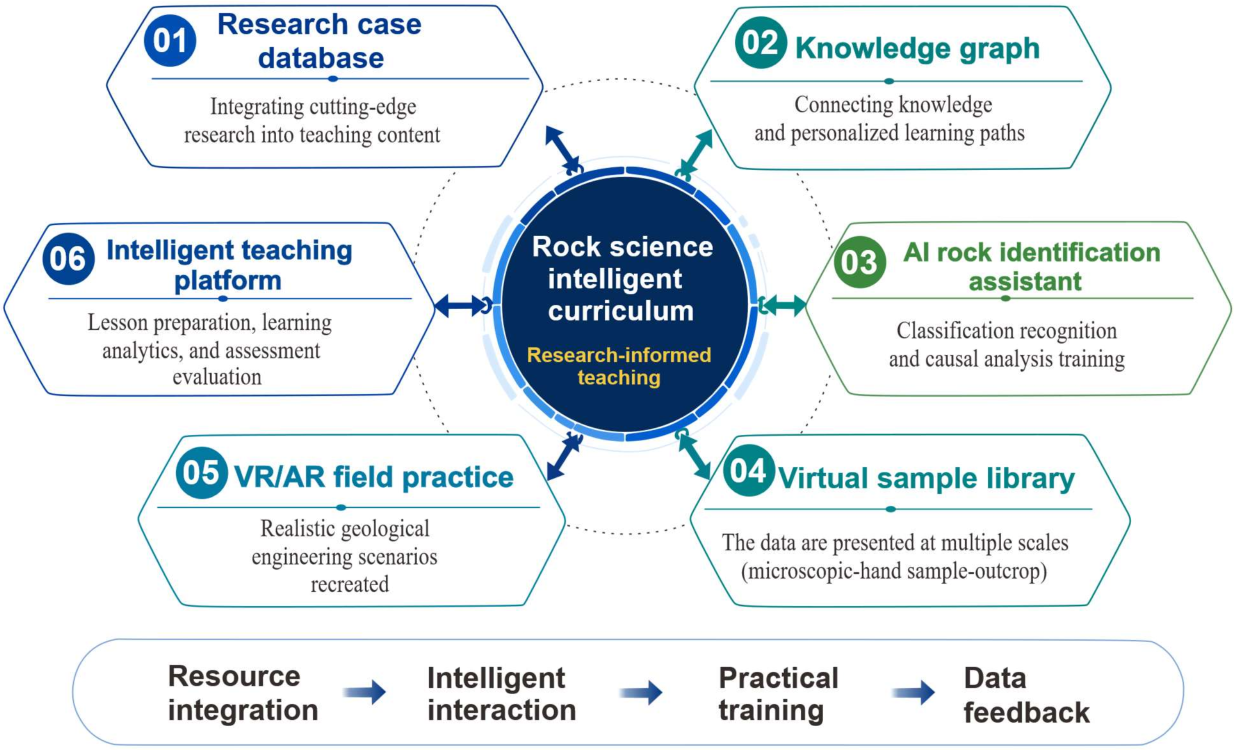

Figure 3 Six-in-one integrated matrix of smart teaching resources

resources, and engineering geology. Pre-assessment results, task performance, and error patterns guided personalized learning pathways. When a gap is identified, the system directs students to relevant micro-lectures, specimens, thin sections, case studies, and exercises. This makes it possible to identify specific weaknesses, navigate resources efficiently, and adapt learning pathways as needed (Li et al., 2024).

3.1.2 AI-assisted identification and virtual specimen library

The AI-assisted rock and mineral identification tool addresses four common tasks: rock classification, mineral identification, description of textures and structures, and genetic interpretation. The instructional sequence combines guided observation, focused questioning, and explicit explanations (Wang et al., 2026). When students upload or retrieve rock images, the system does not simply provide answers. Instead, it directs their attention to diagnostic features such as color, grain size, crystal form, cleavage, aggregate morphology, and contact relationships. This process helps students construct a verifiable chain of observations. Similar specimens and counterexamples are introduced when rock types are easily confused, helping students distinguish between competing interpretations (Liu and Huang, 2026). The virtual specimen library combines polarized-light micrographs, photographs of hand specimens, 3D scanned models, and outcrop panoramas.

