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Bridging Undergraduate and Graduate Research Training in the Era of Generative Artificial Intelligence: A Progressive Human-AI Collaborative Framework for Engineering Education

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Abstract: ***Generative artificial intelligence (GenAI) is lowering the procedural barriers to literature synthesis, coding, data analysis, simulation support, and scholarly communication, thereby creating new opportunities for introducing authentic research earlier in engineering education. Yet easier access to research-like outputs does not necessarily produce research competence, and undergraduate students may enter graduate study with uneven abilities in problem formulation, methodological justification, evidence verification, uncertainty reasoning, and academic responsibility. This design-oriented study develops a progressive framework for AI-enhanced undergraduate research training that explicitly targets graduate-research readiness. Drawing on outcome-based education, constructive alignment, undergraduate research scholarship, and the engineering-education principles of authentic problems, project-based learning, numerical modeling, simulation, and evidence-based assessment, the framework organizes training into four stages: research and AI literacy, guided inquiry, semi-independent research, and a graduate-entry bridge. It further proposes a faculty mentor–graduate near-peer–undergraduate–GenAI collaboration mechanism in which support is distributed but epistemic ownership remains with the undergraduate researcher. For implementation, the study specifies an AI-supported research task chain for mechanical and vehicle engineering and develops a closed-loop readiness assessment based on traceable process evidence rather than the polish of a single AI-assisted product. The proposed approach reframes undergraduate research from isolated participation toward calibrated research independence and provides a practical architecture for improving continuity between undergraduate research experiences and graduate-level research training.***

Keywords: Generative artificial intelligence, Undergraduate research, Graduate-research readiness, Engineering education, Human-AI collaboration, Research competence.

1. Introduction

Generative artificial intelligence is rapidly becoming part of the everyday infrastructure of learning and research. International guidance therefore emphasizes that its educational use should remain human-centered, ethically governed, and pedagogically purposeful [1].

Large language models can assist with explanation, ideation, coding, summarization, and feedback, but the educational value of these functions depends on the learner's ability to verify outputs and understand their limitations [2].

For undergraduate students, this development creates a particularly important opportunity. Research tasks that once required a high procedural threshold can now be approached earlier through AI-supported literature navigation, computational prototyping, data processing, and visualization. At the same time, earlier access to sophisticated tools makes it easier to produce work that appears research-like without developing the underlying capacity to judge a question, defend a method, interpret evidence, or take responsibility for a claim.

Undergraduate research experiences have long been associated with gains in research skills, confidence, scientific thinking, and understanding of how knowledge is produced [3]. Engineering-specific evidence also indicates that participation in undergraduate research can strengthen technical and professional development [4].

Undergraduate research is also relevant to educational continuity because students who participate in research are more likely to pursue graduate or professional education [5]. Students frequently report that such experiences clarify career plans and strengthen preparation for advanced study [6].

The central problem, therefore, is not whether undergraduate students should participate in research, but how research participation should be structured so that it becomes preparation for the qualitatively different expectations of graduate research. Graduate study requires more than completing assigned procedures. It increasingly requires students to formulate defensible questions, select and justify methods, work with incomplete evidence, evaluate uncertainty, manage research records, communicate scholarly claims, and operate with increasing independence.

GenAI sharpens this transition problem. AI literacy includes not only operational proficiency but also the capacity to understand what AI can and cannot do and to evaluate its outputs critically [7]. Institutional policy must likewise establish clear expectations for acceptable use, disclosure, verification, and responsibility [8].

Assessment is especially important because GenAI can improve the surface quality of a report, code fragment, or presentation while masking weaknesses in the underlying reasoning process. Recent review work therefore argues that assessment in the GenAI era should place greater emphasis on responsible learning, self-regulation, and evidentiary

processes [9].

Academic integrity concerns reinforce the same point: the presence of AI requires explicit attention to attribution, verification, and the student's ownership of scholarly work [10]. The objective of undergraduate research training should consequently shift from simply increasing exposure to projects toward building evidence of graduate-research readiness.

