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A Design-Based Learning Approach to Materials Science: Bridging Simulation, Additive Manufacturing, and Experimentation in Engineering Technology Education

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Abstract

Engineering Technology programs increasingly require instructional approaches that integrate digital design, simulation, manufacturing, and experimental validation. This paper presents a design-based, experiential learning module implemented in an undergraduate materials science laboratory that intentionally exposes students to discrepancies between idealized simulation predictions and the physical behavior of additively manufactured parts.

The module guides students through a full design–simulation–manufacturing–testing cycle, including CAD modeling, Finite Element Analysis (FEA), fused deposition modeling, mechanical testing, and iterative redesign. Grounded in experiential and project-based learning frameworks, the activity positions simulation as a hypothesis-generating tool rather than a definitive predictor, encouraging critical evaluation of modeling assumptions and manufacturing constraints.

Instructional impact was evaluated using pre–post Likert-scale surveys aligned with four learning constructs: load-based design confidence, CAD proficiency, simulation interpretation, and data-driven design improvement. Results from two course offerings (n = 9) indicate statistically significant, practically meaningful gains with moderate-to-large effect sizes across multiple constructs, supported by visualization-based analysis and robustness checks.

The paper contributes a replicable pedagogical model for Engineering Technology curricula that strengthens applied understanding of materials behavior while reinforcing engineering judgment through failure analysis, experimentation, and iterative design.

1. Introduction

The rapid evolution of modern manufacturing, often characterized under the umbrella of the Fourth Industrial Revolution (Industry 4.0), has fundamentally altered the skill sets expected of engineering and engineering technology graduates. Contemporary manufacturing environments increasingly rely on tightly integrated workflows that combine computer-aided design (CAD), predictive simulation, digital manufacturing, and data-driven validation [1], [2]. As a result, Engineering Technology (ET) programs are under growing pressure to move beyond isolated theoretical instruction and provide students with authentic, practice-oriented learning experiences that reflect industry realities.

Industry investment trends further reinforce this educational imperative. Significant capital investments in additive manufacturing, digital twins, and advanced materials processing have created strong demand for graduates who can navigate the full design-manufacturing-testing (DMT) cycle. Employers increasingly expect technologists to interpret simulation outputs critically, understand process-induced material behavior, and reconcile discrepancies between predicted and observed performance. Consequently, ET curricula must emphasize not only tool proficiency, but also engineering judgment developed through experiential learning.

Within this context, materials science presents a persistent instructional challenge. While foundational concepts such as stress–strain behavior, elastic and plastic deformation, and failure theories are essential, students often encounter them in idealized forms divorced from manufacturing realities. This paper presents a design-based laboratory module implemented within an undergraduate Materials Science course that intentionally exposes students to the limitations of idealized assumptions through the integration of simulation, additive manufacturing, and physical testing.

2. Problem Statement: Bridging the Conceptual–Application Gap

A well-documented challenge in materials science and mechanics education is the gap between conceptual understanding and practical application. Traditional instruction frequently introduces material behavior using homogeneous, isotropic assumptions that simplify analysis and support early learning. While appropriate for many wrought or machined components, these assumptions are fundamentally misaligned with the behavior of additively manufactured parts.

In fused deposition modeling (FDM), components are fabricated layer by layer, producing anisotropic mechanical properties governed by filament orientation, layer adhesion, thermal history, and print parameters. Numerous studies have demonstrated that FDM parts exhibit direction-dependent stiffness and strength, often deviating substantially from bulk material properties [3], [4]. When students rely exclusively on commercial simulation tools that default to isotropic material models, they may overestimate part performance and fail to anticipate real-world failure modes [5].

This disconnect is particularly problematic in ET education, where graduates are expected to translate digital predictions into manufacturable and reliable physical components. Without explicit instructional interventions, students may develop unwarranted confidence in simulation outputs or treat discrepancies between simulation and experiment as anomalies rather than learning opportunities.

2.1. Instructional Risks of Tool-Centered Learning

An additional challenge arises from the increasing accessibility of sophisticated simulation and design tools. While these tools are invaluable in modern engineering practice, their use in educational settings can inadvertently promote a tool-centered rather than concept-centered mindset. Students may focus on achieving visually appealing stress plots or acceptable safety factors without critically interrogating underlying assumptions, boundary conditions, or material models.

In the context of additive manufacturing, this risk is amplified. Commercial FEA packages often obscure material anisotropy and process-induced defects, reinforcing a false sense of predictive certainty. If unaddressed, such experiences may hinder students' ability to transfer classroom knowledge to industrial settings where uncertainty, variability, and judgment are unavoidable.

The instructional intervention described in this paper was intentionally designed to counteract these risks by positioning simulation as a hypothesis-generating tool rather than a definitive predictor. By requiring students to reconcile digital predictions with physical outcomes, the module encourages epistemic humility and critical evaluation—competencies central to effective engineering technology practice.

The Materials Science laboratory course examined in this study provided an opportunity to directly address this challenge. By embedding a structured design-manufacturing-testing activity within an existing course, the instructional intervention sought to make discrepancies between virtual and physical behavior explicit and pedagogically productive.

