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AI-Supported Reform of a Graduate New Energy Vehicle Technology Course: Integrating Multimodal Learning and Value-Oriented Education

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Abstract: The rapid development of new energy vehicles and the growing use of artificial intelligence (AI) in engineering practice require graduate students in vehicle engineering to reason across increasingly coupled battery, electric-drive, power-electronics, thermal-management, and control subsystems. This paper reports a design-based reform of the graduate course New Energy Vehicle Technology, undertaken to address fragmented knowledge organization, limited opportunities for open-ended system inquiry, and weak connections between technical learning and professional responsibility. The redesigned course combines a cross-subsystem knowledge graph, digital-twin and co-simulation activities, generative-AI-assisted feedback with mandatory engineering verification, multimodal representations, and project-based learning. Preliminary evaluation draws on platform logs, project work and scores, end-of-course survey responses, and instructor observations. Two representative projects—battery state-of-health estimation with vehicle-range prediction and multi-objective optimization of vehicle energy management—show how students move from component knowledge to system-level analysis and from algorithmic output to engineering judgment. Descriptive course records show that active knowledge-graph use increased from 1.2 to 4.7 queries per student per week, while more than 40% of students conducted additional multi-scenario analyses beyond the minimum requirement. The implementation also exposed uneven preparation in programming and AI-related methods and substantial computing demands for the digital-twin environment. Because the comparison cohort is historical, the findings are interpreted as preliminary rather than causal. The study contributes a course-level design logic for integrating AI-supported learning, multimodal inquiry, and value-oriented education in graduate vehicle engineering.

Keywords: Artificial Intelligence; Multimodal Learning; Value-Oriented Education; Vehicle Engineering; Graduate Education

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1. Introduction

1.1 Research Background and Importance

Artificial intelligence (AI) is now part of routine engineering practice rather than only a specialist research topic. Vehicle engineers use data-driven models to estimate component states, optimization routines to compare design alternatives, digital twins to examine system behavior, and generative AI to support information retrieval or code development. For graduate education, the issue is therefore broader than adding a new topic called AI. Students must also learn when an AI-supported result is trustworthy, what assumptions it depends on, and how it should be checked against physical principles and engineering evidence. Research on technology-enhanced learning reaches a similar conclusion: digital tools are most valuable when they are aligned with a defined learning task rather than introduced as stand-alone technology [1-3].

This requirement is especially visible in new energy vehicle engineering. Battery capability can restrict the feasible operating region of the motor; motor efficiency affects both electrical consumption and heat generation; thermal-management power enters the vehicle energy balance; and control decisions couple these effects over a driving cycle. Broader engineering-education research and EV-training studies also emphasize digital competence, system-level reasoning, and the need to connect technology with disciplinary learning [4-7]. In the classroom, however, students often encounter these relationships at different times and in different chapters. Mastering each component principle does not necessarily enable a student to explain a vehicle-level result when several constraints become active simultaneously.

The conventional structure of New Energy Vehicle Technology reflects the logic of the discipline: batteries, electric machines, power electronics, control, and thermal management are typically taught in separate blocks. That structure remains useful for establishing theoretical foundations. The difficulty emerges later, when students are asked to address a vehicle-level problem. A parameter introduced in the battery unit may reappear as a constraint in a motor-control problem, while a thermal-management assumption may alter a conclusion about range. The reform reported here therefore focused less on expanding the syllabus than on helping students retrieve, connect, and apply knowledge that was already distributed across the course.

AI-based methods make the need for engineering judgment even more explicit. A battery SOH model can achieve a small prediction error and still be unreliable outside the conditions represented in its data. An optimization routine can return a numerically attractive solution while overlooking a practical constraint. Generative AI can produce a fluent explanation that is nevertheless physically incomplete [8-9]. In each case, the key engineering questions remain with the user: Are the data appropriate? Does the model remain valid under the intended operating conditions? What is sacrificed when one objective is improved? In the reformed course, these questions were treated as part of technical learning rather than as a separate discussion of AI ethics.

The same reasoning shaped the value-oriented component of the course. Rather than assigning a general value theme to every lecture, discussion was linked to decisions that already carried professional consequences. Thermal runaway raised the issue of acceptable safety margins; SOH estimation led naturally to continued-service and second-life decisions; energy management provided a concrete setting for considering energy use and low-carbon operation; and the development of key battery and control technologies offered examples through which technological self-reliance could be examined. The studies cited above address knowledge organization, technology-enhanced learning, AI-supported instruction, and EV-related digital competence from different angles. The distinctive focus of this study is their course-level orchestration around the same engineering problems, so that AI support, multimodal inquiry, verification, and value-oriented judgment reinforce.