This article addresses three questions. First, what competences should AI-enhanced undergraduate research cultivate before students enter graduate research? Second, how should faculty mentors, graduate near-peers, undergraduate researchers, and GenAI divide and coordinate their roles? Third, what forms of process evidence can distinguish genuine readiness from polished AI-assisted output? To answer these questions, the paper develops a progressive, design-oriented framework grounded in engineering research practice rather than reporting fabricated or premature learning-gain data.

2. From Undergraduate Research Participation to Graduate-Research Readiness

2.1 The Educational Value of Undergraduate Research

Undergraduate research is most educationally powerful when students encounter authentic uncertainty rather than only predetermined laboratory answers. Early evaluation work showed that undergraduate research can develop research-related skills and shape students' understanding of scientific work [3].

In engineering, alumni who participated in undergraduate research reported benefits extending beyond technical content to professional development and educational trajectories [4]. Faculty perspectives similarly indicate that the quality of mentoring and the structure of the research environment are central to the experience rather than incidental features [11].

Large-scale survey evidence has also linked undergraduate research with students' continued plans for postgraduate science education [12]. Broader national evidence has reinforced the role of research experiences in the STEM education pipeline [13].

These findings justify treating undergraduate research as more than an extracurricular enrichment activity. For students who may enter graduate school, it can function as a preparatory environment in which the habits of research are made visible and progressively practiced.

2.2 Participation is Not Equivalent to Readiness

Participation alone does not guarantee that students understand what makes an activity research. Engineering undergraduates may hold heterogeneous conceptions of research, researchers, evidence, and knowledge creation even when they have encountered research-related activities [14].

A student can therefore complete a finite element analysis, train a machine-learning model, or contribute to a laboratory project without being able to explain why a particular problem matters, which assumptions are defensible, how a method should be validated, or what uncertainty limits a conclusion. These gaps become consequential when the student enters graduate education and is expected to work with less scripted tasks.

For this reason, the transition target proposed here is graduate-research readiness rather than mere project completion. Graduate-research readiness is defined as the demonstrated capacity to enter a research group and assume progressively independent responsibility for problem formulation, knowledge construction, method selection, verification, evidence interpretation, research documentation, and scholarly communication.

2.3 GenAI Changes the Meaning of Preparation

GenAI can compress the time required for low-level procedural work and thereby free students to engage earlier with higher-order research decisions. Used well, it can help an undergraduate compare candidate methods, debug code, translate mathematical descriptions into computational workflows, organize literature, or improve a visualization.

Used poorly, the same tools can externalize precisely the cognitive work that undergraduate research is intended to develop. The educational design problem is therefore one of selective delegation: procedural assistance may be delegated to AI, but responsibility for research questions, assumptions, evidence, verification, uncertainty, and final claims should remain with the student.

This distinction also suggests that AI use should become visible in research training rather than being treated as an invisible private activity. Prompt records, source trails, code revisions, verification notes, and statements of AI contribution can all become part of the evidence used to judge whether competence is developing.

3. Design Basis and Principles

The framework combines four design principles. The first is constructive alignment: intended research outcomes, training tasks, support mechanisms, and assessment evidence should be designed as a coherent system [15].

The second is outcome orientation. Outcome-based education begins with what learners should ultimately be able to do and then aligns activities and assessment with those outcomes [16]. In the present context, the relevant outcomes are not isolated software skills but observable research performances such as framing a tractable problem, justifying a model, validating a result, and defending a conclusion.

The third principle is authentic engineering practice. The source reform project emphasizes the use of real engineering cases, modern computational tools, numerical simulation, project tasks, and diversified assessment. Translating these principles to undergraduate research means giving students bounded but genuine engineering questions involving data, modeling, simulation, optimization, fatigue, reliability,

structural analysis, or experimental interpretation.

The fourth principle is progressive fading of support. Active learning is most effective when students are required to engage cognitively rather than merely receive information [17]. Project-based learning further supports autonomy, investigation, collaboration, communication, and reflection around authentic tasks [18].