3. Pedagogical Framework

The instructional design of the module is grounded in experiential and design-based learning frameworks commonly used in engineering and engineering technology education. In particular, the activity aligns with Kolb's experiential learning cycle, in which learning occurs through iterative engagement with concrete experience, reflection, abstraction, and experimentation. Rather than treating design, simulation, manufacturing, and testing as isolated skills, the module integrates these elements into a cohesive workflow that mirrors professional engineering practice. This structure emphasizes learning through iteration, evidence-based decision-making, and reflection on discrepancies between predicted and observed behavior—competencies central to effective engineering technology practice [6].

The pedagogical framework is operationalized through a structured design–simulation–manufacturing–testing cycle implemented within the materials science laboratory. As shown in Figure 1, students begin with CAD-based design and idealized simulation to generate performance hypotheses, followed by additive manufacturing and mechanical testing to provide physical validation. Comparative analysis of simulation predictions and experimental outcomes prompts reflection, failure analysis, and iterative redesign [7], [8]. By engaging students in open-ended, constraint-driven design tasks rather than prescriptive laboratory procedures, the module promotes ownership of design decisions, critical interpretation of simulation outputs, and data-driven improvement. This integrated approach supports applied learning outcomes related to experimentation, modern tool usage, and engineering judgment, while reinforcing the limitations of idealized models in manufacturing-focused contexts.

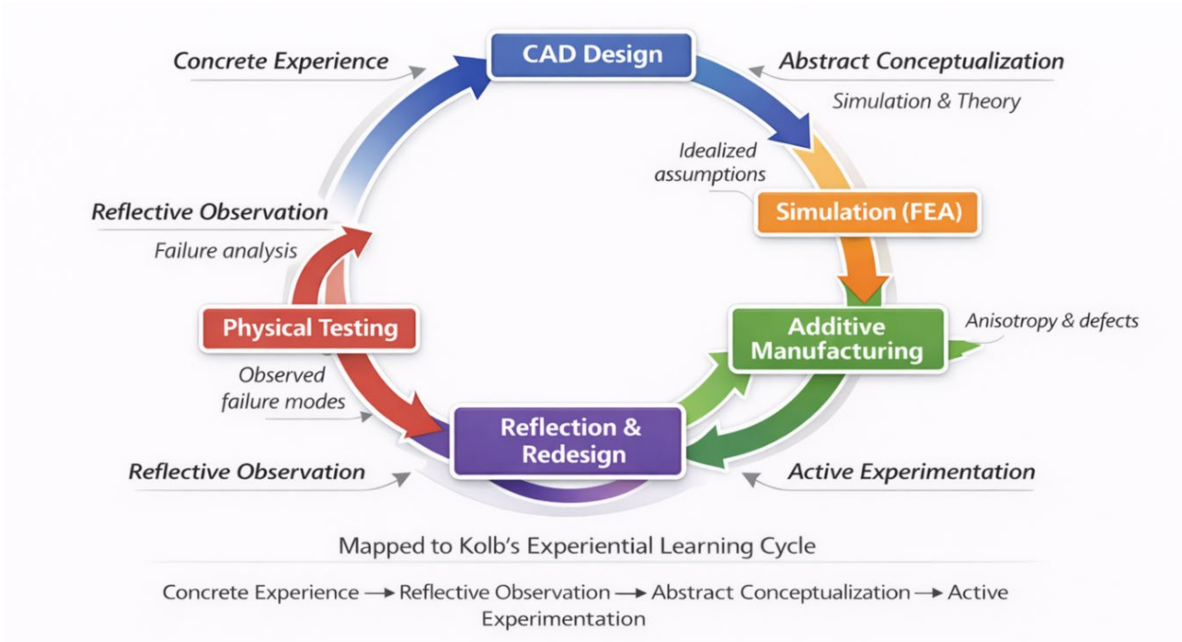

Figure 1. Pedagogical workflow integrating CAD design, simulation, additive manufacturing, and physical testing within an iterative experiential learning cycle.

3.1 Alignment with Engineering Technology Outcomes

The instructional objectives of the module were intentionally aligned with commonly articulated ET program outcomes, including the ability to apply modern tools, conduct experiments, analyze data, and function effectively within realistic engineering constraints. Unlike traditional laboratory exercises that isolate individual concepts, the integrated structure of the module required students to synthesize knowledge across domains.

In particular, the activity emphasized application-oriented problem solving over derivation-based analysis, consistent with the applied focus of ET curricula. Students were required to justify design decisions using a combination of simulation outputs, empirical evidence, and manufacturing considerations, reinforcing outcome-driven learning rather than procedural completion.

4 Laboratory Module Design and Implementation

The design-based module was implemented as a pilot activity within an upper-division undergraduate materials science laboratory course. Importantly, the activity was integrated without restructuring the overall course, allowing for evaluation of instructional impact while maintaining curricular continuity. Figure 2 illustrates a representative student design and corresponding simulated stress distribution, highlighting the influence of idealized modeling assumptions on predicted performance. Both models were analyzed under identical loading conditions and isotropic material assumptions prior to fabrication. Arrows indicate applied tensile loading at the upper hole and fixed constraints at the lower hole, establishing the pre-experimental modeling context used before physical testing and failure observation.

