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ARTICLE

Teaching Reform of the "Human–Machine Collaboration–R-A-R" Model in the Biomedical Detection Technology Course under the New Engineering Paradigm

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Abstract

The New Engineering paradigm emphasizes keeping course content aligned with industrial technological advances, engineering practice needs, and interdisciplinary competency development. The Biomedical Detection Technology course is characterized by strong interdisciplinarity, a short knowledge-update cycle, and high demands on experimental resources. Traditional lecture-centered teaching often results in outdated content, insufficient student engagement, and difficulty in transferring theoretical knowledge to practice [1–3]. In response to the actual teaching conditions of this course, this study proposes a "human–machine collaboration–R-A-R" teaching reform scheme. The scheme reconstructs classroom organization through a three-stage reporting model of Review–Analyze–Reflect, adopts a layered blue-and-red note-taking method to promote students' secondary processing of AI-generated content, and integrates maker projects with AI error-correction tasks to strengthen practical competence and critical thinking. This paper presents the design, implementation process, assessment system, and expected effects of the scheme in detail. The results indicate that, under limited class hours and resource constraints, the proposed approach can effectively enhance students' knowledge integration, engineering communication, and active learning abilities, thereby offering an operable reference for curriculum reform in biomedical engineering.

Keywords: New Engineering; biomedical detection technology; human–machine collaboration; R-A-R flipped classroom; process-oriented assessment

1. Introduction: Dilemmas and Reform Needs of Biomedical Engineering Education in the Intelligent Era

1.1. Structural Contradictions Between Industrial Iteration and Educational Lag

With the development of smart healthcare, wearable devices, and flexible electronics, biomedical detection has evolved from single-signal acquisition to integrated applications covering sensing technology, data processing, and clinical decision support [1,2]. Accordingly, the course content is no longer limited to conventional device principles, but also involves the coordinated design of sensors and algorithms, materials, and application scenarios.

However, curriculum updates often fail to keep pace with technological iteration. Existing teaching content still focuses primarily on classical resistive, capacitive, and piezoelectric devices, while giving limited coverage to emerging developments such as microfluidic detection, flexible sensing, and intelligent analysis of bioelectrical signals [1,2]. Although students may master some basic concepts and formulas, they still face considerable difficulty in applying this knowledge to understand specific products and application chains in contemporary industry.

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1.2. Five Major Pain Points of the Traditional Teaching Model

Based on in-depth teaching investigation, classroom observation, and systematic review of student feedback, the Biomedical Detection Technology course currently faces five structural problems in practice. These pain points are not isolated; rather, they are interwoven and collectively form a negative-feedback loop that hinders improvement in teaching quality.

First, content updates lag behind technological progress. Textbooks have relatively long publication cycles, whereas sensor materials, packaging processes, and intelligent algorithms evolve rapidly, leaving students with insufficient exposure to frontier cases [1,2].

Second, classroom effectiveness is limited. The traditional model emphasizes teacher explanation and student memorization, but lacks highly participatory activities such as information retrieval, oral presentation, and live interaction. As a result, students' autonomous learning and teamwork abilities are insufficiently cultivated [1].