1.2 Research Questions and Study Design

The reform was implemented in the graduate course New Energy Vehicle Technology. We sought to connect four elements that had previously been easier to treat separately: AI-supported learning, multimodal representation, vehicle-level analysis, and value-oriented discussion. In practical terms, the course was redesigned so that students had to move repeatedly between component knowledge and system consequences, and between algorithmic output and engineering verification. The study examined how these changes could be embedded in ordinary course work, how simulation and validation could support cross-subsystem reasoning, and where professional responsibility could be discussed without interrupting the technical logic of the lesson.

The work followed a design-based course-reform process with elements of action research. Teaching activities were adjusted during implementation in response to difficulties observed in student work. The evidence used in the present paper comprises platform logs, project work and scores, end-of-course survey responses, and instructor observations. The available comparison is historical rather than contemporaneous; accordingly, the quantitative indicators are treated descriptively and no causal or statistical-significance claim is made. The analysis therefore emphasizes the design decisions, their enactment in two representative projects, the patterns visible in the available course records, and the limitations identified during the initial implementation.

2. Educational Challenges in Graduate New Energy Vehicle Technology

2.1 Fragmented Knowledge and Cross-Subsystem Reasoning

The traditional sequence of the course follows the technical structure familiar to vehicle engineering students: battery systems, electric machines, power electronics and control, followed by vehicle-level topics. Each subsystem has its own theoretical foundation, so this sequence remains necessary. The limitation becomes apparent when an engineering problem no longer belongs to a single block.

Consider the selection of motor peak power. Appropriate sizing requires more than a motor characteristic curve: battery discharge capability limits available electrical power, inverter capacity imposes a hardware constraint, acceleration demand sets the required vehicle performance, and thermal conditions may further narrow the feasible region. Similar interactions arise when battery energy density is increased: range may improve while cost, mass, and thermal-safety requirements change at the same time. Chapter-based exercises typically isolate one or two of these relationships so that a method can be practiced. Vehicle-level design reverses that simplification and requires the relationships to be considered together.

The reform therefore did not begin by adding a large number of new knowledge points. Most of the required battery, motor, and control theory was already present. The more pressing educational need was to help students retrieve and combine that knowledge when they had to explain a vehicle-level result, identify a limiting constraint, or justify a system-level decision.

2.2 Predetermined Laboratory Work and Limited Inquiry

Standard experiments were retained because students still need direct experience with measured quantities, uncertainty, and laboratory constraints. The problem was not the presence of laboratory work but the extent to which the task had already been decided for the student. In a typical verification exercise, the test object, operating condition, variables, and expected form of the result are specified in advance. Success therefore depends largely on carrying out the procedure correctly, with limited need to redefine the problem or challenge the assumptions behind it.

A research-oriented task is less tidy. Suppose a vehicle-range calculation changes unexpectedly. The cause may lie in battery parameters, motor efficiency, auxiliary power, thermal-management demand, or the structure of the vehicle model itself. A second driving condition may then weaken or reverse the first conclusion. At that point, repeating the original calculation adds little. The student must decide what to vary, what to hold constant, and what evidence would be sufficient to support a revised explanation. Co-simulation and data analysis were therefore placed between theoretical explanation and physical verification. Students could alter an assumption, run another case, compare the response, and then return to measured data or laboratory results. The experiment was not replaced; its role changed from the final step in a prescribed sequence to an independent source of evidence against which a model-based explanation could be checked.

2.3 The Practical Difficulty of Integrating Value-Oriented Education

Value-oriented teaching was least effective when it appeared as a scheduled addition to a technically dense lesson. A short account of industrial development or professional ideals may be relevant, yet students can still treat it as separate from the calculation, model, or design decision that occupies most of their attention. This separation is particularly visible in graduate engineering courses, where the immediate classroom language centers on mechanisms, parameters, models, and quantitative evidence.