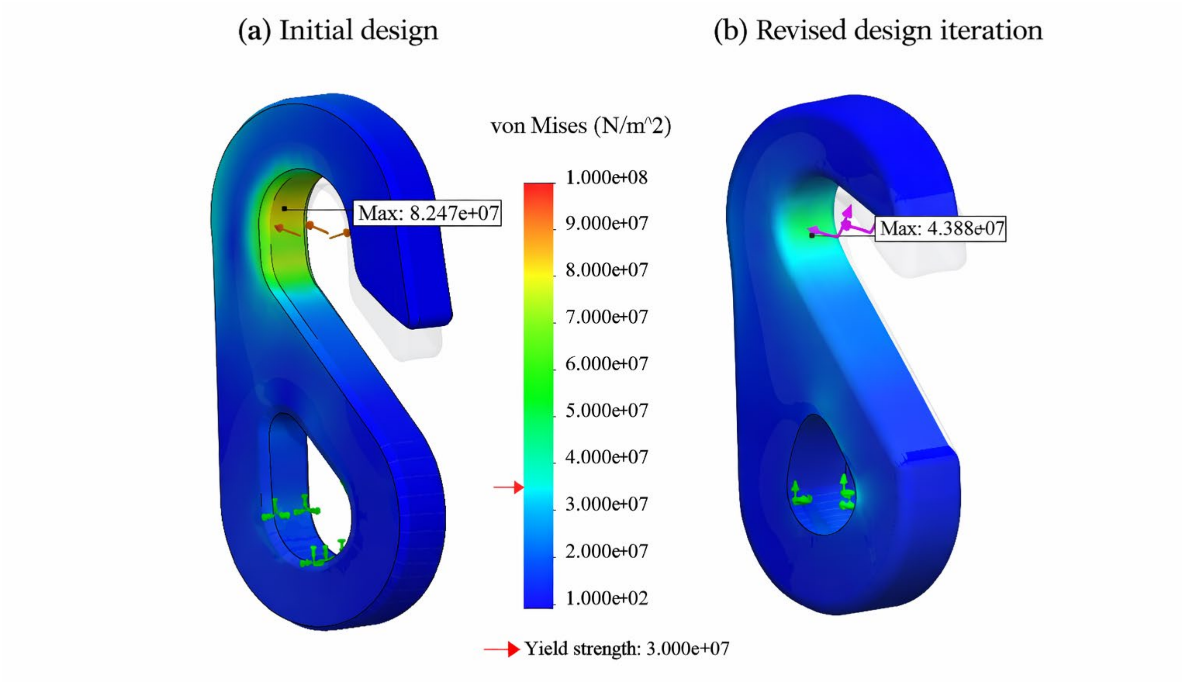

Figure 2 Representative student-designed hooks showing simulated von Mises stress distributions for (a) initial and (b) revised designs under identical loading and isotropic material assumptions.

The core design challenge required students to design and fabricate a functional hook or carabiner capable of supporting a target static load of 120 kg (approximately 1.2 kN). This load requirement was selected to be sufficiently demanding to necessitate thoughtful design and iteration, while remaining within the safe operating limits of available testing equipment.

4.1 Phase 1: Digital Design

Students began by developing CAD models using a commercial solid modeling package. Instruction emphasized design-for-additive-manufacturing considerations, including load path continuity, avoidance of sharp internal corners, appropriate feature sizing relative to nozzle diameter, and build orientation effects. Students were encouraged to justify design choices based on anticipated stress distributions and manufacturing constraints.

4.2 Phase 2: Simulation and Predictive Modeling

FEA was conducted using an integrated simulation environment. Boundary conditions were defined to replicate the laboratory tensile testing configuration. Students assigned nominal isotropic material properties for polylactic acid (PLA), consistent with default software libraries. This intentional simplification served a pedagogical purpose. Rather than correcting for anisotropy a priori, students were asked to generate predictions under idealized assumptions and later reconcile these predictions with experimental observations.

4.3 Phase 3: Additive Manufacturing and Physical Testing

Prototypes were fabricated using instructional FDM 3D printers with PLA filament. Printing parameters were standardized to reduce variability while still preserving anisotropic behavior. Mechanical testing was conducted using a Tinius Olsen 50ST universal testing machine configured for tensile loading. The tensile loading configuration shown in Figure 3 was selected to closely approximate the boundary conditions assumed in the simulation models (Figure 2), while intentionally preserving realistic contact and compliance effects inherent to physical testing. Force–displacement data were recorded continuously until failure, allowing students to identify peak load, break distance, and failure modes.

Figure 3 Tensile testing configuration used to evaluate additively manufactured hook specimens under static loading.

4.4 Phase 4: Comparative Analysis, Failure Modes, and Iteration

Students compared simulated predictions with measured performance and identified discrepancies attributable to material anisotropy, print quality, and geometric stress concentrations. This comparative analysis formed the analytical core of the module and served as the primary catalyst for conceptual change.