These principles imply a training architecture in which the difficulty of research decisions increases across stages while the intensity of direct scaffolding decreases. AI is positioned as a selective scaffold rather than a substitute for disciplinary knowledge or research judgment. Assessment is simultaneously designed to capture long-term capability rather than only immediate task performance [19].

4. A Progressive Pathway from Undergraduate Inquiry to Graduate-Research Readiness

The proposed pathway contains four stages that correspond to increasing epistemic responsibility. The purpose is not to create four rigid academic-year categories, but to provide a progression that can be adapted to different majors, laboratories, and entry points. The complete progression is summarized in Figure 1.

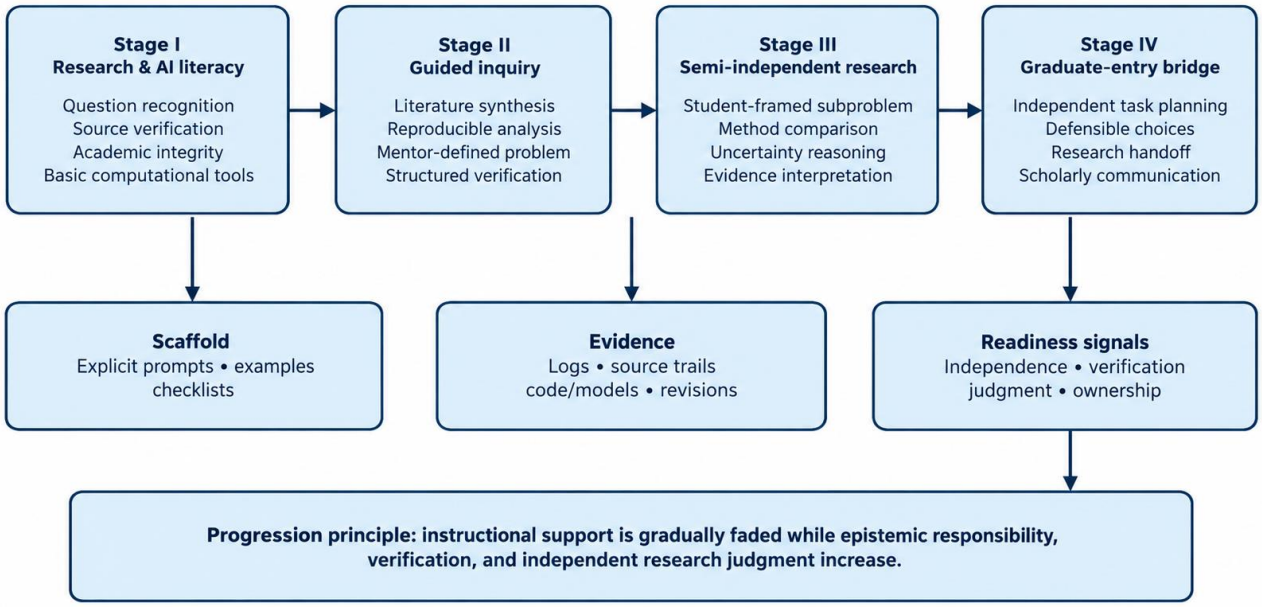


Figure 1: Progressive pathway from undergraduate research participation to graduate-research readiness

4.1 Stage I: Research and AI Literacy

The first stage establishes a common language for research before students are asked to perform independent work. Training focuses on recognizing the difference between a topic and a researchable question, distinguishing primary evidence from secondary summaries, locating and checking sources, maintaining research records, and understanding basic expectations for academic integrity.

AI literacy is introduced at this stage as an element of research literacy rather than as a separate technology module. Students practice asking an AI system to explain a concept or suggest search terms, but they must then verify the explanation against authoritative sources. They also learn that a generated citation, code fragment, model description, or numerical result is provisional until checked.

In engineering programs, the computational component can include basic MATLAB or Python workflows, data visualization, numerical calculation, and introductory simulation interfaces. The goal is to reduce tool friction while ensuring that students can still explain what a computation represents.

