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Construction and Practice of a Blended Smart Course for Environmental Microbiology Under OBE Principles

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Abstract

Persistent challenges in Environmental Microbiology teaching include the mismatch between networked knowledge structures and linear instruction, insufficient support for open-ended engineering scenarios, the gap between blended formats and deep learning outcomes, and weak process-oriented assessment evidence. Guided by Outcome-Based Education (OBE), the course team constructed a four-dimensional curriculum graph integrating ability, problem, knowledge, and resource dimensions, and developed a progressive teaching model of graph-guided learning, intelligent inquiry, and data-driven evaluation. This article reports the design and implementation of a teacher–student–AI collaborative blended smart course and presents a descriptive evaluation of one implementation cycle. The course was implemented over a 16-week semester with 60 third-year environmental engineering undergraduates at Jiangsu University; the previous cohort, taught by the same instructors with conventional blended teaching, served as a historical reference. Data were collected from platform interaction records, blueprint-matched final examination questions, and a piloted questionnaire (58 valid responses; Cronbach's $\alpha = 0.89$), and were analyzed with descriptive statistics, independent samples *t*-tests, and effect sizes; classroom interaction was summarized descriptively because repeated student session observations were clustered within students. Using the module on biological nitrogen and phosphorus removal in wastewater treatment as an example, the article illustrates differentiated pre-class preparation, in-class problem-chain inquiry with AI-assisted scheme design, and post-class learning profiling. Compared with the historical cohort, the implementation cohort showed a descriptively higher classroom interaction rate (90.3% vs. 70.5%), a 15.2-percentage-point higher mean score rate on examination questions targeting microbial regulation (95% CI [10.2, 20.2]; Cohen's $d = 1.12$), and positive student perceptions (91.4% reported that knowledge graphs supported systematic cognition and 84.5% reported increased confidence in analyzing engineering problems). The documented course architecture and implementation pathway may provide a practical reference for the smart transformation of core environmental engineering courses.

Keywords: outcome-based education (OBE); environmental microbiology; smart course; knowledge graph; blended teaching; artificial intelligence

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1. Introduction

Artificial intelligence is driving profound change in higher education [1]. In the past, the main concern was how to put resources online; today, the more important issues are

process reconstruction and ability cultivation. The national strategy for educational digitalization emphasizes the use of data, platforms, and intelligent technologies to empower the whole process of talent cultivation [2]. Engineering education accreditation and emerging engineering education have also placed more practical demands on courses: they should respond to real industrial needs and cultivate students' ability to solve complex engineering problems [3].

The development direction of the environmental protection industry has become increasingly clear: monitoring is becoming intelligent, processes are becoming more precise, operation is becoming low-carbon, and management is becoming data-driven [4]. This means that environmental engineering students must not only master the basic principles of microbiology but also understand the complex relationships among microbial community structure, pollutant-transformation mechanisms, engineering control parameters, and intelligent operational decision-making.

Environmental Microbiology is an important professional foundation course for environmental science and engineering programs, occupying a key position between basic biological knowledge and subsequent specialized courses [5]. It covers fundamental theories such as microbial morphology and structure, physiological metabolism, genetic variation, and ecological distribution, while also involving engineering applications such as pollutant biodegradation, biological wastewater treatment, environmental bioremediation, microbial detection, and risk control. A prominent feature of the course is that it contains many knowledge points, abstract concepts, and clear interdisciplinary characteristics. Teaching practice shows that students can often remember isolated concepts, but they find it difficult to connect microbial metabolic mechanisms, environmental factors, engineering units, and regulation objectives. This directly affects their later professional learning and the cultivation of engineering practice ability.

In recent years, knowledge graphs, generative artificial intelligence, intelligent tutoring systems, and learning analytics have created new possibilities for addressing these difficulties. Knowledge graphs can transform scattered knowledge points into a visual knowledge network; intelligent agents can provide immediate answers and follow-up prompts during learning; and learning analytics can capture behavioral evidence across learning activities, helping teachers adjust teaching strategies in time [6]. Focusing on authentic problems in course teaching, this paper systematically presents the construction logic, implementation pathway, and practical outcomes of the blended smart course of Environmental Microbiology. It responds to three core concerns: how to reconstruct scattered environmental microbiology knowledge into a curriculum graph oriented toward ability cultivation; how to enable teachers, students, and intelligent technologies to collaborate in deep blended teaching; and how to use learning data to promote assessment feedback and continuous course improvement. This article is positioned as a course design and implementation report accompanied by a descriptive evaluation of one teaching cycle, rather than a controlled experimental study of educational effectiveness. The novelty of this work does not lie in the individual components, since OBE, blended learning, knowledge graphs, and AI-supported learning are all established research areas; it lies in their integrated operationalization as a coherent course architecture in which the curriculum graph serves as the shared organizational structure linking learning outcomes, problems, resources, and assessment evidence, together with the transparent reporting of an authentic implementation cycle and its methodological limitations.

Specifically, the evaluation reported in this paper is guided by three questions. EQ1: How can scattered environmental microbiology knowledge be reconstructed into a curriculum graph oriented toward ability cultivation? EQ2: How can teachers, students, and intelligent technologies collaborate to support deep blended teaching in an authentic course

setting? EQ3: What differences in classroom interaction, examination performance, and student perceptions are observed between the implementation cohort and the previous cohort taught with conventional blended teaching?

2. Materials and Methods

2.1. Study Design and Article Positioning

This study combines design-based course development with a historical cohort descriptive comparison. The smart course model was fully implemented in the Spring 2025 cohort (implementation cohort), while the Spring 2024 cohort (historical cohort), taught by the same instructor team with conventional blended teaching, served as the reference condition. Random assignment was not possible because the intervention was delivered at the whole-cohort level as part of regular teaching. Consequently, between-cohort comparisons are reported as descriptive associations; effect sizes and confidence intervals are provided only where the unit of analysis is a single observation per student, rather than as causal estimates. The evaluation followed a pre-specified plan covering three data sources: platform interaction records, final examination results, and an end-of-course questionnaire. The study design, participants, and data sources are summarized in Table 1.

Table 1. Overview of study design, participants, and data sources.

Item	Historical Cohort (Reference)	Implementation Cohort
Semester	Spring 2024 (February–June 2024)	Spring 2025 (February–June 2025)
Program and year	Environmental Engineering, Year 3	Environmental Engineering, Year 3
Class sections	2	2
Enrolled/completed (n)	59/57	62/60
Teaching model	Conventional blended teaching (online videos, lectures, assignments)	Graph-guided, AI-supported blended smart course
Instructors, textbook, syllabus	Same instructor team, textbook, and syllabus	Same as historical cohort
Teaching hours	48 h (16 weeks)	48 h (16 weeks)
Data used in this study	Platform interaction records; final examination	Platform interaction records; final examination; questionnaire (58 valid); AI-dialogue records

2.2. Course Context and Participants

Environmental Microbiology is a compulsory professional foundation course (3 credits, 48 teaching hours over 16 weeks, comprising 40 h of theory and 8 h of in-class case practice) offered in the third year of the four-year environmental engineering program at the School of the Environment and Safety Engineering, Jiangsu University, China. The intervention was implemented from February to June 2025. All students enrolled in the two class sections were eligible; the two students who withdrew before the midterm were excluded, yielding 60 students (32 female and 28 male; mean age 20.6 $\pm$ 0.8 years) in the implementation cohort. The historical cohort comprised 59 enrolled students in Spring 2024, of whom 57 completed the course (30 female and 27 male; mean age 20.5 $\pm$ 0.9 years). The two cohorts had completed identical prerequisite courses. The same two instructors taught both cohorts, using the same textbook, syllabus, credit allocation, and chapter sequence; the implementation cohort additionally used the curriculum graph, AI tutoring, and data-driven evaluation. All students in the implementation cohort used the platform and AI tools as an integral part of course activities.

2.3. Technological and Pedagogical Intervention

The intervention comprised four components. (1) Curriculum graph: the four-dimensional graph was deployed in the knowledge-graph module of the Zhihuishu (Smart Tree) platform and used to publish guiding tasks, navigate learning paths, and bind resources and assessment items. (2) AI tutor: the platform's large-language-model-based assistant (Zhihuishu AI Tutor, 2025 release) was embedded in the course space with a course-specific system prompt that (i) restricts responses to course-relevant content, (ii) applies heuristic scaffolding for design-oriented questions by prompting students to identify constraints, list candidate variables, and judge evidence sources before suggestions are offered, and (iii) appends a standing reminder that AI outputs may contain errors and must be verified against authoritative sources. (3) Scheme design assistant: a structured prompt template coupled with a curated knowledge base of 35 vetted documents (textbook chapters, national discharge standards, and real plant operation cases) generated preliminary regulation suggestions from student-entered parameters; every AI-generated scheme used in class was reviewed by the instructor before debriefing. (4) Learning analytics dashboard: platform records of video learning, quizzes, discussions, assignments, and AI dialogues were aggregated into weekly diagnostic reports and learning profiles.