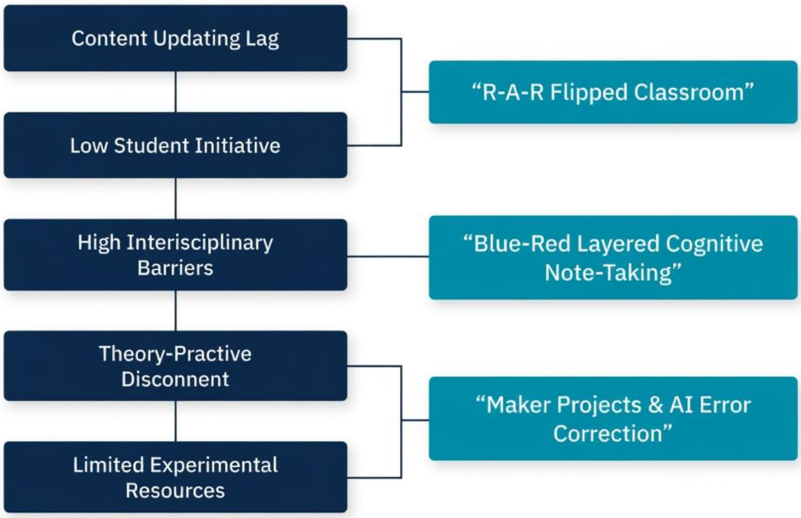

Figure 1. Correspondence between course pain points and reform strategies

Third, the course has a high interdisciplinary threshold. It simultaneously involves electronics, materials science, physiology, and clinical applications. Differences in student background directly affect depth of understanding, and some students easily develop anxiety when confronted with unfamiliar knowledge.

Fourth, the linkage between theory and practice is weak. Students may be able to derive sensor characteristic formulas, yet still struggle to transform them into concrete detection schemes—for example, how to choose a sensing method, configure circuit parameters, and interpret signals for heart-rate monitoring, oxygen saturation detection, or gait analysis.

Fifth, experimental resources are limited. High-end biomedical sensing equipment is expensive and difficult to maintain, so regular teaching often remains at the level of verification experiments and lacks sufficient training in independent design and system debugging [2].

2. Theoretical Framework: OBE and Human–Machine Collaborative Pedagogy

2.1. Backward Instructional Design Based on Outcome-Based Education (OBE)

This study follows the backward-design logic of Outcome-Based Education (OBE) and first clarifies the core capabilities that the course is expected to cultivate: knowledge integration, engineering communication, and evidence-based problem solving [2,3]. Around these goals, the course is organized into seven thematic modules and supported by a continuous task chain including pre-class review, in-class presentation, post-class note-taking, and question-and-feedback activities, so that learning outcomes are linked to observable learning behaviors.

2.2. Human–Machine Collaborative Pedagogy and Cognitive Load Reduction

Within this framework, human–machine collaboration is not treated as a parallel add-on theory, but as the practical pathway for realizing OBE goals. On the one hand, AI is used before class to organize concepts, terminology, and chapter structure, thereby reducing the entry-level cognitive load of interdisciplinary content [4,5]. On the other hand, teachers deliberately introduce AI-generated materials containing factual errors or reasoning gaps, guiding students to identify, justify, and revise them so as to strengthen explanation, verification, and judgment. In this sense, OBE answers the question of "what abilities should be cultivated," whereas human–machine collaboration answers "how the learning process should be organized to achieve those abilities."

3. Classroom Reconstruction: Construction and Implementation of the R-A-R Flipped Presentation Model

To address the core problems of outdated content and weak student initiative, the course reform adopts the R-A-R approach—Review, Analyze, and Reflect—as the entry point for a flipped classroom, redesigning classroom time allocation, student roles, and task organization.

3.1. In-Depth Analysis of the R-A-R Structural Model

R-A-R is not a routine classroom presentation activity, but a classroom structure that emphasizes a continuous cycle of review, analysis, and reflection. Each group presentation must revolve around three links: revisiting prior knowledge, introducing new knowledge, and making extended judgments. This design helps students connect the current lesson with the previous one while pushing the current topic toward practical application and frontier development.

The core task of the review stage is to systematically sort out the key knowledge from the previous lecture. By completing review tasks independently, students first translate what they have learned into their own language and then explain it to their peers. This process itself constitutes an effective mechanism of knowledge restatement and re-encoding [6,7].

The analysis stage focuses on applying sensor principles to real problem situations. Students are required to explore novel devices or application scenarios related to the topic, explain their working principles, applicable contexts, and connections with course knowledge, and thus organically integrate textbook content with actual technological development [1,2].

In the reflection stage, students are expected to make judgments about development trends rather than merely list information. By discussing issues such as the integration of traditional sensors with artificial intelligence, the limitations of textbook sensor technologies, and possible improvement paths, students can build a more systematic cognitive framework.