4.2 Stage II: Guided Inquiry

The second stage places students inside a mentor-defined problem space. The research question is intentionally bounded, data or model resources are partially prepared, and the mentor provides explicit checkpoints. Students conduct literature synthesis, reproduce a baseline analysis, compare their results with a reference, document discrepancies, and explain the effect of assumptions.

For example, students may reproduce a component life-prediction model, build a simplified finite element model of a structural part, or compare alternative regressors for a reliability dataset. AI can support code debugging and method comparison, but the student must maintain a source trail and a verification record.

The most important outcome of this stage is reproducibility. A student who can reproduce and explain a baseline workflow has begun to move from tool use toward research method competence.

4.3 Stage III: Semi-independent Research

The third stage transfers part of the problem-definition burden to the undergraduate. Students are asked to formulate a subproblem within a larger faculty project, identify competing methods, justify one approach, and specify a validation strategy. Mentor support remains available, but it shifts from telling students what to do toward challenging their assumptions and asking for evidence.

AI can now be used for option generation, preliminary coding, parameter-study planning, or drafting alternative explanations. The student, however, must compare options using disciplinary criteria and defend the chosen route. This stage is where uncertainty reasoning becomes explicit: students should state what is known, what is assumed, what is estimated, and which conclusions would change if an assumption fails.

4.4 Stage IV: Graduate-entry Bridge

The final stage is designed as a transition rather than a capstone only. Students plan a bounded research task, define milestones, select tools, document AI use, conduct validation, and present a defensible claim. The task should be sufficiently open-ended that multiple routes are possible but sufficiently constrained that failure remains educationally manageable.

The student also prepares a research handoff package containing a concise problem statement, key literature, model or experiment files, a source trail, validation evidence, unresolved questions, and a statement of limitations. This practice mirrors the documentation discipline expected in a graduate research group and reduces the discontinuity between undergraduate project work and graduate-level inquiry.

The transition criterion is therefore calibrated independence. The student does not need to demonstrate the autonomy of an advanced graduate researcher, but should demonstrate that support can be reduced without transferring intellectual responsibility to AI or to the mentor.

5. Faculty Mentor–Graduate Near-Peer–Undergraduate–GenAI Collaboration

One reason undergraduate research does not always translate smoothly into graduate readiness is that tacit research practices are difficult to convey through formal instruction alone. The framework therefore introduces a graduate near-peer between the faculty mentor and the undergraduate researcher. This role is not intended to replace faculty supervision, but to make everyday research workflows more visible.

The role allocation is illustrated in Figure 2. The undergraduate researcher remains the central agent because readiness cannot be delegated; the other three actors provide different forms of support.

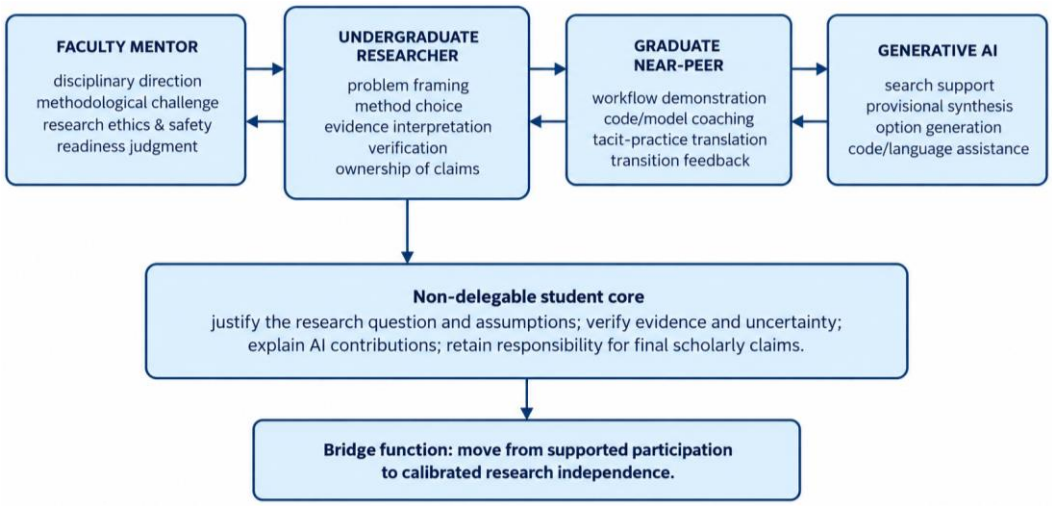


Figure 2: Faculty mentor–graduate near-peer–undergraduate–GenAI collaborative mechanism