The reform therefore focused on technical topics in which a broader judgment was already unavoidable. Thermal runaway involves more than predicting temperature; it also requires a decision about the safety margin a design should preserve. Battery recycling and second-life use make the reliability of SOH estimation relevant to continued-service decisions. AI-assisted engineering raises questions about data quality, model range, and bias. The development of batteries, power electronics, and control technologies also provides a concrete technical basis for discussing technological self-reliance and the responsibilities of engineers working in strategically important fields.

Classroom discussion was therefore framed around the decision rather than around an abstract value label. Students were asked why a technically attractive solution should be accepted, modified, or rejected once safety, resource use, and professional responsibility were considered. This kept value-oriented education close to engineering evidence and reduced the need for material that was only loosely connected to the technical topic.

3. Integrated Reform Framework: AI Support, Multimodal Inquiry, and Value-Oriented Education

The reform used the vehicle-level engineering problem as the common organizing unit. Instead of treating AI, multimodal resources, simulation, and value-oriented education as parallel additions, each problem was revisited through four recurring activities: locating cross-subsystem knowledge, exploring the problem through models or alternative representations, checking claims against physical or experimental evidence, and defending the final engineering decision. The following subsections describe how these activities were implemented.

3.1 Knowledge Organization and AI-Supported Learning

The knowledge graph was built from concepts that recur across several parts of the course. The battery unit contributed SOC, SOH, internal-resistance growth, capacity loss, and thermal runaway; the electric-machine unit contributed external characteristics, efficiency maps, and field-weakening control. Regenerative braking, torque coordination, inverter limits, thermal management, and vehicle energy flow provided vehicle-level links. The graph was deliberately organized around cross-subsystem relationships rather than around the number of stored concepts, consistent with the use of knowledge graphs as scaffolds for interdisciplinary learning.

Motor peak power illustrates the intended use. In the graph, the concept was connected with battery discharge capability, inverter capacity, and vehicle acceleration demand. Battery degradation was connected with resistance growth, terminal-voltage behavior, usable energy, and range. Before discussing a case, students first identified which earlier concepts they expected to constrain the result; the displayed links were then used to compare their reasoning with the course knowledge structure. In practice, the graph served as a prompt to retrieve knowledge learned in different weeks rather than as another way to display definitions.

Generative AI was available during coursework, but not as an answer key. Students used the course assistant for brief explanations, links to related material, or feedback while revising a technical proposal. In a vehicle parameter-matching task, for example, the assistant might draw attention to range, estimated cost, or thermal-safety margin. The student still had to determine which part of the proposal required calculation and whether the suggestion was consistent with the physical model. This use of AI was deliberately framed as supported reasoning rather than delegated judgment [8].

Verification was deliberately included in the assignment. When an AI-generated explanation conflicted with a known physical relationship, students had to identify the conflict. Suggested code was checked against model assumptions before its output was used, and a numerically favorable optimization result was rejected if it violated a battery, motor, inverter, or thermal constraint. Incorrect or incomplete AI output therefore became useful teaching material because students had to articulate why an answer was not yet acceptable as engineering evidence.

3.2 Multimodal Learning Through Cognition, Simulation, and Validation

The multimodal component was organized by the engineering question rather than by the number of media formats. We did not attempt to use every available medium in every unit. Three-dimensional temperature fields were useful when students needed to follow the location and spread of heat during battery thermal runaway. An efficiency map was more appropriate when the task was to locate motor operating points across speed and torque. For vehicle energy flow, a Sankey-type representation made losses, recovery, and auxiliary consumption easier to inspect. Each representation was selected because it exposed a feature of the problem that was harder to see in equations or static prose alone, reflecting the task-centered principle emphasized in multimodal and technology-enhanced learning.

Students then returned to the same question in a digital model. COMSOL, Simulink, and Simscape were used when repeated physical tests would have been impractical. Depending on the task, students either modified an existing model or developed part of it themselves. After the first simulation, they were required to change at least one operating condition or constraint before drawing a conclusion. This requirement prevented a single favorable result from becoming the endpoint of the exercise; a parameter set that appeared effective under one driving cycle could become less attractive when thermal demand or another boundary condition changed.

Where suitable measurements were available, selected simulation results were compared with battery or motor test data. A mismatch was not treated automatically as a failure of the student model. Instead, students inspected boundary conditions, parameter values, and simplifying assumptions on both sides of the comparison. In some cases the model was revised; in others the original interpretation of the experiment had to be reconsidered. The learning process therefore moved repeatedly between explanation, calculation, simulation, and evidence rather than following a fixed linear path.