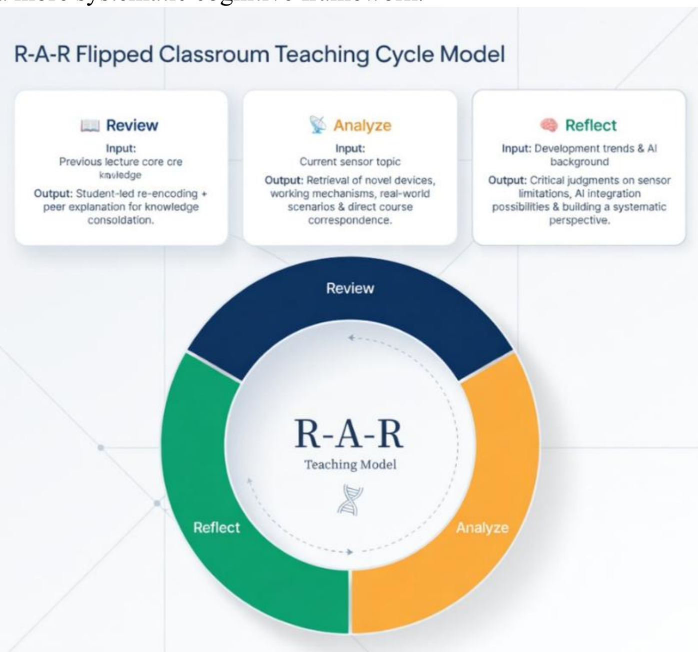

Figure 2. Three-stage cycle model of the R-A-R flipped classroom

3.2. Whole-Class Participation Mechanism and Strategies to Prevent Free Riding

A common problem in group assignments is that a few students undertake most of the work while others participate only minimally. To avoid this, the course adopts a new whole-class participation mechanism in the presentation session. Specifically, each member is responsible for a clearly defined subtask and must present on stage and answer follow-up questions from the teacher. In this way, tasks such as information retrieval, PPT production, presentation practice, and live response cannot be completed by only a few students on behalf of the whole group; responsibility for teamwork is concretely distributed to individuals.

In addition, the scheme introduces a simulated defense session, together with "teacher questioning" (10% of the total score) and "peer questioning" (10% of the total score). The peer-questioning component is mainly intended to promote classroom participation. Only when audience members listen carefully and truly understand the content can they raise targeted questions; thus, the questioning session itself becomes a mechanism for mobilizing whole-class learning. Teacher questioning, by contrast, focuses more on knowledge accuracy and logical completeness. It serves both as a test of presentation quality and as training in students' impromptu speaking and explanatory abilities.

3.3. Thematic Grouping and Coverage of the Knowledge Map

According to the knowledge scope of the course, the content can be divided into seven major themes: bioelectrodes, resistive sensors, capacitive sensors, inductive sensors, piezoelectric sensors, photoelectric sensors, and thermoelectric sensors [1,2]. This grouping facilitates task allocation while ensuring systematic coverage of the major detection principles.

This grouping strategy is not arbitrary, but a deliberately designed knowledge-map coverage scheme. These seven themes basically cover the major physical mechanisms of biomedical signal acquisition:

(1) Bioelectrodes: the basic interfaces for acquiring bioelectrical signals such as electrocardiograms (ECG), electroencephalograms (EEG), and electromyograms (EMG).

(2) Resistive/capacitive/inductive sensors: representative classical passive sensors commonly used to measure mechanical quantities such as blood pressure and respiration.

(3) Piezoelectric/photoelectric/thermoelectric sensors: representative energy-conversion sensors widely used in areas such as ultrasound imaging, pulse oximetry, and body-temperature monitoring.

As the semester progresses, the reporting content of each group is gradually integrated into a complete course knowledge map. Students act as presenters for their assigned theme while also serving as listeners and questioners for other themes, thereby deepening knowledge through repeated cycles of input and output.