Failure-mode observation played a critical instructional role. Many specimens failed through inter-layer delamination or brittle fracture at stress concentrators such as fillet transitions and pin-loading regions. These failure locations frequently diverged from regions of maximum stress predicted by isotropic simulation models, prompting discussion of raster orientation, layer adhesion, and effective load paths.

Students were guided to document failure characteristics using photographs and annotated sketches, linking observed fracture behavior to manufacturing parameters and design geometry. In several cases, students identified that designs meeting simulated strength criteria nevertheless failed prematurely due to poor layer bonding or unfavorable build orientation.

Based on these observations, teams iterated on their designs by modifying cross-sectional geometry, adjusting fillet radii, and reorienting build directions to better align filament paths with principal loading directions. Some teams also introduced redundant load paths or increased infill density in critical regions. These redesign decisions were justified using a combination of empirical evidence, revised simulations, and engineering judgment.

This iterative, failure-informed redesign process reinforced the module's central learning objective: simulation outputs must be interpreted within the context of manufacturing realities and validated through experimentation rather than accepted at face value. Prior studies have shown that failure analysis and redesign activities play a critical role in helping students reconcile theoretical predictions with physical behavior, particularly in manufacturing-focused curricula [9], [2], [10].

The module was implemented with consistent structure, instructional objectives, and assessment methods across both course offerings referenced in this study. While individual student designs and iteration depth varied, core activities and evaluation procedures were held constant to support comparability of results.

5 Assessment Methods

5.1 Survey Instrument

Student learning outcomes associated with the design–simulation–manufacturing–testing module were evaluated using a pre–post survey consisting of Likert-scale items. Likert-type instruments are widely used in engineering education research to capture changes in student confidence, perceptions, and self-reported competence, particularly in applied and design-focused learning environments [11].

Four primary learning constructs were defined *a priori*. Each construct was operationalized using a subset of aligned survey items drawn directly from the pre- and post-instruments (Appendix B). For example, A1 (load-based design confidence) corresponds to items assessing students' ability to design for specified loading conditions, while A3 (simulation interpretation) aggregates items related to interpreting stress, strain, and displacement outputs. Constructs were defined a priori based on instructional objectives rather than derived post hoc, ensuring alignment between learning goals and assessment measures. These constructs—load-based design confidence (A1), CAD proficiency (A2), simulation interpretation (A3), and data-driven design improvement (A4)—were selected to reflect the core learning objectives of the laboratory module and to align with commonly articulated Engineering Technology program outcomes. The use of construct-level analysis supports interpretability while maintaining transparency of the full survey instrument, which is provided in the appendix for replication and future adaptation.

5.2 Data Analysis

Given the ordinal nature of Likert-scale data and the small cohort size ($n = 9$), nonparametric statistical methods were used for inferential analysis. Prior research has demonstrated that Likert-type responses are appropriately analyzed using nonparametric approaches when distributional normality cannot be assumed, particularly in small-sample educational studies [12]. Accordingly, paired Wilcoxon signed-rank tests were employed to evaluate pre–post shifts across the defined learning constructs.

In addition to p-value thresholds, effect sizes were calculated to support interpretation of practical significance independent of sample size [13]. Parametric paired *t*-test results are provided in Appendix A solely as a descriptive robustness reference. Consistent with best practices in educational research, inferential claims in the main text are based exclusively on nonparametric analysis and effect-size interpretation [14].

To consolidate assessment results and support transparent interpretation, Table 1 summarizes each primary learning construct, the corresponding survey focus, the statistical test employed, threshold-based outcomes, associated effect size magnitudes, and the figures used for visualization. This summary is intended to provide readers with a concise overview of how quantitative evidence, visualization strategies, and inferential methods were integrated to evaluate instructional impact, particularly in the context of a small cohort.

Table 1: Summary of assessment constructs, statistical analysis, and visualization methods

Construct	**Survey Focus**	**Primary Test**	**Threshold Outcome**	**Effect Size**	**Visualization**
A1: Load-based design confidence	Ability to design for applied loads	Wilcoxon signed-rank	$p < .01$	Large ($r > 0.65$)	Figure 4, Figure 5
A2: CAD proficiency	Confidence using CAD for functional design	Wilcoxon signed-rank	$p < .01$	Large ($r > 0.65$)	Figure 4, Figure 5
A3: Simulation interpretation	Ability to interpret stress/displacement results	Wilcoxon signed-rank	$p < .05$	Medium–Large	Figure 4, Figure 5
A4: Data-driven design improvement	Iterative redesign using evidence	Wilcoxon signed-rank	Positive shift	Moderate	Figure 4, Figure 5

6 Results

Results are reported at the construct level (A1–A4), as defined in Section 5.2, using both distribution-level and individual-level visualizations.

6.1 Distribution-Level Changes in Self-Reported Learning (Figure 4)

Figure 4 presents diverging stacked bar charts comparing pre- and post-module response distributions for each of the four learning constructs. Across all constructs, post-module responses exhibit a clear rightward shift toward higher agreement categories, indicating increased student confidence following participation in the module.