To address hallucinations, incorrect recommendations, bias, overreliance, and academic integrity, an AI-use protocol was introduced in week 1 as part of the course syllabus. Students were required to disclose AI use in every submitted artifact, to verify AI-generated factual claims against at least one authoritative source, and to defend their schemes orally; submitting unverified AI output as one's own work was treated as a violation of course integrity rules. The instructor monitored AI-dialogue records weekly; 12 instances of factually incorrect or misleading AI suggestions identified during the semester were anonymized and reused as in-class critical-thinking material. The AI tutor used in teaching is distinct from the limited use of generative AI for language polishing and figure preparation during manuscript writing, which is declared in the Acknowledgments.

2.4. Outcome Measures and Instruments

Three primary outcome categories were defined a priori (Table 2). (1) Classroom interaction rate: the proportion of student sessions with at least one observable interaction, where an interaction was defined as an oral contribution, an in-class quiz response, a discussion-board post, or a documented group report contribution; the denominator was the number of students multiplied by the six in-class sessions of the target module (342 student sessions in 2024 and 360 in 2025). Because each student contributed six repeated observations, classroom interaction was treated as a clustered descriptive outcome. (2) Examination performance: the final examinations of both cohorts contained a 25-point block of questions targeting microbial regulation in wastewater treatment (two constructed-response items and one case-analysis item). The two examination blocks were parallel rather than identical. Equivalence was established through blueprint matching: both blocks covered the same target objectives and knowledge nodes, used the same two constructed-response items plus one case-analysis item, retained the same 25-point allocation and cognitive-level weights, and applied the same analytic rubric. Both instructors independently checked the blueprint match before administration; no statistical item equating was conducted. Open-ended responses were graded independently by two trained graders using a standardized analytic rubric (mechanism identification 40%, variable analysis 30%, scheme justification 30%); graders were blinded to cohort identity, and the mean of the two gradings was used (inter-rater ICC = 0.86). Problem-analysis ability and engineering-application ability were operationalized as the rubric subscores for variable analysis and scheme justification on the case-analysis item. (3) Student perceptions:

a piloted end-of-course questionnaire of 12 items in four dimensions (systematic cognition, AI-supported learning, engagement in blended activities, and usefulness of data-driven feedback), each rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The instrument was piloted with 18 students from a parallel course and revised accordingly; internal consistency in the study sample was satisfactory (Cronbach's α = 0.89 overall; 0.78–0.87 across dimensions). Of the 60 students who completed the course, 58 returned valid questionnaires (response rate 96.7%). The questionnaire dimensions, representative items, and reliability coefficients are summarized in Table 3. Learning profiles and ability radar charts were constructed by normalizing rubric scores and platform indicators for each ability dimension to a 0–100 scale and plotting cohort-level medians; they are descriptive visualizations and were not subjected to inferential analysis.

Table 2. Outcome measures, operational definitions, data sources, and analyses.

Outcome	Operational Definition	Denominator/Scale	Data Source	Analysis
Classroom interaction rate	Student sessions with at least one recorded interaction	Students × 6 sessions	Platform records and instructor log	Descriptive only
Examination score rate (target block)	Points earned/25 × 100%	Individual student, 0–100%	Final examination	Independent *t*-test; Cohen's *d*; 95% CI
Problem-analysis and engineering-application ability	Rubric subscores on the case-analysis item	Individual student, 0–100	Blinded rubric grading	Descriptive (median, IQR)
Student perceptions	Likert 1–5; agreement = rating of 4 or 5	58 valid questionnaires	End-of-course questionnaire	Percentage agreement; mean ± SD
Learning profiles and radar charts	Normalized rubric and platform indicators	Cohort medians, 0–100	Platform and rubrics	Descriptive visualization only

Table 3. Questionnaire dimensions, representative items, and reliability (58 valid responses).

Dimension	Representative Item	Items (n)	Mean ± SD	Agreement (%)	Cronbach's α
Systematic cognition	The curriculum knowledge graph helps me connect scattered knowledge points into a systematic structure.	3	4.41 ± 0.62	91.4	0.87
AI-supported learning	Using AI tools increases my confidence in analyzing engineering problems and expressing solutions.	3	4.22 ± 0.71	84.5	0.83
Engagement in blended activities	The problem-chain discussions make me willing to participate actively in class.	3	4.28 ± 0.66	86.2	0.81
Usefulness of data-driven feedback	The learning profile and feedback help me identify and remedy my weak points in time.	3	4.31 ± 0.64	87.9	0.78
Overall	-	12	4.31 ± 0.58	-	0.89

2.5. Data Analysis

Analyses were conducted with SPSS 26.0. Classroom interaction data comprised six repeated observations per student and are therefore reported descriptively as cohort-level percentages rather than analyzed with tests that assume independent student sessions. Examination score rates were compared with independent-samples *t*-tests after normality

checks (Shapiro–Wilk $p > 0.05$), and Cohen's d and 95% confidence intervals were reported. Questionnaire results are reported as the percentage of students rating 4 or 5, together with item means and standard deviations. Missing data were minimal: students absent from a session were conservatively counted as non-interacting for that session, and two incomplete questionnaires were excluded listwise. Two-sided $\alpha = 0.05$ was used. Inferential p-values are reported only for the single examination score obtained from each student. Because the design is a non-randomized historical comparison, p-values are provided for transparency and are interpreted cautiously; all outcomes are framed as observed associations rather than intervention effects.

2.6. Ethical Considerations and Data Governance

The evaluation used routinely generated teaching records, examination scores, and an end-of-course questionnaire for course-improvement research. Use of the learning platform and AI tutor was part of regular instruction rather than an additional research procedure. The evaluation involved no sensitive topics and no greater than minimal risk. Before data analysis, the course team obtained documented confirmation from the School's teaching-research administration that formal ethics committee review and separate written consent were not required for this minimal-risk educational evaluation under institutional requirements. Students in the implementation cohort were informed that de-identified course records could be analyzed for course improvement; questionnaire participation was voluntary, anonymous, unrelated to course grades, and non-participation carried no penalty. Submission of the anonymous questionnaire was treated as consent to use the responses. For the historical cohort, only existing de-identified teaching and examination records were analyzed retrospectively under the same exemption.

For research analysis, direct identifiers were removed from all exported datasets. Platform and examination records were pseudonymized with study codes, while questionnaire responses were collected anonymously. The linking key and analysis files were stored separately on password-protected institutional systems. Raw platform records remained on the Zhihuishu platform under role-based access; exported analysis files were accessible only to the two authors, will be retained for five years after publication, and will then be securely deleted. No identifiable student data are reported in the manuscript.

3. Deep-Seated Problems in Traditional Course Teaching

By reviewing years of teaching practice, collecting student feedback, analyzing online platform data, and comparing these findings with professional training objectives, the course team identified four interwoven deep-seated problems in traditional Environmental Microbiology teaching. These problems cannot be solved simply by adding class hours or supplementing a few cases. They are closely related to the way course content is organized, teaching activities are designed, and assessment evidence is collected.

3.1. The Structural Conflict Between Networked Knowledge Organization and Linear Instruction

The knowledge structure of Environmental Microbiology is clearly networked. Biological nitrogen and phosphorus removal in wastewater, for example, involves microbial physiology and ecology, the nitrogen cycle, phosphorus metabolism, electron donors and acceptors, carbon-source allocation, dissolved-oxygen control, sludge retention time, reactor configuration, and operational regulation. Traditional classes usually proceed chapter by chapter according to the textbook. This approach ensures content coverage, but it also makes it difficult for students to see how different knowledge points are connected within engineering problems [7,8]. As a result, students may understand the concepts of nitrifiers, denitrifiers, and phosphorus-accumulating organisms separately, yet fail to explain why a

change in an engineering parameter can simultaneously affect nitrogen and phosphorus removal efficiency, let alone propose regulation strategies from the perspective of microbial community and process-operation coupling.

3.2. The Mismatch Between Open-Ended Engineering Scenarios and Instructional Support Capacity

The course serves as a bridge from basic theoretical learning to engineering application analysis. However, real environmental engineering problems often involve complex pollutant types, multiple operational constraints, and possible conflicts among control objectives; solutions are usually not unique [9]. In a wastewater treatment plant where ammonium removal efficiency declines, possible causes may include water temperature changes, pH fluctuation, insufficient dissolved oxygen, carbon-to-nitrogen imbalance, toxic shock, reduced nitrifier activity, inappropriate sludge retention time, and unreasonable reflux ratio. Several factors are often coupled. Conventional examples and assignments are mostly oriented toward standard answers. They help consolidate basic knowledge, but they provide limited support for cultivating students' ability to analyze complex situations, identify key variables, construct solutions, and justify decisions. Especially under a high student–teacher ratio, it is difficult for teachers to provide continuous and detailed personalized guidance to every learning group.