5.1 Faculty Mentor: Direction, Standards, and Methodological Challenge

The faculty mentor defines the disciplinary boundary of the training problem, protects research ethics and safety, ensures that the task is educationally appropriate, and judges whether a student is ready for greater independence. The mentor should increasingly ask students to justify decisions rather than simply provide procedures.

Faculty supervision is particularly important when AI generates plausible but technically unsound recommendations. The mentor's role is to establish standards for evidence, not to verify every AI output on the student's behalf.

5.2 Graduate Near-peer: Translation of Tacit Practice

Graduate near-peers can demonstrate how researchers actually manage code versions, organize simulation files, record failed attempts, read a paper strategically, prepare for group meetings, or decide whether an anomalous result is a software error or a meaningful phenomenon. These practices are often too granular for formal lectures but highly consequential for successful entry into graduate research.

The near-peer also provides transition feedback because graduate students can identify which undergraduate habits become bottlenecks in laboratory research. To avoid dependency, near-peer support should be diagnostic and explanatory rather than task-completing.

5.3 Undergraduate Researcher: Epistemic Ownership

The undergraduate must retain ownership of the research question, method choice, interpretation of evidence, verification strategy, and final claims. The framework uses the term epistemic ownership to emphasize that a student should be able to explain why a conclusion is warranted, not merely show that a workflow produced it.

This requirement distinguishes graduate-research readiness from software proficiency. A student who can run an advanced model but cannot defend its assumptions is not yet ready for independent research responsibility.

5.4 GenAI: Provisional Support with Explicit Boundaries

GenAI is used for tasks that benefit from rapid iteration: search-term expansion, provisional synthesis, explanation of unfamiliar concepts, coding assistance, alternative visualization ideas, option generation, and language refinement. These functions can reduce procedural barriers and accelerate learning.

AI outputs should be treated as provisional artifacts. The student remains responsible for checking sources, testing code, validating models, identifying uncertainty, disclosing material AI contributions, and ensuring that final text accurately represents the evidence.

6. AI-Supported Research Task Chain in Mechanical and Vehicle Engineering

The framework is intended to operate through authentic research tasks rather than abstract AI exercises. The engineering context of the source project provides a useful task ecology because mechanical and vehicle engineering naturally combine mathematical modeling, data processing, simulation, experimentation, optimization, and design judgment.

A research task chain should therefore connect four kinds of work: problem and literature framing, computational or experimental implementation, validation and engineering interpretation, and scholarly communication. Each task produces both a technical output and a process record that can be evaluated for readiness.

6.1 Problem Framing and Literature-grounded Inquiry

A suitable undergraduate task begins with a concrete engineering phenomenon rather than a generic prompt to “do research.” Examples include variability in fatigue life, uncertainty in structural response, sensitivity of vehicle dynamics to parameters, or prediction of a reliability indicator from historical data.

Students use conventional databases and original papers to establish what is already known. GenAI may help generate keywords, organize comparison dimensions, or identify terminology, but every substantive claim entering the research plan must be traceable to a verified source.

The deliverable is not merely a literature review. It is a problem memo that states the engineering significance, identifies a tractable gap or comparison, defines the target variable or response, and lists assumptions that will need later verification.

6.2 Computational Modeling and Data Work

The source project emphasizes modern computational tools such as MATLAB and Python together with engineering simulation. For undergraduate research, these tools can be organized into increasing levels of autonomy: reproduce a reference script, modify a parameter study, build a reusable workflow, and finally design a computational experiment.

GenAI can accelerate code scaffolding, library discovery, error diagnosis, and plotting. The student must nevertheless be able to walk through the core algorithm, explain input and output quantities, identify unit consistency, document changes, and reproduce the result from a clean environment.