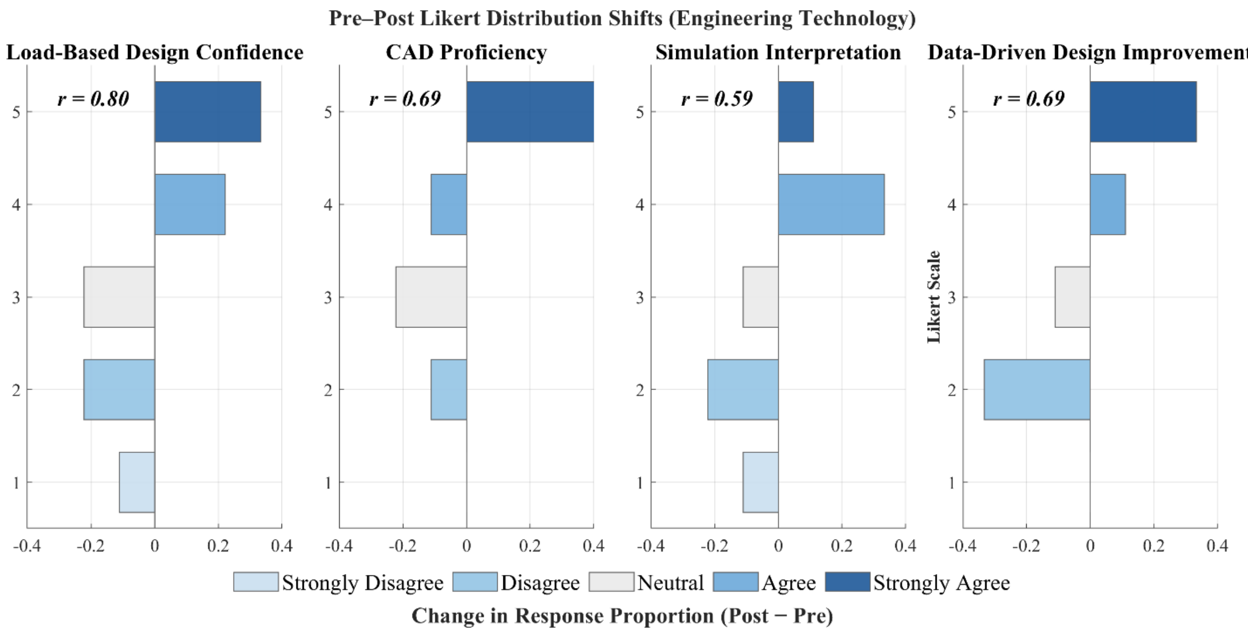

Figure 4: Diverging bar charts showing pre–post changes in Likert-scale response distributions (Post − Pre) across the four assessed learning constructs (A1–A4). Values represent the change in the proportion of respondents selecting each category, where positive values indicate increased selection in the post-survey and negative values indicate decreases. The five-point Likert scale is defined as 1 = Strongly Disagree to 5 = Strongly Agree.

The most pronounced distributional changes are observed for A1 (load-based design confidence) and A2 (CAD proficiency), where the proportion of students selecting “Agree” or “Strongly Agree” increased substantially in the post-survey. These shifts suggest that repeated engagement with CAD modeling, simulation-based prediction, and physical validation reinforced students’ confidence in applying design principles under load constraints. Nonparametric analysis using the Wilcoxon signed-rank test confirmed statistically significant pre–post gains for these constructs (A1: $p < .001$, $r = 0.80$; A2: $p < .01$, $r = 0.69$), indicating large effect sizes despite the small sample size. [12], [13]

Moderate but consistent gains are also evident for A3 (simulation interpretation) and A4 (data-driven design). While pre-survey responses for these constructs were more widely distributed, post-survey results show a contraction toward higher agreement levels, reflecting improved ability to interpret FEA outputs and to integrate experimental data into redesign decisions. These findings align with prior work demonstrating that coupling simulation with physical testing improves conceptual understanding and reduces overreliance on idealized models [18].

Importantly, the use of diverging stacked bars emphasizes changes in response *distributions* rather than mean shifts alone, a visualization approach recommended for Likert-scale data in engineering education contexts [1]. This representation helps avoid overinterpretation of central tendency measures while preserving the ordinal nature of the data.

6.2 Individual Learning Trajectories and Within-Student Shifts (Figure 5)

While Figure 4 highlights aggregate trends, Figure 5 provides a complementary view by plotting individual pre–post responses for each construct. Each data point represents a single student's response trajectory, enabling inspection of both the magnitude and consistency of learning gains across participants.