3.3. The Gap Between Normalized Blended Teaching Forms and Deep Learning Outcomes

The course already has a foundation for combining online resources with offline classroom teaching. However, traditional blended teaching can easily remain at the procedural level of watching videos before class, explaining key points in class, and completing assignments after class. Although online platforms accumulate records of video viewing, quiz scores, and discussion data, these data have not been fully transformed into evidence for classroom problem design, tiered task distribution, and personalized tutoring. In practice, some students complete pre-class learning merely to satisfy requirements, participate weakly in classroom discussion, and show insufficient depth in post-class reflection and extension. Without the guidance of a knowledge graph, the driving force of authentic problems, and the support of intelligent technologies, blended teaching finds it difficult to sustain students' inquiry interest, and the formation of knowledge transfer and higher-order thinking is hindered.

3.4. The Conflict Between Summative Assessment Orientation and Insufficient Process Evidence

Traditional course evaluation mainly relies on the final examination, regular assignments, and laboratory reports, with emphasis on knowledge memory and conceptual understanding [10]. It is still inadequate in characterizing students' abilities in problem identification, evidence analysis, collaborative communication, AI-tool use, scheme justification, and reflective improvement. Teachers often discover students' weak points only after staged tests, so feedback is delayed, and timely intervention becomes difficult. The key to smart course construction is not simply moving assessment items online. Instead, behavioral data and output evidence from the learning process must be stably linked with ability objectives, so that assessment supports ability-oriented learning [11,12].

The deep problems, construction objectives, and reform priorities across these four dimensions are summarized in Table 4. On this basis, the course team further clarified the design philosophy and overall framework of smart course construction.

Table 4. Problems, objectives, and reform priorities in the smart course construction of Environmental Microbiology.

Problem Dimension	Main Manifestations	Construction Objective	Reform Priority
Knowledge organization	Content proceeds linearly by textbook chapters; links among knowledge points are weak; students struggle to build systematic understanding.	Build a visual curriculum knowledge network that supports navigation and diagnosis.	Construct a four-dimensional curriculum graph of ability, problem, knowledge, and resources.
Ability cultivation	Standard exercises dominate, while analysis of authentic engineering problems and scheme design remain insufficient.	Improve students' ability to identify, analyze, and regulate complex environmental engineering problems.	Use problem chains, case libraries, virtual simulation, and agent-supported scheme design.
Teaching interaction	Online and offline activities are not deeply connected; classroom participation and sustained inquiry are limited.	Create an integrated deep blended-learning process across pre-class, in-class, and post-class stages.	Apply graph-guided learning, AI tutoring, group inquiry, and peer assessment.
Evaluation improvement	Summative assessment has high weight, and process data are not fully used for feedback.	Realize data-driven precision assessment and continuous improvement.	Use learning profiles, ability radar charts, formative assessment, and project defense.

4. Design Philosophy and Overall Framework of the Smart Course

Course construction is organized around one core principle: student development. Guided by Outcome-Based Education (OBE), the course objective shifts from completing knowledge transmission to supporting ability achievement. In this course, a smart course is defined as a new teaching paradigm that uses a curriculum knowledge graph as its underlying architecture, relies on generative artificial intelligence and learning analytics, and realizes personalized learning-path planning, precision teaching intervention, and deep cognitive construction through dynamic collection of learning-process data and intelligent feedback [13]. It is not a simple addition of technology to teaching, but a systematic reshaping of teaching logic under data-driven conditions.

According to the talent-training objectives of the environmental engineering program, the course team summarized four core abilities that students should develop. The first is basic cognitive ability: the ability to explain microbial structure, physiology, genetics, and ecological distribution. The second is mechanism-analysis ability: the ability to explain microbial transformation pathways of organic matter, nitrogen, phosphorus, sulfur, and typical emerging pollutants. The third is engineering regulation ability: the ability to identify key microbial processes and propose regulation ideas in scenarios such as wastewater treatment, bioremediation, and solid waste treatment. The fourth is data-evidence and innovative-practice ability: the ability to use literature, platform data, AI tools, and experimental results for scheme justification, teamwork, and reflective improvement.

Based on this ability framework, the course formed an overall architecture of graph-guided learning, intelligent inquiry, and data-driven evaluation. Graph-guided learning uses the curriculum graph to reconstruct learning paths, enabling students to understand before class the ability objectives, core problems, and knowledge nodes supported by each unit. Intelligent inquiry embeds AI tutors, intelligent learning partners, and agent-based scheme design tools into classroom discussion, virtual simulation, and project tasks, encouraging students to move from passive reception to active construction [14]. Data-driven evaluation focuses on collecting, analyzing, and feeding back learning-process data,

thereby forming student ability profiles and evidence for teaching improvement. These three components work together to constitute the basic logic of smart course operation: the graph organizes knowledge, problems activate learning, intelligent technology provides immediate support, and data evidence promotes continuous improvement.

Compared with general online courses, this course places stronger emphasis on the internal consistency between technology and teaching objectives. The knowledge graph is not merely a concept-display tool; it is the core organizational structure connecting course objectives, learning tasks, teaching resources, and assessment indicators. The intelligent tutor does not replace teacher instruction; it undertakes learning-support functions that require immediacy, follow-up questioning, and scalable interaction. Learning data are not simply statistics on logins and viewing time; they are used to identify students' real status in knowledge understanding, problem analysis, engineering application, and reflective improvement. In this framework, teachers' roles are further expanded: they are learning designers, problem guides, evidence interpreters, and value shapers. The course-construction objectives and overall design are shown in Figure 1.

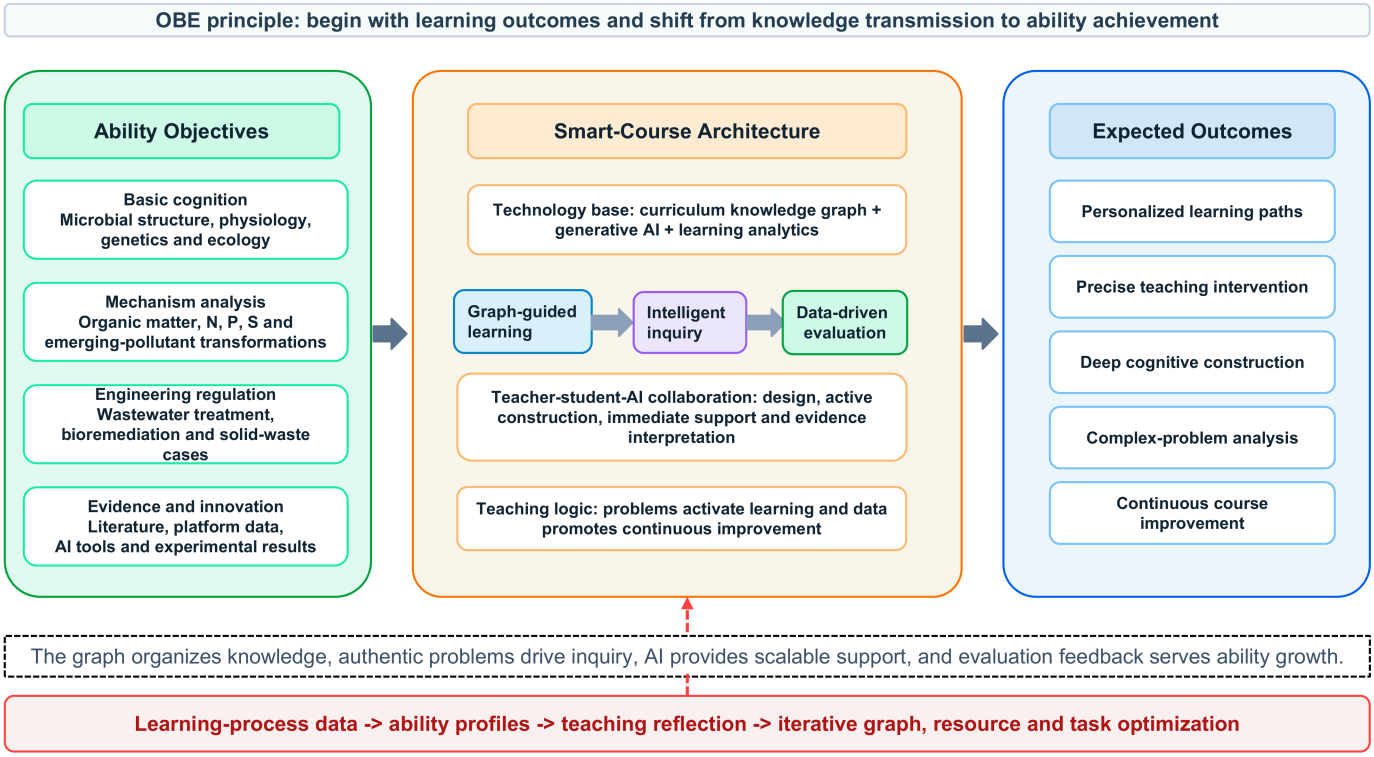


Figure 1. Course-construction objectives and overall framework for Environmental Microbiology.