Where machine learning is used, students should compare at least a baseline model and a more flexible model, describe the data split, check for leakage, and interpret prediction error in engineering terms. The learning objective is not to maximize a metric but to understand how data and modeling decisions affect the credibility of an engineering conclusion.

6.3 Simulation, Verification, and Physical Interpretation

Finite element and other simulation tasks are especially valuable because they expose the difference between obtaining a result and establishing confidence in that result. Students should document geometry simplifications, material assumptions, boundary conditions, mesh choices, solver settings, convergence behavior, and comparison with theoretical, experimental, or benchmark evidence.

AI can explain software messages or propose possible causes of nonconvergence, but students should test those hypotheses through controlled changes. This creates a disciplined verification habit that is directly transferable to graduate research.

Possible training cases include component fatigue reliability, vehicle-body structural response, collision-related structural analysis, dynamics modeling, or optimization under uncertainty. The cases should be chosen for the research decisions they elicit rather than for visual complexity.

6.4 Communication, Defense, and Research Handoff

Every research task should culminate in an oral or written defense of the chain from question to evidence. Students should be asked not only what they found, but why they trusted the result, which alternatives were rejected, what uncertainty remains, and where AI influenced the workflow.

GenAI may be used to refine language after the technical content is established. The student must retain the ability to explain every claim in the report and should preserve version history so that the evolution from rough analysis to final communication remains auditable.

7. Evidence-Based Assessment of Graduate-Research Readiness

If readiness is judged only from a final report, AI assistance can make weak underlying competence difficult to detect. The assessment system should therefore combine product evidence with process evidence. The proposed closed loop is shown in Figure 3.

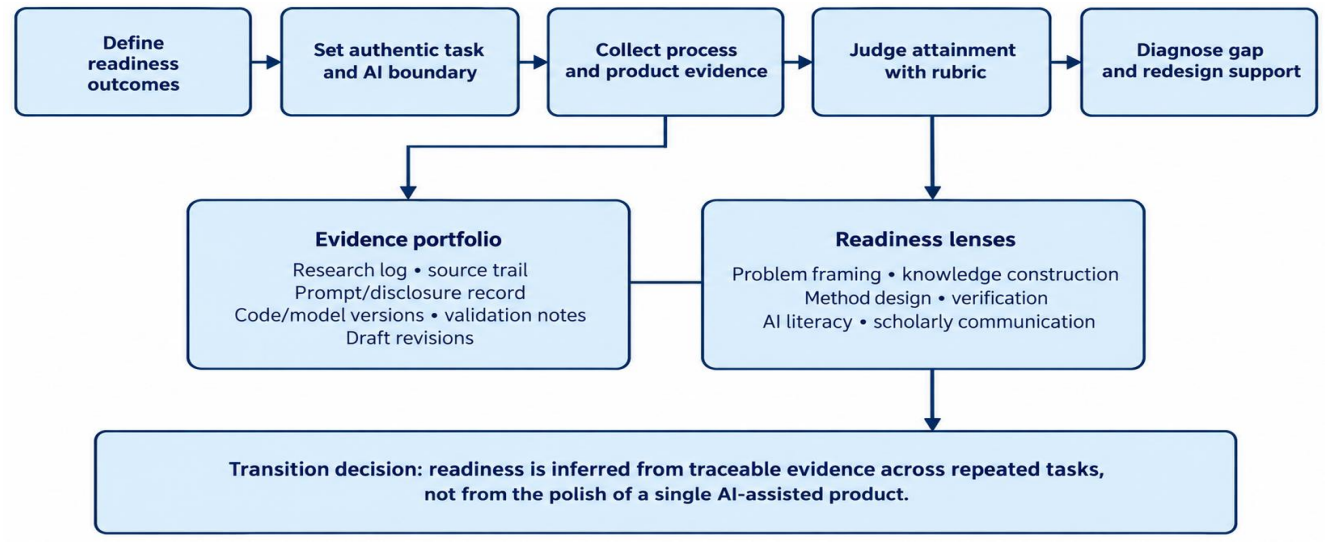


Figure 3: Evidence-based closed loop for assessing graduate-research readiness

The loop begins by defining observable readiness outcomes for a particular stage. An authentic research task and explicit AI-use boundary are then specified. During implementation, students preserve a portfolio containing research logs, source trails, prompt or disclosure records when relevant, code and model versions, validation notes, and draft revisions.