4. Methodological Innovation: The Blue-and-Red Layered Cognitive Note-Taking Method and Its Neuroscientific Basis

Note-taking is not merely a process of organizing learning materials after class; it is also an important pathway through which students transform classroom information into a personal knowledge structure. Given the large number of concepts and the broad interdisciplinary scope of this course, this study proposes a "blue-and-red layered cognitive note-taking method," emphasizing the synergy between AI-assisted organization and deep human processing.

4.1. Blue/Black Pen: AI-Based Construction of a Cognitive Skeleton (Foundational Layer)

After class, students may use AI tools to generate chapter outlines or mind maps based on classroom content.

However, such AI-generated frameworks serve only as foundational learning materials and cannot directly constitute high-quality learning outcomes.

In constructing the basic framework, AI can be used to analyze course materials and generate corresponding knowledge-structure diagrams. Students then adopt a differentiated blue-and-black marking strategy: black handwriting is used to outline the main structure of classroom content and the core knowledge modules, whereas blue handwriting is used to mark key definitions, important knowledge points, and the core content emphasized by the teacher.

The core value of this design lies in helping students first clarify the chapter structure and logical sequence, and then directing their limited learning attention toward difficult points and deeper knowledge connections. For beginners, a clear knowledge framework can effectively reduce the cognitive load of entering a new knowledge field and thus improve learning efficiency.

4.2. Red Pen: Deep Human Processing and Neural Encoding (Incremental Layer)

After the basic framework has been constructed, students are required to correct errors in AI-generated content, supplement omissions in the material, and record their own processes of derivation, comparison, and judgment based on the teacher's explanation of knowledge points and cases in class, thereby achieving high-quality learning.

During construction of the incremental layer, the red-marked portion cannot rely on AI to replace the thinking process. It must include clinical cases orally explained by the teacher but not shown in the slides, corrections to the AI-generated framework, students' own deeper understanding, and the derivation of key formulas. Accordingly, in note assessment, teachers should evaluate only the quality and depth of the handwritten red section.

Existing studies show that handwriting has distinctive advantages in sensorimotor integration, language processing, and memory retention. Therefore, recording key content through handwritten annotation helps students form more stable knowledge representations.

The process from AI-generated framework to manually supplemented details is essentially a cycle of information screening, verification, and reorganization. Combined with the role of color coding in attention allocation and memory retrieval, it enables students to locate key review content more efficiently during revision.

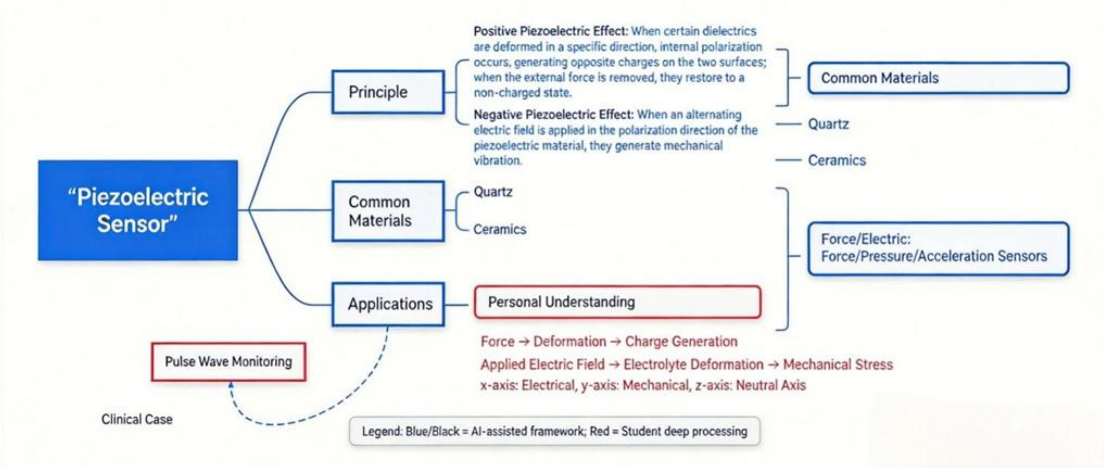

Figure 3. Schematic diagram of the blue-and-red layered cognitive note-taking method

5. Practical Innovation and Critical Thinking Development: Maker Projects and AI-Adversarial Teaching

To compensate for insufficient hands-on practice and weak critical-thinking training, the course reform continuously implements two types of out-of-class tasks: maker projects and an AI error-correction system, corresponding respectively to practice-oriented learning and critical inquiry-oriented learning.