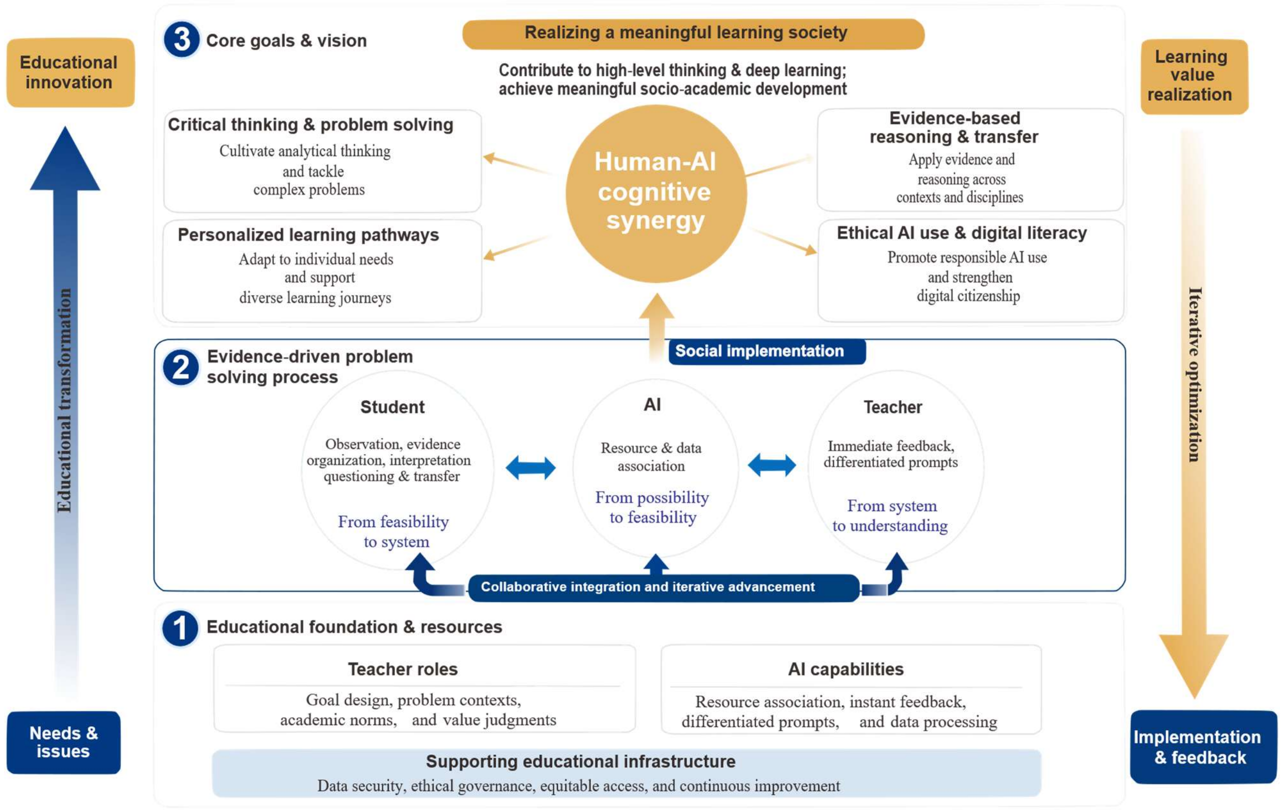

Figure 4 Human-AI collaboration and the data-driven instructional loop

Students can examine the same geological object at microscopic, hand specimen, and outcrop scales and connect local features with their broader geological significance.

3.1.3 VR/AR field practice

The VR/AR module recreates representative rock masses, mining sites, tunnel slopes, and geohazard locations in realistic geological engineering scenarios. Students work through a full sequence of field activities, including planning observation routes, measuring geological attitudes, tracing lithological boundaries, collecting samples, and identifying risks. Within the virtual environment, they can select observation points, annotate evidence, and decide on routes while checking their field interpretations against thin section, geochemical, or petrophysical data. The module can be used to rehearse tasks before fieldwork and to review evidence afterwards, reducing constraints associated with weather, transport, safety, and the limited repeatability of representative outcrops (Lyu, 2024).

3.2 Human-AI collaboration and classroom redesign

Effective classroom integration of AI depends on redistributing cognitive responsibilities rather than replacing teachers' explanations. Teachers define learning objectives, design problem contexts, uphold academic standards, and exercise value judgments. AI links relevant resources, provides real-time feedback and differentiated prompts, and processes activity data. Students are responsible for observing, organizing evidence, interpreting, questioning, and applying knowledge in new contexts. Together, these roles move the classroom away from teacher-delivered conclusions and memorized classifications towards evidence-based problem solving (Figure 4).