Attainment is judged with a rubric that asks whether the student can formulate a problem, construct a domain knowledge base, design or adapt a method, verify evidence, use AI responsibly, and communicate scholarly claims. The judgment then informs the next task and the amount of scaffolding provided.

This process operationalizes the principle that assessment should support future learning rather than merely certify a single performance [19]. It also reduces the risk of mistaking fluent AI-supported communication for genuine research independence.

To make the framework operational, Table 1 summarizes six readiness dimensions, the evidence expected from undergraduate research, the boundary for AI assistance, and the indicator used to judge transition toward graduate-level research responsibility.

Table 1: Indicator system for AI-assisted undergraduate graduate-research readiness

Competence dimension	Evidence from undergraduate research	AI-use boundary	Graduate-entry readiness indicator
Problem formulation	Problem memo; question iterations; scope decisions	AI may generate candidate questions; student must select, narrow, and justify the final question	Frames a tractable problem and explains its significance, assumptions, and boundaries
Knowledge construction	Verified literature map; annotated sources; synthesis notes	AI may support search terms and provisional synthesis; original sources must be checked	Builds a coherent evidence base and distinguishes source evidence from AI-generated summaries
Method design and implementation	Research plan; code or model versions; experiment/simulation record	AI may scaffold code or suggest options; student must understand and defend the selected method	Selects a method for disciplinary reasons and can reproduce the workflow
Verification and interpretation	Benchmark comparison; convergence checks; uncertainty notes; sensitivity analysis	AI may suggest diagnostics; verification decisions and acceptance criteria remain human responsibilities	Explains why a result is credible, what uncertainty remains, and how evidence supports the claim
AI literacy and research integrity	Prompt/disclosure record; source trail; correction log	AI contributions are disclosed when material; unverifiable output cannot be used as evidence	Uses AI selectively, identifies errors or limitations, and preserves academic responsibility
Scholarly communication and independence	Progress presentation; defense; handoff package; revised report	AI may refine expression after technical reasoning is established	Defends claims without relying on AI in real time and can plan the next research step with reduced scaffolding

8. Implementation Strategy and Safeguards

8.1 Build a Research-group Pathway Rather than Isolated Projects

Undergraduate research is often organized as a collection of individual projects with different expectations. A transition-oriented model instead treats the research group as a developmental environment. Students entering at Stage I should be able to see what Stage III and Stage IV performances look like through examples, group meetings, code repositories, model archives, and near-peer demonstrations.

Graduate near-peers should receive brief mentoring guidance so that they do not simply solve problems for undergraduates. Their role is to externalize reasoning, demonstrate research routines, ask diagnostic questions, and point students toward verification.

8.2 Establish an Explicit AI-use and Disclosure Protocol

Each task should specify which forms of AI use are permitted, which require disclosure, and which are inappropriate because

they would replace the target competence. For example, AI-assisted syntax debugging may be acceptable in a task assessing modeling decisions, while unrestricted generation of the literature synthesis would undermine a task assessing knowledge construction.

Policy clarity is preferable to vague prohibition because students need to learn responsible AI use before entering graduate research. A useful protocol asks students to record material AI contributions, verify factual claims against original sources, test generated code, and identify any output that influenced a substantive research decision.

Institutional AI-policy research likewise supports the need for explicit educational guidance rather than assuming that students will infer appropriate boundaries on their own [8].

8.3 Increase Task Difficulty while Fading Scaffolds

The transition from Stage I to Stage IV should be driven by demonstrated performance, not simply by time spent in a laboratory. Students who show reliable source verification and reproducible computation can be given greater freedom in problem selection. Students who produce polished outputs but weak explanations should receive more diagnostic tasks rather than more advanced tools.