5.1. Maker Culture and Low-Cost Sensor Fabrication

Under limited laboratory conditions, low-cost maker solutions are more feasible. Students can use the Arduino platform, optoelectronic components, and basic amplification circuits to build simple detection devices, thereby obtaining a complete practical experience from sensor principles to real application within a controllable budget. In this study, students participate in maker activities in groups and use low-cost materials such as Arduino boards and simple electronic components to develop basic biomedical sensor prototypes, such as a simple photoelectric pulse meter or a galvanic skin response sensor. Teachers need to make it clear that the core value of such experiments does not lie in pursuing device complexity, but in guiding students to confront real engineering challenges, including component selection, signal-noise suppression, structural stability optimization, and result interpretation. Through systematic debugging, students not only cultivate problem-solving ability, but also learn to deal with practical issues not covered in the textbook, thereby gaining deeper understanding.

In process-oriented assessment, maker projects are graded on observable evidence rather than solely on the final demonstration. The assessment dimensions include prototype functionality (40%), debugging records and engineering reasoning (30%), and reflective optimization and teamwork (30%).

5.2. AI Scenario Discussion and Learning Through Correcting AI Errors

In addition to practical tasks, the course also introduces AI-related scenario discussions and error-correction activities. This design is intended to guide students to treat AI as a collaborative tool rather than a direct answer source, while consolidating what they have learned through practice. For example, the teacher may assign a scenario task such as “design a gait-monitoring system for patients with Parkinson’s disease,” requiring students to synthesize their acquired sensor knowledge, use AI tools to formulate a preliminary scheme, and then discuss its feasibility, potential risks, and directions for optimization.

During the review stage of the course, the teacher can provide AI-generated review texts containing several knowledge errors and organize rapid-response group analysis, in which students identify the errors and explain the correct principles, thereby strengthening review effectiveness. Students may further be required not only to point out the errors, but also to explain the basis for their judgment and support it by citing relevant statements in the AI-generated text or existing cases, thus enhancing understanding and evidence awareness.

As suggested in relevant studies [4,5], this design helps prevent students from blindly trusting or over-relying on AI-generated content, while also better aligning with future engineering practice’s demand for information discernment and critical thinking.

AI error-correction tasks are incorporated into assessment as independent learning outputs. Their evaluation dimensions include accuracy of error identification (40%), evidence-based explanation (30%), feasibility of the revision scheme (20%), and participation in group discussion and feedback (10%).

6. Reconstruction of the Assessment System: Process Orientation and Multidimensional Quantification

The current assessment system still relies mainly on the final examination, whereas the course reform advocated here emphasizes learning processes such as oral expression, collaboration, and sustained participation. It is therefore necessary to shift the center of assessment forward to the learning process and improve its evaluation mechanism.

6.1. Refined Presentation Rubrics

The presentation rubric covers multiple dimensions, including content accuracy, structural completeness, presentation performance, time management, and teamwork. It transforms assessment standards from subjective impressions into objective indicators, thereby significantly improving fairness and reference value.

	Criteria
Level 1 (90–100)	The PPT is well designed; the presentation is clear, fluent, and persuasive; the R-A-R structure is complete; ideas are accurate and appropriately extended; time is controlled at around 5 minutes; team members divide labor clearly and transition naturally.
Level 2 (80–89)	The PPT is relatively well prepared and the presentation is clear; the R-A-R structure is basically complete; ideas are explicit and relevant; time control generally meets the requirement; teamwork is good.
Level 3 (60–79)	There are some deficiencies in the PPT, delivery, or expression of ideas, but the group can complete the basic reporting task; the structure is relatively complete; time control shows slight deviation; task division is basically clear.
Level 4 (40–59)	The PPT is relatively rough, the delivery lacks coherence, and some content deviates from the topic; time control deviates considerably; teamwork is average and the division of labor is not sufficiently clear.
Level 5 (0–39)	The PPT is poorly prepared; the presentation is disorganized or obviously off topic; time is seriously insufficient or excessively long; teamwork is weak and effective coordination is lacking.