3.2.1 Smart lesson planning and learning analytics

Before each class, teachers align learning objectives with knowledge graph nodes, research cases, and task templates. The platform combines historical learning data with pre-test results from the current cohort to predict difficulties and help teachers design tasks at three levels: foundational, progressive, and challenging. During the lesson, responses from polls, annotations, identification exercises, and reasoning activities are aggregated in real time and displayed as a class-wide knowledge heatmap. The heatmap highlights recurring misconceptions, including confusion between textural or structural features and genetic indicators, reliance on color alone to identify minerals, and failure to consider contact relationships. Teachers can adjust the selected cases, follow-up questions, and demonstration sequences as needed.

3.2.2 Scientific reasoning in virtual and physical settings

Classroom learning begins with the direct observation of physical specimens and polarizing microscopes supplemented by virtual specimens, 3D models, and AI agents. Students first describe and classify samples independently before comparing their interpretations with AI-generated alternatives. They weigh the available evidence, identify missing observations, and consider how competing explanations can be ruled out, thereby completing a reflective cycle. During petrogenetic analysis, AI can act as a peer reviewer by directing attention to material provenance, crystallization sequence, P-T conditions, and tectonic setting. This progression moves students beyond conventional descriptions to explain the geological mechanisms behind their observations (Derouech et al., 2026).

Table 2 Practical pathways for digital and AI-enabled petrology instruction

Development areas	Core tasks	Key technologies and resources	Representative teaching scenarios	Primary data outputs	Expected outcomes
Knowledge restructuring	Develop a multi-level knowledge graph linking course concepts, specimens, and task tags.	Knowledge-graph platform, curriculum standards, and a library of research cases	Pre-class guidance, concept linking, and personalized learning pathways	Rates of node mastery and pathway completion	Visualization of knowledge structures and targeted resource recommendations
Multiscale resource development	Develop an AI-assisted rock/mineral identification tool and a virtual specimen library	Image recognition, 3D scanning, and microscopy-image stitching	In-class identification, comparison of similar specimens, and independent practice	Observation tags, identification steps, and chains of evidence	More accurate identification and stronger connections across observation scales
Expanded virtual fieldwork	Develop VR/AR scenarios for fieldwork and engineering geology	Panoramic images, 3D modeling, and spatial positioning	Fieldwork rehearsal, route selection, and on-site review	Records of observation points, routes, measurements, and judgements	Fewer time and location constraints and better transfer to real field settings
Classroom redesign	Create a collaborative teaching model involving teachers, AI, and students	Smart classrooms, AI agents, and real-time interactive tools	Classification discussions, petrogenetic reasoning, and peer review	Interaction frequency, reasoning logs, and revision histories	A shift from memorizing conclusions to reasoning from evidence
Data-driven assessment with continuous feedback	Integrate learning, practice, testing, and evaluation; adjust teaching strategies continuously	Learning analytics, competency profiling, and a feedback engine	Diagnostic support, tiered tasks, and ongoing course improvement	Knowledge heatmaps, error categories, and competency profiles	Traceable assessment and continual improvement of teaching

3.3 Data-driven instructional loop

The platform uses a task engine that links learning, practice, testing, and evaluation. It records resource access, image annotations, identification procedures, reasoning logs, collaborative discussions, quiz results, and reflective revisions. These records make students' learning traceable throughout the instructional process. Assessment extends beyond whether students reach correct conclusions. It also considers the adequacy of their observations, coherence of their evidence, completeness of their reasoning, clarity of their explanations, and ability to apply knowledge in unfamiliar situations (Liu et al., 2026; Zhang et al., 2026).

Learning data inform instruction at three levels. At the class level, a concept mastery matrix and recurring error patterns reveal weaknesses in teaching. At the student level, individual competency profiles and recommended learning pathways support differentiated instruction. At the course level, comparisons of learning gains across cases, resources, and activities guide ongoing improvements to course content and teaching methods. Updated research cases, common misconceptions, and examples of strong reasoning can also be incorporated into the knowledge graph and AI prompting strategies so that teaching resources, classroom instruction, and assessment continue to develop together (Majumdar et al., 2026).

For digital and AI-enabled petrology teaching, practical implementation can be described under six headings: areas of development, core tasks, technical resources, instructional scenarios, data outputs, and expected outcomes (Table 2).