5. Graph-Based Reconstruction of Course Content and Resources

Under the guidance of OBE, the logical starting point of course design is the learning outcomes that students should ultimately achieve, rather than the content that teachers need to cover [15,16]. Therefore, the course first derives core ability objectives from graduation requirements, then uses these objectives as anchors to trace back the key problems that drive ability formation, the core knowledge that supports problem-solving, and the corresponding learning resources. This reverse derivation chain of ability, problem, knowledge, and resources is a concrete mapping of the OBE principle of beginning with the end in course content organization. Its final product is a four-dimensional curriculum graph. The graph supports teachers' lesson preparation and teaching design, while also serving students' autonomous learning and process diagnosis. It reflects the design logic

that objectives are traceable, problems are guiding, knowledge is connected, and resources are accessible. The four-dimensional curriculum graph is shown in Figure 2.

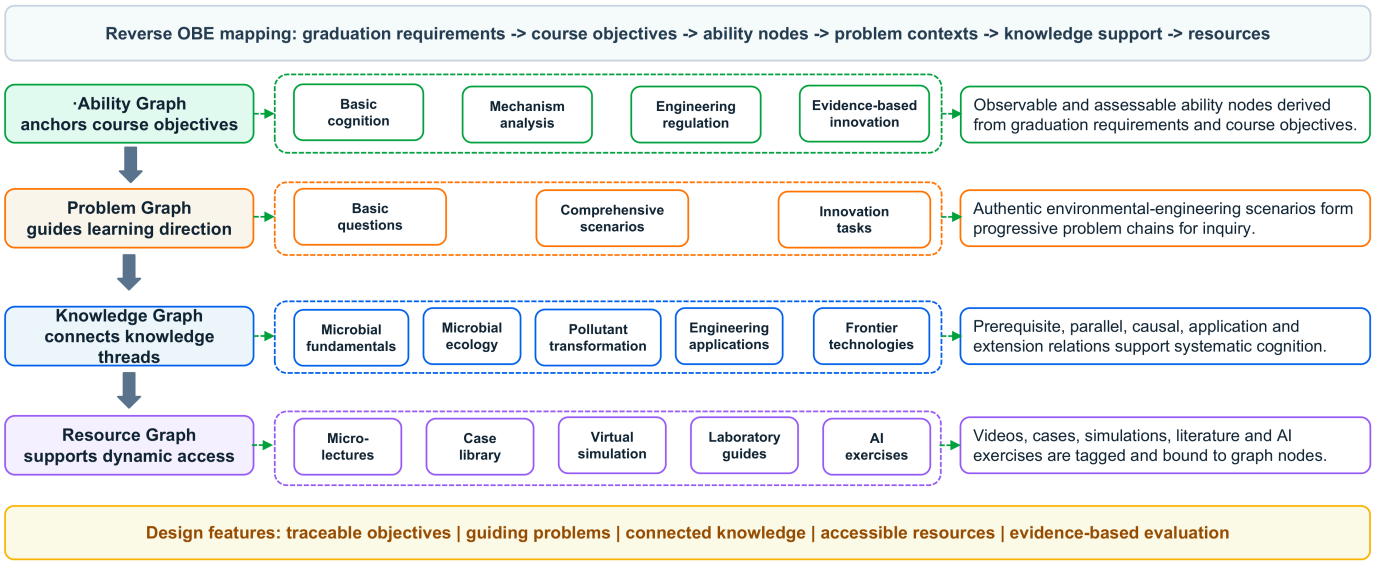


Figure 2. Four-dimensional curriculum graph system of ability, problem, knowledge, and resources.

5.1. Ability Graph Construction and Anchoring of Course Objectives

The ability graph starts from professional graduation requirements and course objectives, refining goals such as understanding the basic laws of environmental microorganisms, analyzing mechanisms of pollutant biotransformation, explaining biological treatment processes in environmental engineering, designing microbial regulation schemes, and conducting evidence-based expression and teamwork into observable and assessable ability nodes. Each ability node has corresponding knowledge support, problem scenarios, and assessment evidence. For example, the node of microbial regulation ability in wastewater treatment corresponds to knowledge of nitrification and denitrification, anaerobic phosphorus release and aerobic phosphorus uptake, microbial community structure, and process parameter optimization. It also requires students to propose reasonable microbial regulation schemes under given influent and effluent water-quality and operational-parameter conditions.

5.2. Problem Graph Construction and Guidance of Learning Direction

The problem graph uses authentic environmental engineering scenarios as carriers and forms a progressive structure of basic, comprehensive, and innovative questions. Basic questions support conceptual understanding, such as why nitrifying bacteria are sensitive to low temperatures and low dissolved oxygen. Comprehensive questions promote knowledge integration, such as how to balance denitrification and phosphorus removal when the carbon source is insufficient. Innovative questions guide students toward frontier extensions, such as whether wastewater-treatment early-warning models can be built based on microbiome information. The problem graph shifts classroom activities from one-way explanation of knowledge points to the process of problem solving, allowing students to experience the value of knowledge through sustained inquiry.

5.3. Knowledge Graph Construction and Connection of Knowledge Threads

The knowledge graph is organized around five modules: microbial fundamentals, microbial ecology, pollutant transformation, environmental engineering applications, and frontier technologies. It establishes prerequisite, parallel, causal, application, and extension

relationships among nodes. For example, the node of electron acceptors is related to aerobic respiration, denitrification, sulfate reduction, and anaerobic digestion. The node of biofilm is connected with immobilized microorganisms, wastewater-treatment processes, microplastic biofilms, and bioremediation. Through graph navigation, students can enter an associated knowledge network from a single concept and gradually form a systematic understanding of Environmental Microbiology.

5.4. Resource Graph Construction and Dynamic Updating of Course Resources

The resource graph tags and manages existing course videos, slides, cases, virtual simulations, laboratory guides, literature readings, and AI-assisted exercises, and binds them with ability, problem, and knowledge nodes. Students with weak foundations can receive concept micro-lectures, guiding questions, and basic exercises; students with stronger progress can access frontier papers, open discussion topics, and engineering cases. Operational data from wastewater treatment plants, reports on environmental pollution events, advances in microbiome research, and changes in industry standards are transformed into teaching materials in a timely manner, keeping course resources open and continuously updated. As a result, course content is no longer a static chapter collection, but a resource system that grows with teaching practice and disciplinary development.

The four-dimensional curriculum graph provides a structured content base and cognitive navigation system for teaching implementation. However, the graph itself is only a static map. Its value must be activated and evaluated in practice in dynamic teaching activities. Specifically, the ability graph anchors target orientation for pre-class preparation, allowing students to understand why they learn; the problem graph provides an inquiry thread for in-class discussion, keeping students focused on what problem is being solved; and the knowledge and resource graphs offer precise retrieval and matching support for post-class review and scheme justification, enabling students to locate the required knowledge by following the graph. Together, these graphs integrate otherwise scattered learning behaviors into a complete path with clear objectives, problem guidance, accessible resources, and evidence-based evaluation.

5.5. Graph Construction Process, Scale, and Validation

The four-dimensional graph was constructed by the four-member course team between September 2024 and January 2025 in three steps. First, the ability nodes were derived from the graduation-requirement indicators of the environmental engineering program and decomposed into 18 observable ability nodes. Second, for each ability node, the team formulated driving problems (45 problem nodes in three tiers: 18 basic, 19 comprehensive, and 8 innovative) and identified the supporting knowledge nodes (132 nodes across the five modules described in Section 5.3). Third, existing and newly developed resources were tagged and bound to the corresponding nodes (216 resource nodes, including 46 micro-lecture videos, 38 case items, 24 virtual-simulation and laboratory items, 72 literature and reading items, and 36 exercise sets). Relationships were recorded as directed edges and classified functionally into four mutually exclusive edge sets: ability-problem support, problem-knowledge driving, knowledge-knowledge linkage, and resource binding/application. Knowledge-knowledge edges were further labeled as prerequisite, causal, parallel, application, or extension. These classifications yielded 592 unique relationships in total. The graph was implemented in the knowledge-graph module of the Zhihuishu platform, which supports node editing, relation typing, path navigation, and the binding of resources and assessment items.