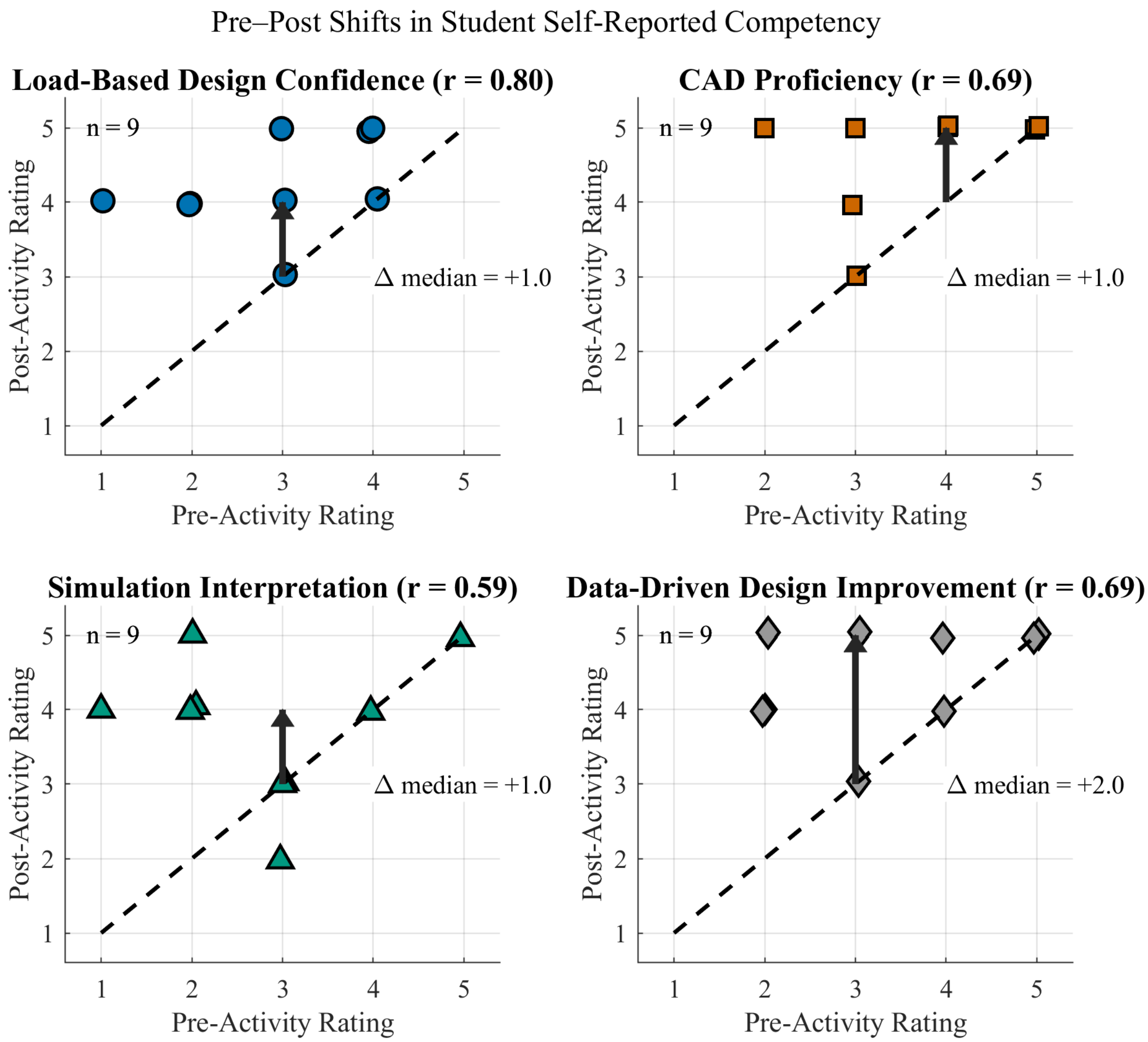

Figure 5: Individual pre- and post-activity response trajectories for each learning construct, illustrating within-student changes.

Across all four constructs, the majority of students demonstrate positive upward shifts from pre- to post-survey, with few instances of regression. This pattern supports the robustness of the observed gains and suggests that improvements were not driven by a small subset of highperforming students [1], [15]. The clustering of post-survey responses at higher Likert levels further indicates convergence in self-reported gains following completion of the module.

Notably, A3 (simulation interpretation) exhibits greater variability in individual shifts compared to A1 and A2. This dispersion likely reflects differences in prior exposure to FEA and underscores the cognitive complexity associated with interpreting simulation outputs.[14], [16] However, the overall upward trend, coupled with a statistically significant Wilcoxon result ($p < .05$, $r = 0.59$), indicates meaningful learning gains even in this more challenging domain.

The individual-level visualization also provides evidence supporting the pedagogical structure illustrated in Figure 2. Students who engaged in iterative cycles of prediction, fabrication, testing, and reflection demonstrated measurable gains in data-driven reasoning (A4), reinforcing the role of experiential learning frameworks in promoting deeper conceptual understanding [2], [9]. Such within-student analyses are particularly valuable in pilot studies with limited enrollment, where traditional parametric comparisons may be underpowered.

7 Discussion

The findings demonstrate that structured laboratory activities can effectively support experimental reasoning and data interpretation in engineering technology education [9], [16], [17].

The results support the effectiveness of integrating design, simulation, and physical testing within a single instructional module. By explicitly confronting discrepancies between idealized simulation and experimental behavior, students developed a more nuanced understanding of material behavior and manufacturing constraints.