4. Implementation outcomes and validation

Direct evaluation is needed to determine the success of a research-informed teaching reform. Empirical studies of petrology curricula worldwide provide evidence of three aspects of implementation: comparative teaching outcomes, the development of integrated competencies, and the transferability of the teaching model.

4.1 Comparative evaluation of teaching outcomes

At Xinjiang University, the Petrology course, led by the first author, has recently received provincial recognition as a first-class course. Its teaching team has systematically revised both course content and instructional methods around the principle of "research-informed teaching". Recent findings from the first author's research group in carbonate sedimentology, reservoir geology, and related fields have been converted into teaching cases and added to the course teaching material repository. These findings include a Cambrian carbonate platform facies model of the Tarim Basin and a reconstruction of Cambrian-Ordovician paleowind directions in the Tarim Basin. Moreover, the course draws on the "foundation-specialty-comprehensive" three-tier framework and the "course-training-competition-innovation" four-dimensional experimental teaching system

Table 3 Comparison of learning outcomes between the conventional (2023) and reformed (2025) cohorts

Assessment dimension	Conventional (2023, n=118)	Reformed (2025, n=120)	Mean gain	Percentage gain	p-value
Theoretical knowledge	74.3±8.1	86.8±6.5	+12.5	+16.8%	<0.001
Practical identification	70.8±10.2	89.5±5.8	+18.7	+26.4%	<0.001
Integrated case analysis	67.4±11.5	88.7±7.2	+21.3	+31.6%	<0.001
Overall composite	71.6±9.4	88.6±6.1	+17.0	+23.7%	<0.001

developed by the Experimental Teaching Demonstration Center of Geology and Mining Engineering at Xinjiang University. Within this framework, students use a virtual microscope for interactive identification and complete integrated petrology training based on authentic research data.

To quantitatively evaluate the actual teaching effectiveness of the above reform measures, this study adopted a quasi-experimental design, selecting the 2023 cohort $n = 118$ as the control group (traditional lecture-and-laboratory instruction) and the 2025 cohort $n = 120$ as the experimental group (reformed three-tier framework, digital and AI resources, and data-driven feedback loop); both cohorts were taught by the same teaching team, and the final assessments all comprised three dimensions: theoretical knowledge, practical identification, and integrated case analysis, with all scores converted to a 100-point scale and consistent marking rubrics. The assessment results show that the experimental group significantly outperformed the control group in all indicators: the mean theoretical-knowledge score increased by 12.5 points, practical identification improved by 18.7 points, integrated case analysis rose by 21.3 points, and the overall composite score increased by 17.0 points; paired t-tests indicated that all differences were statistically significant ($p < 0.01$) (Table 3). In addition, in the post-course self-evaluation, the experimental group's confidence score (5-point Likert scale) for "identifying rocks and minerals in unfamiliar geological contexts" was 4.3, significantly higher than the control group's 3.1; analytical logs from the AI-assisted identification tool also showed that the frequency of common error patterns (e.g., confusing similar textures, over-reliance on color) in the experimental group decreased by 42% compared with the control group.

4.2 Development of integrated competencies

Course-based undergraduate research has produced substantial educational gains in the Petrology course taught by the first author. The course draws on more than 20 research projects led by the first author, including National Natural Science Foundation of China projects and Xinjiang Key Research and Development projects. Authentic research activities (e.g., carbonate microfacies analysis and studies of reservoir diagenesis) have been incorporated into integrated training projects. Students undertake research tasks closely aligned with course content, including carbonate thin-section identification and sedimentary microfacies classification, which substantially improves their petrographic identification and geological data analysis skills. Furthermore, the course emphasizes the engineering applications of research findings. Specifically, the team's work on the depositional model and hydrocarbon accumulation conditions of the Dabasong Uplift in the Junggar Basin has been developed into a case study entitled "Application of Sedimentary Petrology in Petroleum Exploration". This case helps students understand how theoretical petrological knowledge is applied in engineering practice. The most far-reaching contribution of research-informed teaching is that it moves students from fragmented, descriptive reasoning to integrated systems thinking (Panorkou et al., 2025). The KamenCheck framework organizes learning into three stages: material properties, observational experiments, and Earth system connections. Through these stages, the framework guides students towards a broader understanding of interactions among tectonics, climate, and the biosphere in petrological systems (Brajković and Žvab Rožič, 2026). Those taught through this framework performed significantly better than those in conventional classes on open-ended questions regarding the relationship between petrogenesis and plate tectonics. Integrating computational thinking into petrological inquiry strengthens students' data literacy (Lore et al., 2024). For example, computational-modelling tasks focused on volcanic-hazard prediction have improved students' understanding of scientific content and their skills in data visualization, parameter adjustment, and interpretation of modelling results (Figure 5).