Before deployment, two domain experts who had not participated in graph construction—one professor of environmental microbiology and one senior wastewater-treatment

engineer—independently reviewed all 411 nodes and 592 proposed relationships. Node clarity and dimensional assignment were checked using written definitions. For relationship validation, each expert judged the correctness, direction, and label of each proposed edge as appropriate or requiring revision. Cohen's κ was calculated as $\kappa = (Po - Pe)/(1 - Pe)$, where Po was the observed proportion of agreement, and Pe was the chance-expected proportion; the resulting κ was 0.82. Discordant edges were discussed and revised until consensus was reached. This procedure documents expert agreement on graph content and does not by itself establish educational effectiveness.

The graph is updated each semester; during the Spring 2025 implementation, 14 nodes and 23 relationships were revised in response to error-rate diagnostics. The composition of the graph is summarized in Table 5, and Table 6 provides a worked example of the mapping among learning outcomes, tasks, resources, and assessment evidence for one representative ability node.

Table 5. Composition of the four-dimensional curriculum graph.

Dimension	Node Content (Examples)	No. of Nodes	Relations (No.)
Ability	Observable ability objectives, e.g., microbial regulation ability in wastewater treatment	18	Ability-problem support (52)
Problem	Basic, comprehensive, and innovative driving problems, e.g., balancing denitrification and phosphorus removal under carbon-source shortage	45	Problem-knowledge driving (96)
Knowledge	Knowledge points in five modules, e.g., electron acceptors; phosphorus-accumulating organisms	132	Prerequisite (128), causal (96), parallel (74), application (24), extension (17)
Resource	Micro-lectures, cases, virtual simulations, literature, exercise sets	216	Resource binding and application (105)
Total	-	411	592

Table 6. Worked example of the mapping among learning outcome, task, resources, and assessment evidence (ability node A7).

Element	Content
Learning outcome (ability node A7)	Propose microbial regulation schemes for nitrogen and phosphorus removal under given influent quality and operating conditions
Driving problem/task	Case analysis: fluctuating ammonium and total-phosphorus removal in a wastewater treatment plant approaching discharge limits
Linked knowledge nodes	Nitrification and denitrification; phosphorus-accumulating organism metabolism; effects of dissolved oxygen, sludge retention time, and carbon source
Bound resources	Micro-lectures M-21 to M-24; plant case C-09; scheme design assistant; Discharge Standard GB 18918-2002 [17]
Assessment evidence	Case-analysis examination item graded with rubric RG-2; group scheme defense; review of AI-dialogue records

6. Implementation of Blended Smart Teaching Through Teacher-Student–AI Collaboration

Supported by the curriculum graph, teaching implementation unfolds across pre-class, in-class, and post-class stages, forming a closed loop of intelligent guidance, data-intelligent deepening, and smart improvement. In this process, teachers, students, and intelligent technologies each assume clear roles. Teachers are responsible for objective design, problem

organization, value guidance, and quality assurance. Students are responsible for active learning, collaborative inquiry, scheme expression, and reflective improvement. Intelligent technologies are responsible for resource matching, immediate feedback, data analysis, and learning support. Only through collaboration among these three actors can blended teaching become deep and continuous. The teacher–student–AI collaborative blended smart-teaching model is shown in Figure 3.

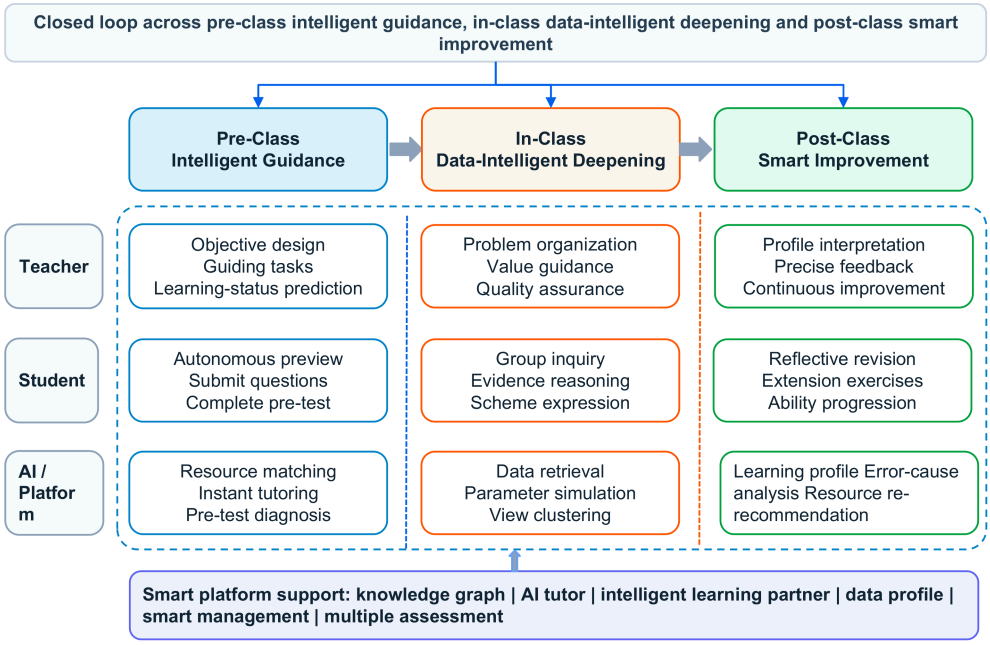


Figure 3. Teacher–student–AI collaborative blended smart-teaching model.

6.1. Pre-Class Stage: From Uniform Preparation to Differentiated Learning Paths

Before class, teachers release guiding tasks based on the curriculum graph and clarify the ability objectives, core problems, and prerequisite knowledge requirements of the unit. The smart platform automatically pushes differentiated resource packages according to students' previous quiz scores, video-learning records, discussion participation, and mastery of knowledge points. Students with weaker foundations receive concept-explanation videos, knowledge-point lists, and basic self-tests, while students with faster progress receive case readings, frontier literature, and open-ended questions. The AI tutor provides immediate answers during preparation, but for design-oriented questions it uses heuristic responses, prompting students first to identify constraints, list possible variables, and judge evidence sources rather than directly offering complete answers. Teachers can use the pre-class diagnostic report generated by the platform to understand common weak points and individual differences in advance, thereby determining the focus of classroom discussion.

6.2. In-Class Stage: From Knowledge Instruction to Problem-Chain Inquiry

In-class teaching follows authentic problem chains and adopts a process of problem introduction, graph localization, group discussion, AI assistance, teacher guidance, and outcome presentation. Teachers first create engineering scenarios and guide students to identify the microbiological mechanisms behind the problems. They then use the knowledge graph to locate relevant nodes and help students build knowledge connections. Student groups use the AI tutor to retrieve resources, verify concepts, generate lists of ideas, or conduct parameter simulation, while teachers focus on students' reasoning processes, evidence use, and value judgment. Intelligent technology in the classroom is not introduced to create superficial excitement. Rather, it provides immediate information support and

tools for making thinking visible, allowing teachers to devote more time to guiding higher-order problems and shaping professional values [18].

6.3. Post-Class Stage: From One-Time Assignments to Continuous Improvement

After class, students complete extension exercises, case analysis, or project tasks based on classroom problems. The platform comprehensively analyzes quiz results, discussion quality, assignment texts, AI-dialogue records, and group peer assessment to form learning profiles covering knowledge-point mastery, learning engagement, problem-analysis ability, and engineering-application ability. Students receive personalized review suggestions and resource recommendations accordingly, while teachers adjust subsequent teaching arrangements based on the group profile. For example, when the system finds a high error rate in the node linking microbial metabolic regulation with process parameters, the teacher can add parameter-sensitivity analysis and case-comparison discussion in the next class.

7. Teaching Case: Practice in the Module on Regulation of Biological Nitrogen and Phosphorus Removal in Wastewater

The regulation of biological nitrogen and phosphorus removal in wastewater is one of the course modules that best reflects the combination of environmental microbiology theory and engineering application. The blended smart-teaching design for this module is shown in Table 7. Students have already learned basic content on microbial morphology and structure, physiological metabolism, ecological distribution, and material cycles. This module requires them to further understand the role of microorganisms in advanced wastewater treatment and to analyze engineering problems from the perspectives of microbial communities and operational parameters. The module is designed as a complete learning task that includes graph-guided pre-class learning, AI-assisted in-class inquiry, and targeted post-class improvement.

Table 7. Blended smart-teaching design for the module on regulation of biological nitrogen and phosphorus removal in wastewater.

