ISSN 2522-6398 Vol. 9, Issue 10: 1-7, DOI: 10.25236/FER.2026.091001

From Summative to Value-Added: AI-Driven Learner Profiling for Three-Dimensional Outcome Attainment in an Integrated Undergraduate–Graduate Plasma Technology Course

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Abstract: *Graduate course assessment still relies heavily on summative instruments such as end-of-term papers, which reveal little about students' incremental growth in knowledge, competence, and literacy. Addressing the knowledge discontinuity between the undergraduate course Engineering Electromagnetic Fields and the graduate course Plasma Technology and Applications, together with the limited variety of existing assessment methods, this study develops a three-dimensional attainment evaluation system—knowledge attainment, competence attainment and literacy attainment—under the guidance of Outcome-Based Education (OBE), and proposes an implementation pathway for value-added assessment driven by AI-enabled learner profiling. Anchored in a course knowledge graph, the system maps three categories of process evidence—AI self-tests and concept-graph matching, virtual simulation reports and case-analysis depth, and observed ideological-and-political engagement with research-failure portfolios—onto a unified three-dimensional indicator space; time-series capture of learning behaviors and within-student computation of value-added gains shift the paradigm from summative to process-oriented value-added assessment. Piloted in the graduate course Plasma Technology and Applications (36 credit hours, 2 credits) across two consecutive cohorts (N = 54), the study completed the full loop of pre-test, process capture, value-added computation, tiered feedback, and re-test, demonstrating its operability and data availability; the course teaching-evaluation score rose from 98 to 99.42, providing authentic evidence at the level of teaching organization. This is a design-based study reporting the design and pilot observation rather than causal estimation of teaching effects; the three-dimensional attainment values presented are illustrative.*

Keywords: *value-added assessment, AI-driven learner profiling, three-dimensional attainment, Outcome-Based Education (OBE), integrated undergraduate–graduate curriculum, plasma technology and applications*

1. Introduction

The high-quality development of graduate education calls for a shift from outcome certification to process value-added assessment. The Overall Plan for Deepening Educational Evaluation Reform in the New Era explicitly calls for improving summative assessment, strengthening process assessment, exploring value-added assessment, and refining comprehensive assessment. These principles point the way for reform of graduate course assessment [1]. However, graduate course assessment continues to depend primarily on final papers, course reports, or one-off examinations. Such results reflect students' absolute level of achievement, but fail to answer the key question of how much each student has progressed relative to his or her own starting point, and do not capture heterogeneous growth trajectories. At the same time, integrated undergraduate–graduate training has become an important direction of emerging engineering education reform. Between the undergraduate course Engineering Electromagnetic Fields and the graduate course Plasma Technology and Applications, there is a marked knowledge discontinuity: the former focuses on static electromagnetic-field equations and boundary conditions, while the latter deals with dynamic plasma behavior, magnetic confinement configurations, and diagnostics of major engineering devices. If assessment remains at the summative level, students' prior knowledge, competence growth, and value evolution cannot be precisely captured.

Against this background, the present study uses the graduate course Plasma Technology and Applications at University of Shanghai for Science and Technology (course code 14020002, 36 credit

ISSN 2522-6398 Vol. 9, Issue 10: 1-7, DOI: 10.25236/FER.2026.091001

hours, 2 credits) as the implementation context, and constructs a three-dimensional attainment evaluation system—knowledge, competence, and literacy—under the guidance of Outcome-Based Education (OBE) [2]. It also proposes an AI-driven learner profiling pathway for value-added assessment. The study aims to address three questions: (1) How should three-dimensional attainment be designed to connect with prerequisite knowledge in an integrated undergraduate–graduate course? (2) How can AI-enabled learner profiling integrate multi-source process evidence? (3) Is the pathway from summative to value-added assessment operable in a real graduate course? The contribution of this paper lies in the design and pilot implementation of the evaluation scheme rather than in causal estimation of teaching effects; the pilot adopts a one-group pretest–posttest design with a limited sample (N = 54) and no parallel control group, so no statistical inference is made on the value-added gains.