4.3 Transferability analysis

The transferability of research-informed teaching has been demonstrated in various international contexts; however, the specific approach presented in this study, implemented at Xinjiang University, offers a transferable model that requires further validation across multiple institutions to fully establish its generalizability. The GETSI modules, SPARKS open-source resource library, and the review by Semken et al. have demonstrated their effectiveness in various educational contexts. These sources also indicate that core strategies can be implemented in different instructional settings (Haroldson et al., 2024; Semken et al., 2025).

A common feature of the international examples discussed above is the integration of distinctive regional geology into broadly applicable teaching strategies. In Xinjiang, the tectonic configuration commonly described as "three mountain ranges flanking two basins" has produced a nearly complete rock record spanning the Proterozoic to the Cenozoic, providing rich natural resources for teaching. The team has translated two research findings into practical projects: the Cambrian carbonate platform facies model of the Tarim Basin and the Jurassic delta system of the Junggar Basin. In these projects, students analyze thin sections from local cores and examine outcrop sections. Magmatic and

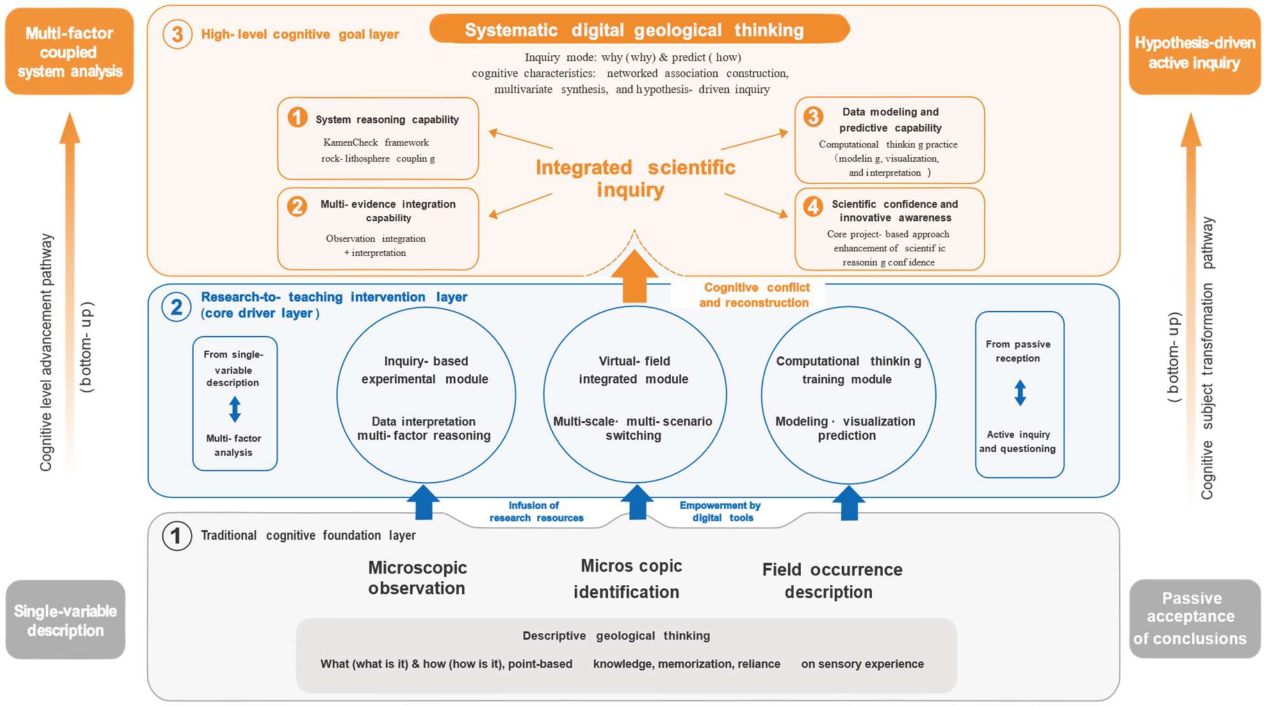

Figure 5 Model of students' cognitive transition in research-informed petrology courses