Stage	Teacher Activities	Student Activities	Intelligent Technology Support	Formative Evidence
Pre-class	Release guiding questions; set pre-tests and tiered resources.	Watch micro-lectures, complete pre-tests, and submit questions.	Knowledge-graph navigation, resource recommendation, and AI tutoring.	Pre-test scores, question lists, and resource-learning records.
In-class	Create a scenario of abnormal wastewater-plant operation and organize problem-chain discussion.	Analyze causes in groups, retrieve resources, and form regulation schemes.	View clustering, parameter simulation, preliminary scheme review, and problem visualization.	Group reports, discussion contributions, and records of scheme justification.
Post-class	Assign extension tasks and provide targeted feedback based on learning profiles.	Complete personalized exercises and case reflection, and revise schemes.	Learning profiling, error-cause analysis, and resource re-recommendation.	Assignment quality, ability profiles, and reflection reports.

7.1. Personalized Learning Path Driven by the Pre-Class Knowledge Graph

Before class, teachers constructed a thematic graph on microbial regulation for wastewater nitrogen and phosphorus removal on the smart platform, as shown in Figure 4. The graph includes subnodes such as microbial nitrogen-removal principles, biological phosphorus-removal mechanisms, process-parameter optimization, abnormal-operation diagnosis, and frontier technology extension. According to pre-test results, the system

pushed differentiated resources. Students with weak foundations focused on basic micro-lectures on nitrification, denitrification, anaerobic ammonium oxidation, and phosphorus-accumulating organism metabolism, and completed concept-discrimination questions. Students with stronger foundations read extension materials on shortcut nitrification-denitrification, coupled anaerobic ammonium oxidation processes, and microbiome monitoring in wastewater treatment, while also answering open-ended questions.

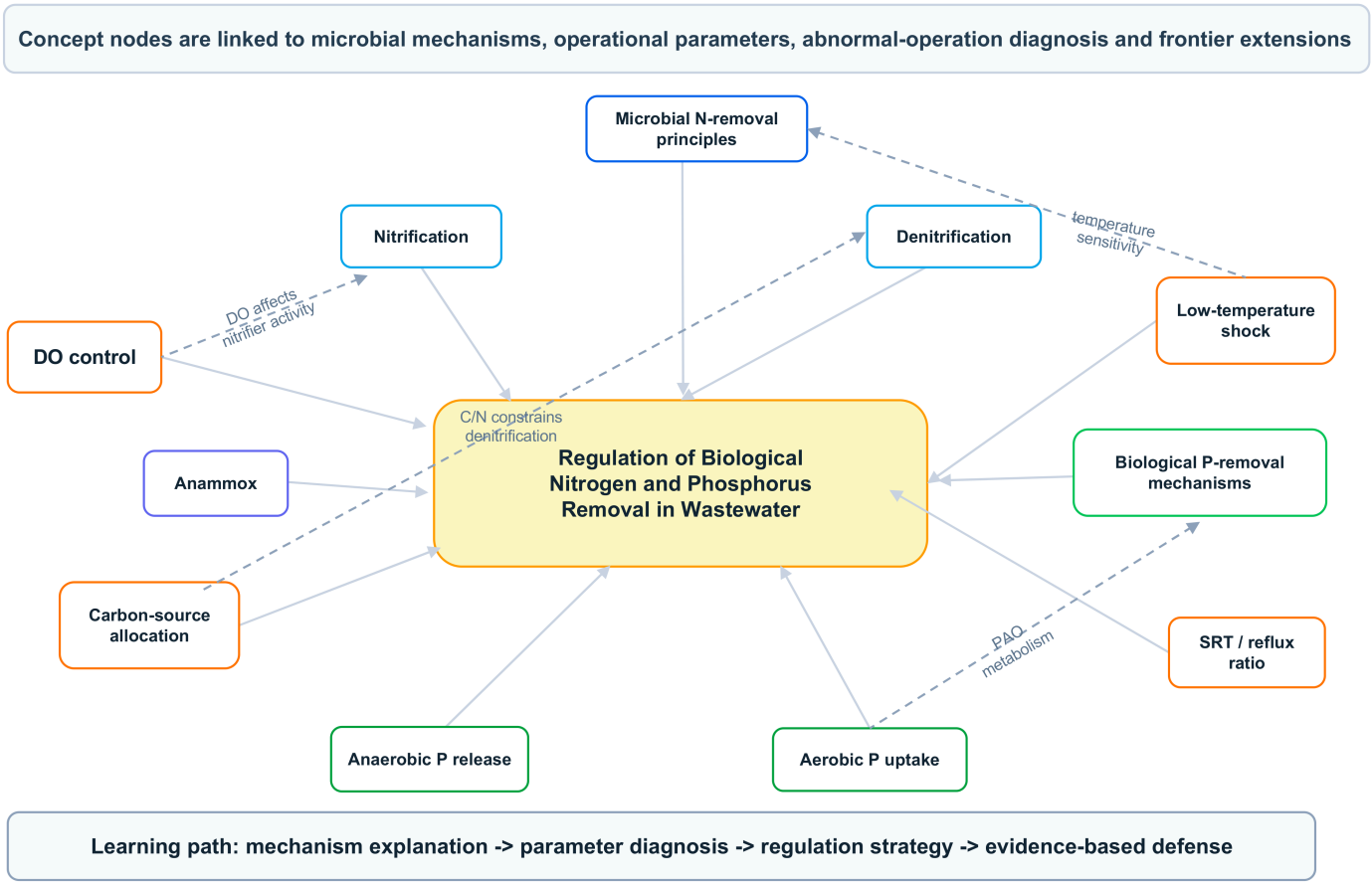


Figure 4. Thematic knowledge graph for regulation of biological nitrogen and phosphorus removal in wastewater.

7.2. AI-Empowered Problem-Chain Discussion and Scheme Design Practice

The classroom began with the scenario that the ammonium and total-phosphorus removal rates of a wastewater treatment plant had recently fluctuated and the effluent indexes were approaching discharge limits. The teacher first raised a problem chain: What is the relationship between water eutrophication and nitrogen and phosphorus discharge? Which microbial communities and environmental conditions are required by nitrification, denitrification, and biological phosphorus removal? What effects will insufficient influent carbon source, low-temperature shock, or improper aeration control have on nitrogen and phosphorus removal? Working in groups, students located relevant nodes in the knowledge graph and used the AI tutor to summarize possible causes, gradually forming an analytical framework of microbial activity, operational parameters, process structure, and monitoring indicators. The platform's diagnostic feedback on students' pre-tests and weak knowledge points is shown in Figure 5.

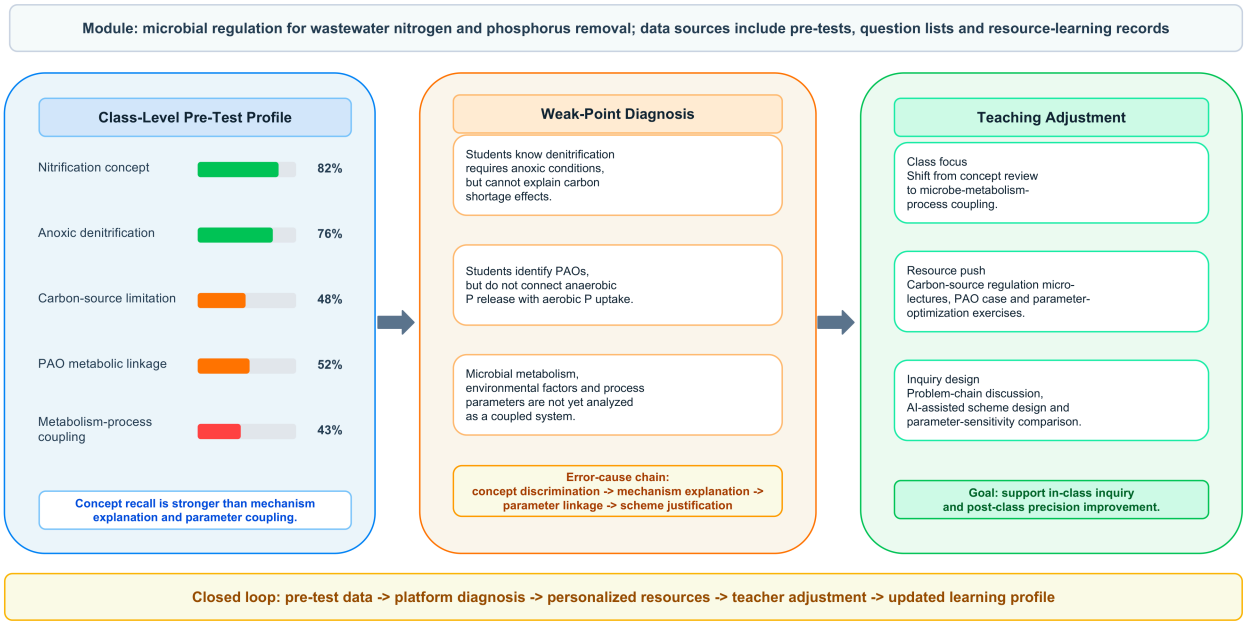


Figure 5. Empirical diagnostic feedback from the learning platform on students' pre-test results and weak knowledge points. Values were calculated from actual Spring 2025 pre-test records for the 60 implementation-cohort students; for each tagged knowledge node, accuracy = correct responses/total responses × 100%. The figure is descriptive and does not represent simulated data or an inferential model.