This approach makes failure educationally useful. A nonconvergent model, contradictory literature result, or poor predictive fit can become evidence of competence if the student diagnoses the issue systematically and revises the method on defensible grounds.

8.4 Use Feedback to Redesign Both Student Tasks and the Training System

Feedback should operate at two levels. At the student level, it identifies the next competence to develop. At the program level, recurring weaknesses reveal where tasks, resources, mentoring, or AI-use rules should be redesigned.

The source reform project emphasizes continuous evaluation through programming assignments, project reports, simulation tasks, student feedback, and iterative course adjustment. The same logic can be extended to undergraduate research by treating the evidence portfolio as both an assessment record and a source of information for improving the training pathway.

9. Discussion

9.1 From Research Exposure to a Transition Architecture

The primary contribution of the framework is to shift the organizing question from "How can undergraduates participate in research?" to "What evidence should demonstrate that an undergraduate is ready to assume graduate-level research responsibility?" This change connects the well-established benefits of undergraduate research to the specific demands of educational transition.

The framework does not diminish the value of exploration or curiosity. Instead, it adds an explicit progression so that experiences in literature reading, simulation, coding, experimentation, and communication accumulate into a coherent readiness profile.

9.2 The Graduate Near-peer as a Continuity Mechanism

The addition of graduate near-peers is important because undergraduate-to-graduate transition involves tacit knowledge as well as formal competence. Students must learn how research groups actually manage uncertainty, failed attempts, iterative models, documentation, and scholarly discussion. Graduate near-peers can make these practices visible while also modeling the transition the undergraduate is preparing to make.

This role should remain bounded. Faculty retain responsibility for research quality and educational design, while near-peers support workflow learning and provide developmental feedback.

9.3 Why GenAI Should be Governed by Epistemic Responsibility

A prohibition-centered approach would miss the fact that future graduate researchers are likely to work in environments where AI-supported search, coding, analysis, and communication are commonplace. A laissez-faire approach would be equally problematic because it could allow students to outsource the very reasoning that research training is meant to cultivate.

The proposed alternative is to regulate AI use by epistemic responsibility. Assistance is acceptable when the student can explain and verify the resulting work; assistance becomes educationally problematic when it obscures who made the decision, how evidence was checked, or why a claim is justified. This principle is consistent with human-centered guidance for GenAI in education and research [1].

It is also consistent with evidence that assessment practices must be redesigned in response to GenAI rather than merely adding detection mechanisms [9].

9.4 Limitations and Research Agenda

This paper is a conceptual and design-oriented contribution. It does not claim that the proposed framework has already improved grades, research output, graduate admission, or later research performance. Such claims would require empirical evidence that is not available at this stage.

Future work should therefore evaluate the framework longitudinally. Useful measures include the quality of problem formulations, reproducibility of computational work, accuracy of source verification, quality of validation strategies, independence during oral defense, reduction in mentor intervention, and performance during the first year of graduate research.

Research should also compare different levels of AI access and different near-peer mentoring structures. The most important outcome is not whether students use more or less AI, but whether they become better able to exercise research

judgment while using contemporary tools responsibly.

10. Conclusions

GenAI creates an opportunity to move authentic research training earlier into undergraduate engineering education, but it also makes superficial research performance easier to produce. The resulting educational challenge is to ensure that undergraduate students gain not only access to advanced tools but also the epistemic responsibility required for graduate research.

This study proposes a four-stage pathway from research and AI literacy to a graduate-entry bridge, a collaboration mechanism linking faculty mentors, graduate near-peers, undergraduate researchers, and GenAI, and an evidence-based closed loop for judging graduate-research readiness. The framework is operationalized through authentic mechanical and vehicle engineering tasks involving literature synthesis, numerical computation, data analysis, simulation, verification, and scholarly communication.

The core principle is calibrated independence: support should be progressively reduced while students assume greater responsibility for questions, assumptions, evidence, uncertainty, verification, and claims. By making that progression explicit and assessable, undergraduate research can function not only as a valuable educational experience in its own right, but also as a coherent bridge into graduate research.

Acknowledgments

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