2. Theoretical Foundation and Literature Review

2.1. Integrated Undergraduate–Graduate Curriculum Articulation

Integrated undergraduate–graduate curriculum articulation emphasizes vertical coherence in goals, content, and competence development. Biggs (1996) proposed constructive alignment, which asserts that learning objectives, teaching activities, and assessment should be mutually aligned [3]; otherwise, students are likely to experience knowledge discontinuity and decreased motivation. Studies in China have largely focused on curriculum restructuring and the optimization of training plans, but have paid insufficient attention to the integrated design of assessment, especially longitudinal value-added tracking in graduate courses at the research frontier.

2.2. Three-Dimensional OBE Attainment Evaluation

OBE stresses learning outcomes as the organizing principle of education; assessment is therefore about determining whether students have achieved specified outcomes. Spady (1994) classified OBE outcomes into knowledge, competence, and quality dimensions [2], while engineering education accreditation has made attainment evaluation a common practice [4,5]. Existing attainment evaluation, however, mostly adopts a post-test compliance model and ignores starting-point differences and growth processes. Combining attainment evaluation with value-added assessment therefore provides the methodological starting point of this study.

2.3. Value-Added Assessment and Learner Digital Profiling

Value-added assessment originated in evaluations of teacher effectiveness in school education. Sanders and Rivers (1996) provided a multilevel linear model for controlling students' prior achievement [6], and Braun et al. (2010) further discussed its applicability in higher education [7]. Learner digital profiling draws on learning analytics to model students' learning behavior, knowledge state and competence development, and has been systematically reviewed for study success in higher education [8,9]. Bringing AI-driven learner profiling into value-added assessment enables automatic capture of process data, differential diagnosis of heterogeneous groups, and personalized feedback.

2.4. Research Gap

The literature shows three gaps. First, three-dimensional value-added attainment evaluation for graduate courses at the research frontier is underexplored. Second, most studies rely on questionnaires or examination scores and lack integration of multi-source process evidence. Third, the deep integration of AI-enabled learner profiling with integrated undergraduate–graduate course assessment has not been fully discussed. This study addresses these gaps by proposing and pilot-testing a transferable framework for AI-driven learner profiling for three-dimensional value-added attainment evaluation [10,11].

3. Design of the Three-Dimensional Attainment Evaluation System

3.1. Knowledge Transition Path: From Electromagnetic Fields to Plasma

The integrated undergraduate–graduate knowledge path is divided into three layers (the upper portion of Figure 1). The foundation layer relies on the core knowledge of the undergraduate course Engineering Electromagnetic Fields [11], including Poisson's equation, Maxwell's equations, Lorentz force, and

ISSN 2522-6398 Vol. 9, Issue 10: 1-7, DOI: 10.25236/FER.2026.091001

boundary conditions. The advanced layer introduces knowledge transition points such as Debye shielding, magnetic confinement configurations, electromagnetic-wave energy coupling, discharges, and diagnostics. The innovation layer focuses on EAST/ITER magnetic-confinement fusion cases and Hall-thruster electric-propulsion cases, enabling the transition from theory to industrial application. Three-dimensional attainment evaluation runs through all three layers, corresponding to knowledge, competence, and literacy attainment.