In the scheme design stage, each group entered hypothetical parameters such as influent COD, ammonium nitrogen, total nitrogen, total phosphorus, temperature, dissolved oxygen, and sludge retention time, and used the microbial-regulation scheme design assistant to generate preliminary regulation suggestions. Figure 6 shows how the AI tutor summarized student questions and supported classroom discussion. The system reminded students to consider scheme constraints: increasing aeration favors nitrification but may inhibit denitrification; adding external carbon sources can improve total-nitrogen removal but increases operating cost; extending sludge retention time helps maintain nitrifiers but may affect excess-sludge discharge. The teacher did not directly judge whether a scheme was good or bad, but guided students through questions such as what the evidence is, what the key variables are, and how the scheme should be adjusted if parameters change. In this way, students completed the transition from knowledge retrieval to engineering justification.

7.3. Targeted Improvement Supported by Post-Class Learning Profiles

After class, students submitted group schemes and individual reflections, focusing on the possible causes of reduced nitrogen and phosphorus removal efficiency, the microbiological principles used as evidence, the proposed process-regulation measures, and their potential risks. The platform integrated test scores, scheme texts, classroom contributions, and AI-dialogue records to form learning profiles, marking students' achievement in dimensions such as nitrogen-cycle microorganisms, phosphorus-removal metabolic mechanisms, effects of process parameters, and scheme justification expression. For students with insufficient conceptual mastery, the platform pushed basic explanations and targeted exercises. For students with weak scheme justification, it pushed typical wastewater-plant commissioning cases and parameter-optimization tasks. Students who performed well could access frontier extension materials on anaerobic ammonium oxidation, granular sludge, smart water management, and microbiome monitoring.

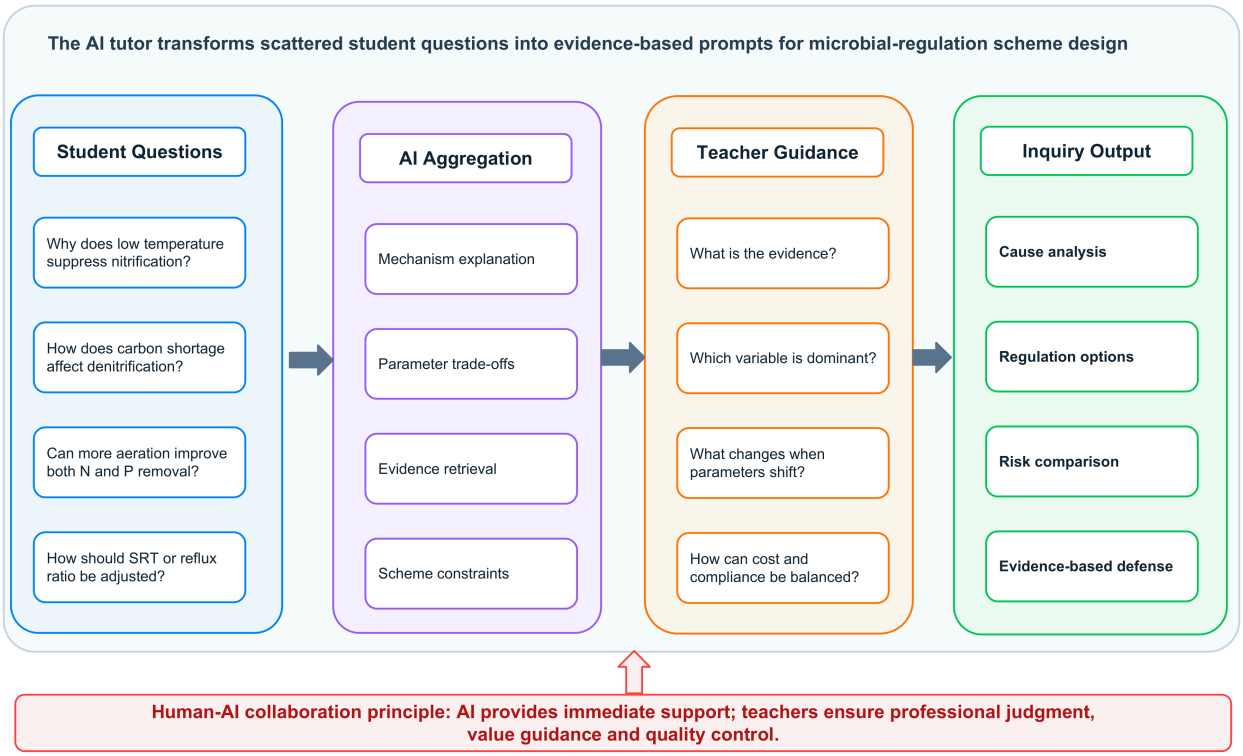


Figure 6. AI tutor summarizing student questions and supporting classroom discussion.

The value of this case lies in naturally integrating ideological and political education, engineering ethics, and professional ability cultivation into the learning process. When analyzing the hazards of eutrophication, aquatic ecological risks, and wastewater-plant operational regulation, students can appreciate the social responsibility behind environmental-governance technologies. When discussing external carbon addition, energy-consumption control, and discharge stability, they can also understand that engineering schemes must balance environmental benefits, economic costs, and operational safety. The classroom is therefore not only a place for knowledge learning, but also an important space for students to develop an environmental-protection mission and engineering professional responsibility.

8. Data-Driven Evaluation System and Observed Outcomes

The smart course evaluation system was reconstructed around the objectives of assessing knowledge, process, ability, and innovation. The course did not abolish summative examinations. Instead, while retaining assessment of basic knowledge, it incorporated online learning, classroom discussion, case schemes, project defense, learning reflection, and smart platform data into comprehensive evaluation, providing fuller process evidence related to ability development. Evaluation results serve both students' self-improvement and teachers' teaching reflection and continuous course optimization.

8.1. Extension of Evaluation Indicators from Single Grades to Multidimensional Ability Profiles

Course evaluation consists of summative assessment, process assessment, and innovative-practice assessment, as summarized in Table 8. Summative assessment mainly examines students' mastery of basic concepts, core mechanisms, and typical applications. Process assessment focuses on students' continuous performance in preparation, discussion, quizzes, exercises, and reflection. Innovative-practice assessment emphasizes case analysis, scheme design, teamwork, and oral defense. Learning profiles generated by the platform cover dimensions such as knowledge mastery, learning engagement, problem-analysis

ability, engineering-application ability, human–AI collaboration ability, and reflective-improvement ability, allowing students to see their strengths and weaknesses directly.

Table 8. Evaluation indicators and data sources for the smart course of Environmental Microbiology.

Evaluation Dimension	Main Indicators	Data Sources	Feedback Use
Knowledge mastery	Conceptual understanding, correctness of knowledge points, and types of errors.	Pre-tests, unit tests, and final examination.	Locate weak knowledge areas and push basic resources.
Learning process	Video learning, discussion participation, task completion, and question quality.	Smart platform behavior data and classroom interaction records.	Identify engagement status and adjust the teaching pace.
Engineering application	Problem identification, variable analysis, scheme rationality, and evidence support.	Case reports, project schemes, and classroom presentations.	Improve problem-chain design and practice tasks.
Innovation and collaboration	AI-tool use strategies, team division of labor, reflective revision, and oral defense.	AI-dialogue records, group peer assessment, and defense evaluation.	Cultivate human–AI collaboration and team innovation ability.

8.2. Observed Outcomes: Classroom Interaction, Examination Performance, and Student Perceptions

Table 9 summarizes the main quantitative results. The classroom interaction rate in the target module was 70.5% (241 of 342 student sessions) in the historical cohort and 90.3% (325 of 360 student sessions) in the implementation cohort, a descriptive difference of 19.8 percentage points; because the six session-level observations were nested within students, no χ^2 test or Cohen's h is reported for this outcome. The mean score rate on the blueprint-matched 25-point examination block targeting microbial regulation was 62.3% (SD = 14.6, $n = 57$) in the historical cohort and 77.5% (SD = 12.4, $n = 60$) in the implementation cohort, a difference of 15.2 percentage points (95% CI [10.2, 20.2]; $t(115) = 6.08$, $p < 0.001$; Cohen's $d = 1.12$). The content of students' questions also shifted from concept explanation toward higher-order issues such as parameter effects, process conflicts, and scheme selection: the share of analysis- and evaluation-level discussion-board posts rose from 24% to 47%. Questionnaire results showed that 91.4% of respondents (53 of 58) agreed or strongly agreed that knowledge graphs helped them build systematic cognition, and 84.5% (49 of 58) reported that AI tools increased their confidence in analyzing engineering problems and expressing solutions. Because these outcomes derive from a non-randomized historical comparison in a single course, they are reported as descriptive associations; they cannot be attributed solely to the intervention and may partly reflect cohort, instructor, novelty, or measurement effects.