6.2. Reconstruction of Composite Weighting

The conventional course assessment system is reconstructed as a dual-module model combining “classroom presentation performance” and “post-class notes and assignment assessment.” These two modules correspond respectively to the capability dimensions of expressive presentation and sustained learning, so as to avoid having a single score obscure differences in students’ expression, thinking, or practical skills. Among them, PPT presentation should carry a relatively high weight because it comprehensively reflects students’ depth of understanding of course knowledge, information organization, oral communication, and teamwork. The presentation process should include both teacher questioning and peer questioning, which jointly constitute the overall evaluation system, strengthening classroom interaction and academic-defense training while ensuring disciplinary rigor. The post-class notes and assignments module, by contrast, focuses on students’ systematic sorting, deep restructuring, and practical transfer of knowledge after class.

Specifically, the post-class notes and assignments module consists of three parts: layered cognitive notes, maker projects, and AI error-correction tasks, corresponding respectively to knowledge reconstruction, practical implementation, and critical argumentation. In implementation, both maker projects and AI error-correction tasks are incorporated into the post-class module as formal assessment objects rather than being treated as informal extension activities. The former mainly evaluates prototype implementation, debugging logic, and reflective improvement, whereas the latter focuses on error identification, evidence-based argumentation, and revision quality. In this way, the task design in Chapter 5 corresponds directly to the process-oriented assessment framework in Chapter 6.

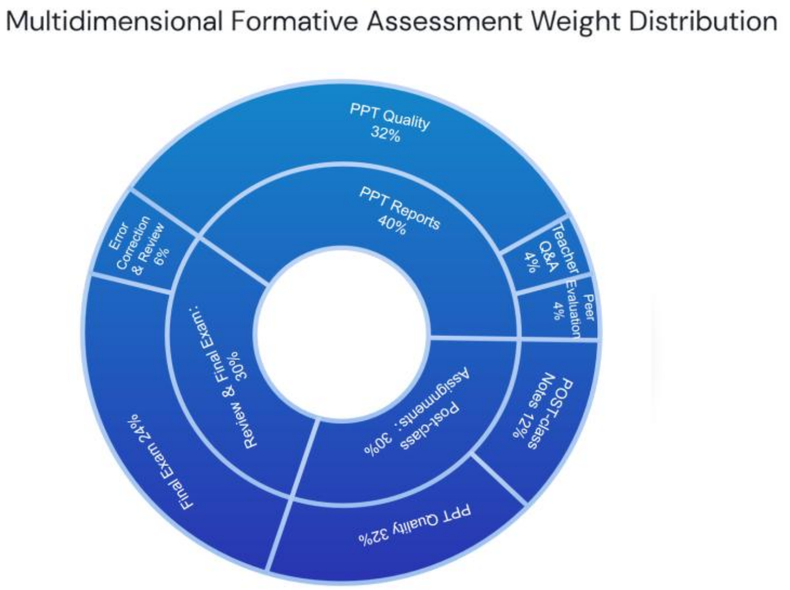

Figure 4. Weight distribution in the course process assessment

7. Implementation Path and Analysis of Expected Outcomes

7.1. A Closed Logical Loop for Solving the Pain Points

Overall, the reform scheme constructs a closed-loop teaching system of “problem identification–classroom reconstruction–post-class processing–process assessment.” By introducing frontier literature retrieval and thematic presentation, it addresses the problem of outdated content; by adopting whole-class presentations and interactive questioning, it enhances learning initiative; by establishing a systematic note-taking mechanism, it alleviates the interdisciplinary learning bottleneck; by designing maker tasks and scenario simulation, it bridges the gap between theory and practice; and by using AI to generate and support low-cost, high-quality teaching resources, it alleviates resource shortages.