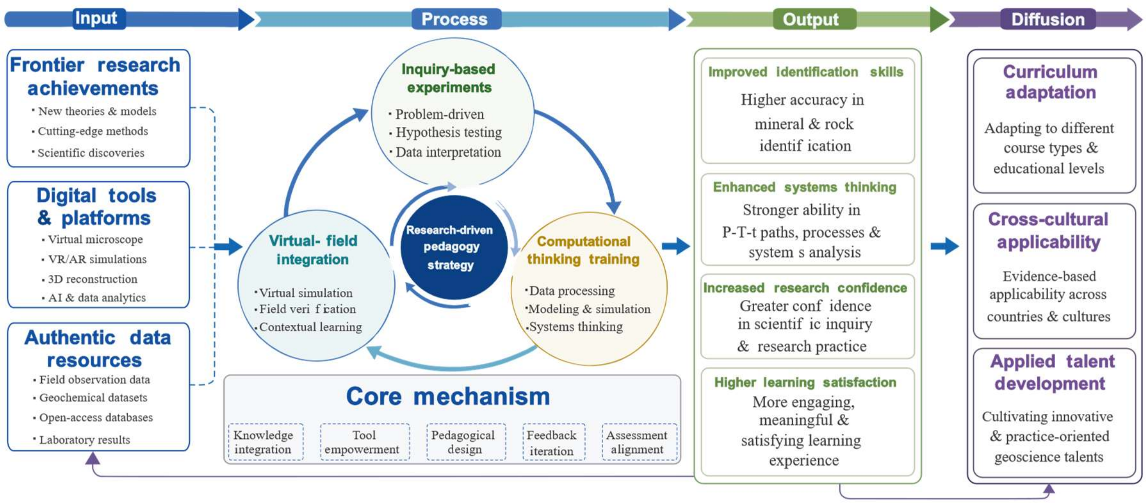

Figure 6 Implementation-effectiveness model for research-informed petrology teaching

metamorphic rocks representing multiple geological episodes in the Tianshan Orogenic Belt provide additional first-hand teaching specimens. The three-tier "foundation-specialty-comprehensive" practical curriculum includes field trips to classic geological sections along the northwestern margin of the Junggar Basin and the northern piedmont of the Tianshan Mountains. These routes put the principle of "the field as the classroom" into practice. This sequence of "regional resource exploration-translation of research findings into teaching-practical training design" lowers the barriers to implementing research-informed teaching and offers a transferable model for institutions with relatively limited research capacities.

4.4 Integrated validation framework

Overall, an implementation-effectiveness model for research-informed petrology teaching was constructed from the findings and organized around four connected stages: "input-process-output-diffusion" (Figure 6). The inputs include current research findings, digital tools, and authentic datasets. The process comprises active student inquiry, integrated virtual and physical training, and system thinking development. The outputs include stronger disciplinary knowledge, a broader set of integrated competencies, and positive learning experiences. Diffusion refers to the successful application of a model across institutions and regions. The model demonstrates that research-informed teaching does not simply combine individual technologies. Instead, it optimizes the educational environment through coordinated interactions among disciplinary knowledge, technological tools, and teaching practice.

5. Conclusions and outlook

This study developed a research-informed reform model for a smart petrology course and identified three principal innovations. First, its three-tier framework of “core streamlining, cross-disciplinary supplementation, and frontier transformation” refined essential knowledge. It incorporated diverse engineering cases, converted advances in AI-based rock and mineral identification and digital rock mechanics into teaching modules, and established a two-way “research-teaching-research” feedback cycle. Second, a “six-in-one” collection of smart teaching resources combined knowledge graphs, AI identification assistants, virtual specimen libraries, and VR/AR modules across the full sequence of learning, practice, assessment, and evaluation. This integration made disciplinary knowledge visible and learning processes traceable. Third, a data-driven feedback loop tracked learning at the class, individual, and course levels, enabling continuous refinement of teaching content. This framework supported Emerging Engineering education in three ways. Authentic research problems strengthened data literacy and systems thinking, while engineering cases and digital technologies helped students apply their knowledge across contexts and bridge the gap between rock identification and its practical application. The closed-loop assessment enabled individualized instruction. These approaches offer a transferable model for preparing interdisciplinary professionals in intelligent technologies, geology, and engineering.

Large multimodal models will bring profound changes to teaching. Future work will focus on developing an AI-based question-answering system for petrology, building identification models that combine images from multiple sources, and creating open virtual environments for inquiry. These efforts will move instruction beyond knowledge delivery towards the development of higher-order thinking.

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Conflicts of interest

The authors declare no competing interest.

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