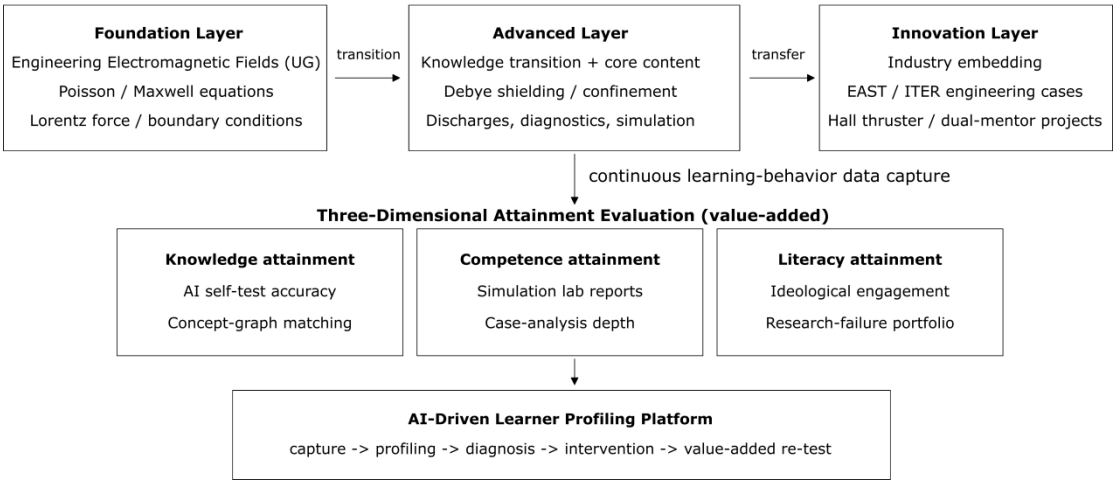


Figure 1: Overall framework of the integrated undergraduate–graduate "electromagnetic fields to plasma" knowledge transition and three-dimensional attainment evaluation.

3.2. Definition of the Three Dimensions

Knowledge attainment concerns whether students can connect undergraduate electromagnetic-field theory with graduate plasma-physics core concepts. Competence attainment concerns students' ability to analyze magnetic-confinement plasma problems, use virtual simulation for diagnostic modeling, and propose engineering solutions based on real industry cases. Literacy attainment concerns students' appreciation of scientific beauty, engineering ethics, academic integrity, and commitment to serving the nation through science and technology, as exemplified by the EAST ("artificial sun") fusion program [10]. The literacy dimension specifically introduces a structured reflection task and a designed-failure portfolio, turning research failure into evidence of literacy growth.

3.3. Indicator System and Data-Source Mapping

Based on the OBE principle of consistency among objectives, evidence, and assessment, the three dimensions are refined into observable, quantifiable, and traceable indicators. Table 1 presents the observation indicators, data sources, assessment methods, and weighting for each dimension.

Table 1 Three-dimensional attainment indicators, data sources, assessment methods, and weighting

Dimension	Observable indicator	Data source	Assessment method	Weight
Knowledge	Concept-graph matching degree	Pre/post AI self-tests, knowledge-graph node paths	AI auto-scoring + instructor sampling	0.30
Knowledge	AI self-test accuracy	Concept quizzes, online item bank	System log	0.20
Competence	Virtual simulation lab report	COMSOL Plasma simulation, B-dot / Langmuir-probe signal simulation	Rubric scoring (scientific / complete / innovative)	0.25
Competence	Case-analysis depth	EAST / ITER and Hall-thruster industry case discussions	Peer review + instructor scoring	0.15
Literacy	Ideological engagement observation	Class participation, group presentations, reflection on scientist spirit	Behaviorally anchored rating	0.05
Literacy	Research-failure analysis portfolio	Structured reflection task: cause analysis, corrective procedure, and conceptual gain	Portfolio assessment	0.05

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4. AI-Driven Learner Profiling for Value-Added Assessment

4.1. Overall Architecture

The overall architecture for AI-driven value-added assessment comprises three layers: data capture, learner profiling, and evaluation feedback (the lower portion of Figure 1). The data-capture layer continuously records learning behavior and process evidence through AI self-tests, virtual simulations, ideological-and-political behavior observation, and research-failure portfolios. The profiling layer vectorizes these evidence streams and maps them into the three-dimensional indicator space. The evaluation-feedback layer computes value-added gains and delivers tiered tasks and Socratic guidance to students, forming a diagnose–intervene–re-test loop [12].

4.2 Data Capture and Profiling

The AI self-test platform captures students' knowledge-node access paths, item accuracy, and error patterns. The virtual simulation system records students' operation trajectories in COMSOL Plasma modules such as tokamak magnetic-field configuration design and B-dot/Langmuir-probe signal simulation. Ideological-and-political behavior observation is recorded by instructors and graduate counsellors using behaviorally anchored rating scales. The research-failure portfolio requires students to submit anomalous experimental data and complete a structured reflection identifying the cause of failure, the corrective procedure, and the resulting conceptual gain. After cleaning, these multi-source data are used to construct a high-dimensional learning vector for each student.