Notably, the largest gains aligned with activities requiring sustained engagement and iteration [2], [9]. Students were required to make and defend design decisions, observe failure firsthand, and revise their approaches based on evidence. This iterative cycle appears to be particularly effective in promoting durable understanding, consistent with experiential learning theory.

Variability observed in simulation interpretation highlights an important instructional consideration [14], [16]. While students readily engaged with simulation tools, translating numerical stress and displacement outputs into physical intuition remained challenging for some participants. This finding suggests that additional scaffolding—such as guided interpretation exercises or explicit discussion of modeling assumptions—may further enhance learning outcomes.

7.1 Implications for Engineering Technology Education

For ET programs, the findings underscore the value of integrating digital tools with physical experimentation rather than treating them as separate skill sets [6], [9]. The module demonstrates that relatively modest curricular modifications can yield meaningful learning gains without requiring new courses or extensive resources.

This reinforces the role of simulation as a decision-support tool whose limitations must be understood [8]. This perspective aligns closely with industrial practice and addresses a critical competency gap frequently noted by employers of ET graduates.

7.2 Instructional Scalability and Transferability

Because the module was implemented within an existing laboratory structure, it is readily scalable and transferable to similar ET programs [7], [18]. Required resources—including entry-level FDM printers and standard testing equipment—are increasingly common in undergraduate laboratories. The design challenge can also be adapted to different materials, loading conditions, or manufacturing processes, providing flexibility for diverse institutional contexts.

7.3 Implications for Assessment and Program-Level Outcomes

Beyond individual course outcomes, the findings have implications for program-level assessment in Engineering Technology curricula. The integrated nature of the module allows a single activity to simultaneously address multiple learning outcomes, including experimental competency, tool usage, data interpretation, and applied design decision-making [6], [14].

The use of visualization-supported statistical analysis provides a viable assessment strategy for small cohorts typical of emerging or specialized ET programs [1], [13]. By combining effect-size reporting with transparent visualizations, instructors can generate defensible evidence of learning without overreliance on large-sample statistical assumptions.

At the program level, such modules may contribute artifacts suitable for accreditation documentation, including student work samples, assessment data, and evidence of continuous improvement. Embedding these activities within required courses further strengthens alignment between instructional practice and stated ET program objectives.

7.4 Guidance for Adoption and Instructional Implementation

The module is most effective when implemented after students have developed baseline familiarity with CAD, simulation tools, and material behavior concepts, typically in the latter half of a course. However, earlier implementation is also feasible with additional scaffolding and may encourage students to critically evaluate modeling assumptions throughout subsequent laboratory activities.

For instructors seeking to adopt or adapt this module, several implementation considerations emerged from the pilot deployment. First, simulation activities should be explicitly framed as hypothesis-generation exercises rather than predictive endpoints. Introducing modeling assumptions and material idealizations prior to simulation use helps prevent premature overconfidence in numerical results.

Second, sufficient instructional time should be allocated for physical testing and failure observation. Observing unexpected failure modes was central to triggering reflection and redesign, and compressing this phase risks reducing the activity to a verification exercise rather than an experiential learning cycle [2], [9].

Assessment strategies should prioritize visualization-supported interpretation and effect-size reporting over strict reliance on p-values, particularly when cohort sizes are small [1], [6]. Combining individual trajectory plots with distributional summaries allows instructors to communicate learning gains transparently while avoiding overinterpretation.

Finally, instructors are encouraged to archive student design artifacts, test results, and reflective commentary. These materials provide valuable evidence for formative feedback, continuous improvement, and program-level assessment, particularly within accreditation contexts.

8 Limitations and Future Work

This study is limited by its small sample size and reliance on self-reported measures. As a pilot implementation, the results should be interpreted as exploratory rather than definitive. Additional limitations include the absence of a control group and potential instructor effects, as the module was implemented within a single instructional context. Variations in facilitation style, feedback, and student engagement may influence outcomes and are not isolated in the current design.

Future work will involve scaling the module to larger cohorts, incorporating direct assessment of design artifacts, and examining longitudinal retention of learning gains [14]. Additional extensions may include alternative additive manufacturing processes, advanced materials, and cost or sustainability constraints.

9 Conclusion

This paper presents a design-based learning module that integrates CAD, simulation, additive manufacturing, and mechanical testing within an undergraduate materials science laboratory. The results indicate that such integration enhance student self-reported confidence and perceived competence in core ET skills while fostering critical evaluation of simulation tools. The instructional framework is readily transferable and aligns well with the evolving demands of modern manufacturing education.

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Appendix A. Supplemental Statistical Analysis

Appendix A provides parametric results for descriptive robustness only; inferential interpretation is based exclusively on the nonparametric framework described in Section 5.2.

In particular, **Figure A1** presents mean pre–post Likert ratings for the four primary learning constructs (A1–A4) using a paired *t*-test framework. While parametric statistics are not used for inferential claims due to the ordinal nature of Likert data and the small sample size ($n = 9$), this visualization is provided as a descriptive reference to illustrate the direction and relative magnitude of observed gains. The primary interpretations in this paper remain grounded in nonparametric tests and effect sizes, as discussed in Section 6.