From the perspective of learning outputs, group case reports in the implementation cohort descriptively showed fuller analysis of the relationships among microorganisms, environmental factors, and engineering parameters, and scheme justification began to reflect awareness of multi-objective trade-offs. Students were able to analyze possible causes of changes in nitrogen and phosphorus removal efficiency from variables such as dissolved oxygen, carbon source, sludge retention time, temperature, and reflux ratio, and they attempted to propose phased regulation strategies. These observations are based on the instructors' rubric-guided review of group artifacts and are qualitative in nature. In extension tasks, some students actively focused on frontier topics such as anaerobic ammonium oxidation, granular sludge, microbiome monitoring, and intelligent control of wastewater treatment, which may indicate increased professional interest; whether

this interest persists and transfers to other courses remains to be examined in longer-term follow-up.

Table 9. Main quantitative results for the historical and implementation cohorts.

Outcome	Historical Cohort (2024)	Implementation Cohort (2025)	Difference [95% CI]	Test Statistic; Effect Size/Reporting Note
Classroom interaction rate	70.5% (241/342 student sessions)	90.3% (325/360 student sessions)	+19.8 pp (descriptive)	Descriptive only (six repeated observations per student)
Examination score rate, target block (mean ± SD)	62.3% ± 14.6 (n = 57)	77.5% ± 12.4 (n = 60)	+15.2 pp [10.2, 20.2]	$t(115) = 6.08$, $p < 0.001$; $d = 1.12$
Knowledge graph supports systematic cognition (% agree or strongly agree)	-	91.4% (53/58)	-	-
AI increases confidence in problem analysis (% agree or strongly agree)	-	84.5% (49/58)	-	-

8.3. Teacher Development: From Experience-Driven Judgment to Evidence-Based Iteration

Smart course construction was accompanied by changes in teachers' teaching methods. Teachers relied less exclusively on classroom observation and impressions from assignments to judge learning status. Instead, they can combine platform data, discussion texts, AI dialogues, and project outputs to identify students' real difficulties. Data feedback can show where students spend more time, which questions have high error rates, and which groups need improvement in discussion quality. Teachers then adjust case selection, task design, and classroom pacing accordingly. The course team has continuously improved its teaching-resource library, case library, and assessment rubrics around smart course construction, and teaching-research activities have moved from experience sharing toward evidence analysis.

At present, relying on online platforms such as Zhihuishu, the course has formed a relatively complete set of online resources, curriculum graphs, typical cases, and blended-teaching processes.

9. Discussion

9.1. Principal Findings and Interpretation

This study set out to examine how a blended smart course for Environmental Microbiology could be constructed and implemented under OBE principles. With respect to EQ1, the four-dimensional curriculum graph was constructed and internally reviewed: 411 nodes and 592 relationships were derived from graduation requirements through a reverse-design process, and expert review showed high inter-rater agreement on the appropriateness of the mapped relationships (Cohen's $\kappa = 0.82$). Students also perceived the graph as supportive of systematic cognition (91.4% agreement), consistent with previous reports that knowledge-graph-based navigation helps learners organize fragmented content into coherent structures [6,13]. With respect to EQ2, the teacher–student–AI collaborative model was implementable in an authentic course setting: the AI tutor and the scheme design assistant undertook immediate and repeatable support tasks, while teachers concentrated on problem guidance, evidence interpretation, and value shaping. The descriptively higher classroom interaction rate observed in the implementation cohort (90.3% vs. 70.5%) is in line with prior findings that AI-enabled systems can expand opportunities for classroom participation when teachers deliberately orchestrate their use [14,18].

With respect to EQ3, the implementation cohort showed descriptively more favorable results than the historical cohort across all three measured domains: classroom interaction, examination performance on the target block, and student perceptions. These differences are pedagogically plausible. The problem-chain design required students to retrieve, connect, and apply knowledge rather than merely recognize it, and the AI-assisted scheme design tasks provided repeated practice in analyzing coupled variables, which aligns with the abilities assessed by the case-analysis items. The qualitative review of group artifacts points in the same direction, as students increasingly justified their schemes in terms of multi-objective trade-offs. Nevertheless, given the non-randomized historical-comparison design, these results should be interpreted as descriptive associations that are consistent with the intended mechanisms of the course model rather than as causal evidence of its effectiveness.

9.2. Limitations and Future Research Directions

Several limitations should be considered when interpreting these findings. First, the evaluation was conducted in a single course at a single institution with a modest sample, which constrains statistical power and external validity. Second, the comparison relied on a historical cohort without randomization. Although admission scores, prerequisites, instructors, textbook, and teaching hours were comparable between the two cohorts, unmeasured differences in student composition cannot be excluded, and cohort, instructor, and maturation effects may partly account for the observed differences.

Third, several measurement limitations apply. The two examination forms were blueprint-matched rather than identical, and no statistical item equating was conducted, so score differences may partly reflect residual differences in item difficulty. The perception outcomes were collected only in the implementation cohort through self-reported questionnaires and are therefore subject to social-desirability bias and novelty effects associated with the introduction of AI tools. All measurements were short-term and confined to one semester; no delayed or transfer measures were obtained, leaving the durability of the observed patterns unknown. In addition, the learning profiles and ability radar charts are descriptive aggregates whose psychometric properties have not been formally validated.

Finally, the study did not directly measure potential negative effects of AI use, such as overreliance, reduced independent reasoning, or academic integrity violations; although an AI-use protocol was in place and AI dialogues were monitored weekly, these risks warrant dedicated investigation. Future research should employ controlled or quasi-experimental designs across multiple institutions, incorporate delayed and transfer measures, validate the psychometric properties of learning-profile indicators, and examine the long-term effects of AI-supported learning on academic integrity and independent reasoning.

10. Conclusions

This paper addressed authentic problems in Environmental Microbiology teaching and documented a blended smart course scheme guided by OBE, centered on curriculum graphs, supported by intelligent technologies, and closed by data-based evaluation. The implementation experience suggests that the key to smart course construction is not the simple accumulation of digital tools. Rather, technology should be used to reconstruct the logic of course knowledge organization, learning activities, and assessment feedback, creating conditions for students' knowledge understanding, ability practice, and value formation in authentic problem contexts.

In summary, the course construction offers three main experiences. First, knowledge graphs may help address the scattered and complexly connected knowledge points of Environmental Microbiology, potentially supporting students' movement from point-based

memory to systematic cognition. Second, collaboration among teachers, students, and intelligent technologies may deepen blended teaching: teachers can focus on higher-order guidance, students can receive immediate support, and intelligent technologies can serve personalized learning and engineering-scheme training. Third, learning profiles and data feedback can shift evaluation from result judgment to process diagnosis, providing evidence for teachers' continuous teaching improvement and students' targeted learning support.

In the future, the course team will continue to improve the dynamic updating mechanism of the curriculum graph, strengthen graph connections with courses such as Water Pollution Control Engineering, Environmental Monitoring, Solid Waste Treatment, and Environmental Biotechnology, and build an intelligent resource and case library for the course group. The team will also continue to optimize the professional knowledge boundaries, assessment rubrics, and data-ethics norms of the AI tutor, avoiding students' overdependence on tools and strengthening their evidence awareness, critical thinking, and engineering responsibility. The team will also conduct multi-institution, controlled or quasi-experimental evaluations with delayed measurements to examine the durability and transferability of the observed patterns. Through continuous iteration, the course may better support the cultivation of innovative and interdisciplinary environmental engineering professionals.

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Institutional Review Board Statement: Ethical review and approval were not required for this study because it was a minimal-risk evaluation of routine educational practice using de-identified teaching records and an anonymous voluntary questionnaire, with no research procedure beyond regular instruction and no collection of sensitive personal data; documented confirmation of this exemption was obtained from the School's teaching-research administration.

Informed Consent Statement: Separate written informed consent was not required under the documented minimal-risk educational-evaluation exemption described in Section 2.6. Students were informed about the use of de-identified course records for course improvement; questionnaire participation was voluntary and anonymous, and submission of the questionnaire was treated as consent to use the responses.

Data Availability Statement: The de-identified data used in this study are available from the corresponding author upon reasonable request, subject to institutional data-governance requirements. Identifiable student records and the pseudonymization linking key are not publicly available.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence

CI	Confidence Interval
COD	Chemical Oxygen Demand
ICC	Intraclass Correlation Coefficient
IQR	Interquartile Range
OBE	Outcome-Based Education
pH	potential of hydrogen
SD	Standard Deviation

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