3.3 Value-Oriented Education Embedded in Engineering Decisions

Value-oriented discussion followed the technical case rather than a predetermined distribution of themes. Battery technology, for example, created two different occasions for discussion. When students compared domestic and international technology development, the focus was on the engineering work required to build technological capability. When the same unit moved to thermal runaway, the question changed to safety: how much margin should be retained when range, power, or packaging targets place pressure on the design?

Energy-management work created another setting. Energy efficiency, auxiliary demand, thermal losses, and battery utilization could be read directly from the model, so low-carbon operation was discussed through engineering quantities rather than through a general policy statement. AI-related tasks raised a different question: when a recommendation looked attractive numerically but was difficult to justify physically, what additional evidence would an engineer need before accepting it? The discussion therefore centered on the boundary between algorithmic output and professional judgment.

AI-based tagging was used mainly to organize supplementary material on battery safety, recycling, energy conservation, engineering ethics, and industrial development. The instructor reviewed suggested material before it entered a lesson, and items were omitted when their connection to the technical problem was too broad or superficial. This filtering was important: adding more cases did not necessarily improve learning. Resources were retained when they helped students interpret a specific engineering choice and omitted when they merely increased the volume of information.

4. Course Implementation, Teaching Cases, and Preliminary Outcomes

4.1 Reorganization of Content, Learning Environments, and Assessment

The theoretical backbone of the original course was retained. Electrochemistry, electric-machine theory, power electronics, and control principles continued to be taught because the later AI-supported activities depended on them. What changed was where the new tools appeared. Machine-learning-based SOH estimation was placed in the battery unit; data-driven efficiency analysis was introduced with electric-machine content; and digital-twin-based energy-management analysis appeared when the course reached vehicle-level integration. Cross-subsystem cases then required students to return to earlier material rather than treating each completed unit as closed.

Classroom explanation, simulation work, and engineering validation were connected by the same problem, but they did not always occur in that order. A lecture might introduce a relationship that students later challenged in co-simulation. A simulation result could expose a contradiction and lead to another calculation or to a check against experimental data. In other cases, a measured result forced students to revisit the model. The important design feature was continuity of the problem across settings rather than adherence to a fixed teaching sequence.

Assessment was aligned with this way of working. The written examination contributed 30% of the final grade and combined basic theory with cross-domain cases. Project work contributed 40%; marking considered parameter selection, data treatment, model construction, comparison across operating conditions, validation, and explanation of unexpected results. The remaining 30% came from an open-ended research task in which students stated and defended the assumptions behind their proposal. AI-assisted feedback was permitted during revision, but the final mark was based on the student's own reasoning, evidence, and justification.

4.2 Teaching Case I: Battery SOH Estimation and Vehicle-Range Prediction

The first case connected the battery unit with vehicle-level energy analysis. Students began with battery-aging mechanisms, including SEI-film growth, internal-resistance increase, capacity fade, and common definitions of SOH. The knowledge graph was then used to trace how degradation could propagate through resistance increase and terminal-voltage behavior to usable energy, vehicle energy consumption, and driving range.

Students worked with a battery-cycling dataset containing charge-discharge data collected at different temperatures and current rates. After preprocessing, they developed SOH-estimation models using support vector regression or long short-term memory networks in Python. Evaluation considered prediction accuracy together with an explanation of why performance changed across operating conditions. The trained model was then embedded in a vehicle energy-flow simulation, allowing students to compare vehicle behavior at different battery-health levels and to examine whether the energy-management strategy should change as the battery aged.

The key pedagogical step was to move beyond model accuracy. Students had to explain what an SOH-estimation error might mean if the result were used to support decisions about continued vehicle operation, battery replacement, recycling, or second-life use. The project therefore linked data processing and machine learning to vehicle-level performance, safety, and resource responsibility, making the consequences of model use part of the technical task itself.

4.3 Teaching Case II: Multi-Objective Optimization of Vehicle Energy Management

The second case broadened the problem boundary to the battery, motor, electronic-control, and thermal-management subsystems. Students were given a vehicle-level design question: under a specified driving cycle such as WLTC, how should an energy-management strategy be configured when driving range, system cost, and thermal-safety margin cannot all be improved simultaneously?