Core Pain Point	Reform Measure	Mechanism and Expected Outcome
Lagging content updates	R-A-R analysis and reflection stages	Students retrieve the latest literature and industry cases and introduce them into the course through classroom presentations, thereby realizing dynamic updating of teaching content.
Insufficient learning initiative	Relay-style presentation + AI error-correction tasks	Through individual responsibility allocation and problem-driven interaction, free riding is reduced and students' willingness to participate and invest in class is stimulated.
Difficulty in interdisciplinary understanding	Blue-and-red layered cognitive note-taking method	AI-generated structured frameworks serve as cognitive scaffolds, while handwritten red-pen correction and supplementation strengthen deep processing of key and difficult points.
Disconnection between theory and practice	Low-cost sensor fabrication, simulated defense, and AI scenario discussion	Students are guided to transfer abstract principles into prototype construction and scenario-based problem solving, completing the transition from knowledge understanding to engineering application.
Limited experimental resources	AI simulation + simple sensor fabrication	AI simulation and low-cost prototyping supplement the shortage of expensive equipment and expand the space for practical learning under constrained conditions.

7.2. Fundamental Transformation of the Teacher's Role

Within this teaching paradigm, the focus of teachers' work shifts from traditional one-way knowledge transmission to curriculum design and learning facilitation. Teachers therefore need to design learning tasks with explicit competency-development objectives and carefully consider the guiding role of presentations, assignments, and questioning sessions. In classroom teaching, teachers should emphasize heuristic guidance and in-depth probing to help students integrate fragmented information into systematic knowledge structures. In addition, teachers must adhere strictly to academic standards and accurately calibrate teaching content.

In defining the boundaries of AI use, ensuring the accuracy of professional expression, and maintaining fairness in assessment, teachers must set an example through their own practice. This indicates that teachers need not only strong disciplinary expertise, but also corresponding digital literacy and teaching-organization competence.

7.3. Adaptation Paths for Chinese Universities

In the context of Chinese universities, teaching reform in biomedical engineering courses is usually constrained by large class sizes, differences in students' prior preparation, limited access to open laboratory resources, and relatively heavy teaching workloads. Therefore, the reform path should not simply transplant overseas models, but should instead follow localized principles of being low-cost, replicable, and scalable. By contrast, comparable programs in Europe and North America often benefit from more mature modular experimental platforms, more stable support for interdisciplinary projects, and closer industry–academia–research collaboration. Based on this comparison, a more feasible improvement direction for domestic universities is to adopt a gradual advancement path: in the early stage, structured R-A-R reporting, AI-assisted note organization, and low-cost prototype fabrication can serve as practical entry points; once teacher capacity, platform conditions, and external collaboration mature, the reform can be further extended to shared case-bank construction, cross-course project linkage, and deeper collaboration with hospitals and enterprises.

8. Conclusion and Prospects

To address the problems existing in the Biomedical Detection Technology course, this paper proposes a reform scheme based on the "human–machine collaboration–R-A-R" teaching model and systematically designs it from four dimensions: classroom organization, post-class note-taking, practical tasks, and the assessment system. Compared with the traditional path of merely increasing the frequency of AI tool use, this scheme places greater emphasis on students' central role in information discernment, knowledge reconstruction, and engineering expression. The core of the reform is not to use AI to replace the learning process, but to use AI to guide students from passively receiving teacher explanations and memorizing knowledge points toward actively applying AI tools for knowledge practice and engineering transformation.

In the future, with the continued development of generative AI, personalized AI teaching assistants (an AI-tutoring mechanism) may be further introduced to provide each student with customized experimental guidance and code-debugging support, thereby enabling truly individualized cultivation in large-scale education. The implementation experience of this scheme may also provide a useful paradigm for the digital transformation of other engineering courses that face problems of outdated content and weak practical links. Future studies may track student performance, output quality, and course satisfaction over longer teaching cycles, while also optimizing task-difficulty hierarchies and assessment indicators in light of the cognitive characteristics of students from different disciplinary backgrounds.

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