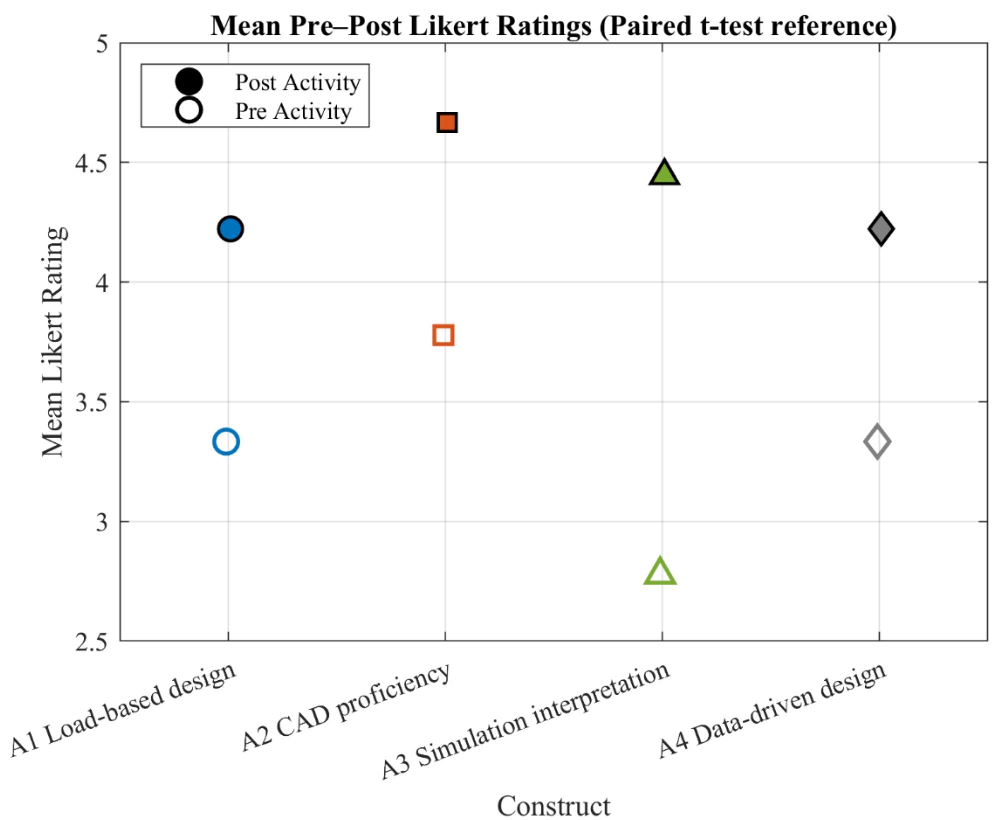

Figure A1. Mean pre- and post-activity Likert-scale ratings by construct shown for descriptive comparison.

Appendix B. Survey Instrument for Transparency and Replication

This appendix provides the complete pre- and post-activity survey instrument used to assess student perceptions of learning and engagement in the material lab design–simulation–testing module. The full instrument is included to support transparency, replicability, and future adaptation by other Engineering Technology programs.

All Likert-scale items used a five-point response format: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

B.1 Pre-Activity Survey

Section A: Confidence and Familiarity

A1. I am confident in my ability to design a part that meets specific load requirements.

A2. I feel comfortable using CAD software (e.g., SolidWorks) to create 3D models.

A3. I understand how material testing relates to design decisions.

A4. I feel confident interpreting simulation data (stress, strain, displacement).

A5. I understand how to use test results to improve a design.

Section B: Understanding and Application

B1. I understand the steps involved in the engineering design process.

B2. I can describe how simulation tools can predict part performance.

B3. I understand the role of prototyping and iteration in product design.

B4. I can explain how material properties influence manufacturing outcomes.

Section C: Engagement and Motivation

C1. I am interested in learning how digital tools are applied in real-world manufacturing.

C2. I enjoy hands-on, project-based learning activities.

C3. I feel confident working on open-ended design problems.

B.2 Post-Activity Survey

Section A: Confidence and Skill Development

A1. I am now confident in my ability to design and test a part to meet load requirements.

A2. I can effectively use CAD software to design and modify components.

A3. I can interpret both simulation and experimental results with confidence.

A4. I can identify design weaknesses based on testing data.

A5. I feel more confident integrating digital and physical design tools.

Section B: Learning and Application

B1. The design–simulation–testing–redesign cycle improved my understanding of the engineering design process.

B2. Comparing simulation and experimental data helped me understand material behavior.

B3. I can use simulation to predict performance and guide design improvements.

B4. I can apply lessons from this activity to future coursework or professional projects.

Section C: Engagement and Reflection

C1. This module helped connect theoretical concepts to practical application.

C2. The activity was engaging and relevant to my learning.

C3. I would recommend including similar design-based labs in future courses.

B.3 Open-Ended Reflection Prompts

R1. What part of the activity (design, simulation, prototyping, or testing) contributed most to your learning?

R2. What challenges did you encounter, and how did you address them?

R3. How has this activity changed the way you think about the design and manufacturing process?

R4. Any feedback and suggestions to improve this activity for future offerings?