Before optimization, students used the knowledge graph to identify two sets of coupled relationships. The first linked battery discharge rate, motor-efficiency region, thermal-management power consumption, and driving range. The second linked battery energy density, system cost, and thermal-safety risk. These relationships became constraints in the optimization problem rather than remaining separate theoretical topics.

Students then used the digital-twin environment to build or modify a vehicle energy-flow model, test alternative energy-management parameters under multiple operating conditions, and collect performance data. A multi-objective genetic algorithm (NSGA-II) was used to obtain Pareto-optimal solutions. The educational focus began after the Pareto set had been generated: students compared candidate solutions and justified why one compromise should be preferred in a particular engineering context. A longer-range solution might reduce thermal-safety margin, while a safer solution might increase cost.

During the project defense, students were asked how an engineer should respond when range objectives and safety requirements conflict. The algorithm could identify non-dominated alternatives, but it could not determine which compromise was professionally acceptable. This discussion linked system-level optimization with engineering ethics and made value-oriented education part of the technical evaluation rather than an external addition to it.

4.4 Preliminary Outcomes and Implementation Reflections

The reform has been piloted in the graduate New Energy Vehicle Technology course. The available evidence is exploratory and is reported descriptively. Platform records showed that active knowledge-graph queries increased from an average of 1.2 to 4.7 queries per student per week. Digital-twin records indicated that most students completed at least two cross-subsystem co-simulation projects, and more than 40% conducted additional multi-scenario comparisons beyond the minimum course requirement. These indicators do not establish learning gains by themselves, but they show that students used the cross-subsystem resources beyond the minimum prompted activity.

Course records also indicated higher performance on end-of-term cross-domain case-analysis questions than in the historical comparison cohort, while project reports used system-level terms such as system coupling, multi-objective trade-off, and constraint conditions more frequently. Because the comparison cohort was historical and the present manuscript does not report a full inferential analysis of score distributions, these differences are treated as descriptive signals rather than evidence of a causal effect.

Anonymous end-of-course responses provided complementary qualitative evidence. Students frequently mentioned battery-safety ethics, the development of China's new energy vehicle industry, and AI-related ethical issues as memorable parts of the course. The implementation also exposed substantial differences in technical preparation. Students with prior programming or machine-learning experience entered model development more quickly, whereas others spent considerable time on software operation and debugging. This suggests that future offerings should provide more structured introductory support for Python, data processing, and model use before complex projects begin.

Two further implementation constraints were identified. First, value-oriented content worked best when it was directly connected with safety, resource use, or professional decision-making; forced insertion into weakly related topics could interrupt technical learning. Second, concurrent use of the digital-twin platform placed considerable demand on computing resources, which may become a barrier if the course is scaled to larger groups. Future evaluation should therefore combine clearer baseline measures, reported cohort characteristics, transparent score distributions, and longer-term follow-up with continued refinement of the instructional infrastructure.

5. Conclusion

This study addresses a specific course-design problem rather than making a general claim that AI automatically improves engineering education. In New Energy Vehicle Technology, students already encounter most of the necessary battery, motor, control, and thermal-management theory; the more difficult educational task is to bring these ideas together when a vehicle-level problem activates several constraints at once. The contribution of the reform is therefore a design logic that keeps the engineering problem continuous across knowledge retrieval, multimodal representation, simulation, verification, and decision-making. The two projects show how this logic operates in practice. In the SOH project, prediction accuracy had to be interpreted in terms of vehicle range, safety, and battery-use decisions. In the energy-management project, a Pareto set was only the beginning; students still had to defend a compromise among range, cost, and thermal safety. These were also the points at which value-oriented education became most natural, because professional responsibility was already embedded in the technical choice. Knowledge graphs, co-simulation, experimental evidence, and generative AI therefore served different but complementary functions: they supported reasoning, but none replaced the student's responsibility to justify an engineering conclusion. The preliminary evidence suggests that the approach is feasible, but the current study has clear limitations. Students entered the course with unequal programming experience, the digital-twin environment imposed substantial computing demands, and the comparison group was historical rather than contemporaneous. The next phase should report cohort characteristics and baseline measures more explicitly, strengthen quantitative and qualitative outcome analysis, and examine whether the same design logic transfers to other graduate vehicle-engineering courses. The long-term objective is not simply to make a course more "intelligent," but to prepare engineers who can use intelligent technologies while preserving physical reasoning, system-level thinking, and professional responsibility.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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