4.3. Value-Added Gain Calculation

To avoid the twin pitfalls of relying on either final score alone or prior attainment alone, this study adopts a within-student value-added gain calculation. Let $S_{i,post}$ denote the observed post-test score of student i. Using the pre-test score $S_{i,pre}$ and process data X_i as predictors, the expected post-test score is estimated by linear regression:

$$\hat{S}_{i,post} = \alpha + \beta S_{i,pre} + \gamma X_i + \varepsilon_i \quad (1)$$

The value-added gain for student i is then $V_i = S_{i,post} - \hat{S}_{i,post}$. A positive V_i indicates that the student's actual progress exceeds the expected progress; a non-positive V_i signals the need for targeted intervention. This method controls for starting-point differences while still crediting process effort.

4.4. Feedback Loop

Based on the value-added gains and three-dimensional weaknesses, the AI learner profiling platform automatically generates three types of feedback: knowledge gaps trigger micro-learning and concept-graph paths; competence gaps trigger virtual-simulation tasks; literacy gaps trigger cases on engineering ethics and scientific spirit. Instructors then organize Socratic group discussions, after which students enter the value-added re-test to iterate the loop (Figure 2a) [13].

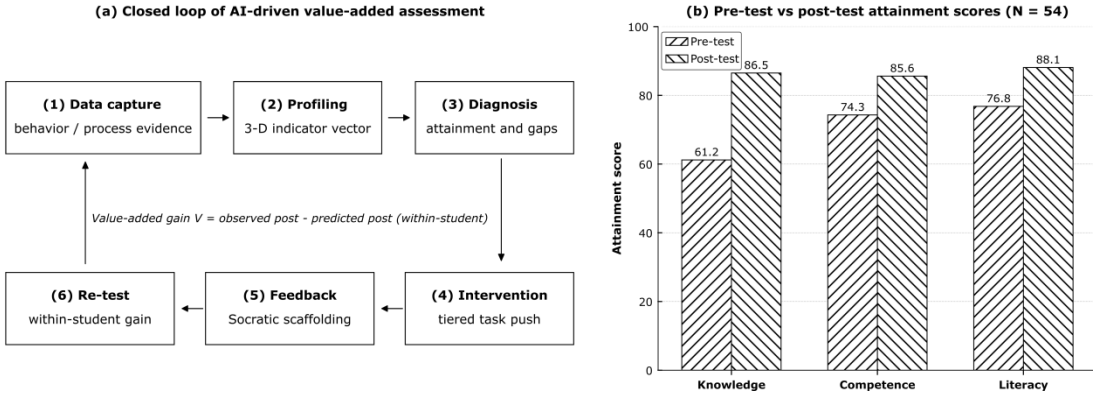


Figure 2: AI-driven learner profiling for value-added assessment: (a) diagnose–intervene–re-test loop; (b) pre-test and post-test means of three-dimensional attainment (illustrative data, shown to demonstrate the output format; N = 54 denotes the pilot cohort size; bar values are illustrative).

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5. Implementation and Effectiveness Analysis

5.1. Implementation Context and Participants

The study was implemented in the graduate course Plasma Technology and Applications, a discipline-specific elective of 36 credit hours and 2 credits in the electrical-engineering program at University of Shanghai for Science and Technology. The course team consists of four internal faculty members and one external dual-mentor expert from a research institute. The pilot covered two consecutive cohorts from the 2024–2025 academic year to the 2025–2026 academic year, with a total of 54 graduate students. The prerequisite undergraduate course Engineering Electromagnetic Fields (48 credit hours, 3 credits, compulsory for second-year undergraduates) had 236 students in the same period, indicating an available pool of prerequisite-knowledge records.

5.2. Implementation Process

Implementation was divided into four phases: diagnosis and restructuring, resource construction, pilot operation, and summarization. The diagnosis phase completed the mapping of the undergraduate–graduate knowledge graph and made prerequisite electromagnetic-field modules explicit. The resource-construction phase completed the AI self-test item bank, the virtual-simulation experiment prototype, and the industry case library. The pilot-operation phase implemented a blended model of dual-mentor lectures, project-driven learning, and flipped seminars, embedding structured failure-reflection tasks into experimental instruction. The summarization phase aggregated OBE three-dimensional attainment data and produced this research report.

5.3. Pilot Observation and Feasibility Analysis

(1) Procedural feasibility (observed). All 54 students across the two cohorts completed the pre-test and post-test sessions. The capture channels for the four categories of process evidence—AI self-tests, virtual-simulation tasks, ideological-and-political behavior observation, and research-failure portfolios—were all operative, and the three-dimensional indicators could be aggregated according to Table 1. The loop of pre-test, process capture, value-added computation, tiered feedback, and re-test ran to completion within the normal sequence of the course. The course teaching-evaluation score increased from 98 (2024–2025-1) to 99.42 (2025–2026-1), providing authentic evidence at the level of teaching organization. (2) Presentation of three-dimensional change (illustrative data). To demonstrate how indicators are read and displayed, Figure 2b presents a set of illustrative values as system output: pre-test means of 61.2, 74.3 and 76.8 and post-test means of 86.5, 85.6 and 88.1. These values are illustrative, set for the purpose of demonstrating the output format; they are not measured results from the 54 students and do not support any claim about teaching effectiveness.

6. Discussion: Innovations and Features

6.1. Assessment Paradigm Innovation: From Summative to Value-Added

This study introduces value-added assessment into graduate course attainment evaluation, overcoming the limitation of the traditional post-test compliance model. By computing within-student gains, assessment results no longer simply rank students against one another; instead, they reveal each student's longitudinal progress relative to his or her own starting point, thereby better serving educational equity and differentiated instruction.

6.2. Assessment Dimension Innovation: Three-Dimensional Integration

Most existing studies focus on knowledge and competence; this study establishes literacy attainment as an independent third dimension and uses research-failure portfolios and structured reflection tasks as distinctive evidence sources. This design responds to the value-led requirements of engineering education for engineering ethics, academic integrity, and national-service awareness.

6.3. Technical Innovation: AI-Driven Learner Profiling

By integrating multi-source data from AI self-tests, virtual simulations, and behavior observation, the

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study achieves data-driven learner profiling. Unlike traditional one-off final assessment, digital profiling can dynamically track students' knowledge-node mastery, competence growth, and literacy evolution, providing a data foundation for targeted instruction.

6.4. Educational Innovation: University–Institute Dual-Mentor and Industry-Case Integration

The course draws on institute- and industry-based expertise in pulsed-power supplies and plasma engineering, building a three-part model that combines university–institute dual-mentor teaching, industry cases, and virtual simulation. Students come to understand not only the physics of the EAST ("artificial sun") project but also its engineering implementation pathway, translating national research missions into concrete learning engagement.

6.5. Limitations and Prospects

This study has four methodological limitations. First, the pilot adopts a one-group pretest–posttest design without random assignment or a parallel control group; value-added gains can therefore be interpreted only as deviations from expectation, not as causal effects of the instructional intervention. Second, the sample comprises only 54 students, which limits the stability of the regression estimates; accordingly, no statistical inference on value-added gains is attempted, and future work should extend the pilot to further cohorts and to courses such as Fundamentals of Electrical Technology and Engineering Electromagnetic Fields. Third, the three-dimensional scales were developed for this course and have not yet undergone reliability and construct-validity testing, which directly affects the comparability of value-added gains. Fourth, AI profiling relies on continuous capture of learning-behavior data; its ethical boundaries and privacy protection (informed consent, data minimization, explainability) still require institutional regulation. Nonlinear extensions of value-added computation, such as multilevel models and quantile regression, represent an important direction for future research.

7. Conclusion and Future Work

This study completes the design and pilot implementation of an AI-driven learner profiling system for three-dimensional value-added attainment evaluation, using the graduate course Plasma Technology and Applications as the implementation context. The pilot observation shows that the system is fully implementable in a real graduate course: the four categories of process evidence can be captured, the three-dimensional indicators can be aggregated, value-added gains can be computed, and tiered feedback can be delivered, so that the evaluation loop operates within the normal sequence of the course. Future research could incorporate multimodal learning data such as classroom discussion audio and eye-movement trajectories in virtual simulation to improve the comprehensiveness and real-time responsiveness of the profile; it could also explore transferring the framework to undergraduate courses such as Fundamentals of Electrical Technology and Engineering Electromagnetic Fields, forming an evaluation loop that covers the entire integrated undergraduate–graduate training process.

Acknowledgements

This work was supported by the University of Shanghai for Science and Technology through the Integrated Undergraduate-Postgraduate Curriculum Development Project, the Teaching Research and Development Project of Academic Continuing Education (Project Nos. JXJY202610) and the Undergraduate Course Development Project (YLKC262513).

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