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Integrating Research, Design, and Communication Learning Outcomes in the Materials Science and Engineering Curriculum

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Abstract

Learning outcomes in undergraduate capstone, design, and laboratory courses are typically centered around hands-on experience, providing students with the technical skills necessary within their engineering discipline. However, leaders in engineering education suggest that these hands-on courses should encompass a broader set of learning outcomes in order to train students to "think like an engineer". Problem development, experimental design, and technical communication skills have been increasingly prioritized in engineering programs, but implementing curriculum that both addresses these skills and integrates them with essential technical content has proved challenging. In this work, we present a framework for incorporating research, design, and communication learning outcomes into the materials science and engineering undergraduate curriculum. Through this framework, we explore how course design and the use of continuous self-assessment influence student metacognition and self-perception.

Introduction

Undergraduate engineering programs tout the importance of laboratory, design, and capstone courses as crucial to a student's education and development. These courses are typically positioned in the later stages of the curriculum, offering students an opportunity to apply fundamental knowledge from previous courses, develop technical skills necessary within their discipline, and work collaboratively to accomplish complex tasks that increasingly explore broader societal impacts [1-3]. In total, many in engineering (and in several other STEM disciplines) describe the collection of these learning outcomes as "hands-on" learning, an essential component of the curriculum for students to learn by doing in both authentic and simulated environments [4-6].

Recently, leaders in science and engineering education have suggested that these laboratory, design, and capstone courses should encompass a broader set of learning outcomes in order to achieve all of the benefits of hands-on learning. They argue that students should be introduced to cognitive tasks associated with experts [7-11], often described colloquially as preparing students to "think like an engineer". This includes cognitive activities related to problem development (e.g. What question am I asking? Is it feasible and worthwhile to answer it?), experimental design (e.g. How will I actually address my question? What kind of evidence do I need?), and technical communication (e.g. How do I present my methods and evidence in a way that can be broadly understood and appreciated?).

However, implementing curriculum that incorporates these higher-order learning outcomes is inherently challenging [10-11]. Students need multiple opportunities to practice and apply concepts at an introductory and intermediate level before they can begin to think like an expert. In turn, instructors and departments must scaffold both their individual courses and their curriculum as a whole for students to achieve these higher-order learning outcomes. Implementing open-ended experiments and projects also requires extensive preparation and troubleshooting and may not always be scalable. Instructors and departments often have to balance authentic approaches with practical limitations.

In this work, I present a framework for incorporating higher-order learning outcomes into the materials science and engineering undergraduate curriculum through a single, redesigned course positioned at the beginning of a laboratory or capstone sequence. These learning outcomes focus on expert-level cognitive tasks related to problem development, experimental design, and technical communication, which I will term research, design, and communication (RDC) learning outcomes moving forward. The course itself requires no laboratory or design equipment and should be scalable to other institutions and to other engineering disciplines with slight modifications to the learning outcomes and assessments based on the exact skills and cognitive tasks required in each discipline. Through this framework, I explore the use of continuous self-assessment and its influence on student metacognition and self-perception of their skills and abilities.

Background and Course Design

Spurred by changes in instruction at the beginning COVID pandemic, I redesigned the Nanomaterials Laboratory course (MatSci 160) at Stanford University in 2020. The course was repositioned as the first of a series of laboratory courses for materials science and engineering undergraduates. The intended audience included sophomore- and junior-level students, although seniors and masters-level students also participated (Table 1). The course has now been offered four times since its initial development, both at Stanford University and at Northwestern University, with a total enrollment of 70 students. All but 3 were enrolled in materials science and engineering degree programs.

Table 1: MatSci 160 Course Enrollment

Instructor Term	Kumar S24-NU	Yan F23-SU	Kumar F22-SU	Kumar F21-SU	Totals
Sophomore	6	0	3	5	14
Junior	10	3	5	7	25
Senior	0	3	3	6	12
Masters-level	0	12	2	5	19
Total Enrollment	16	18	13	23	70

Traditionally, students in MatSci 160 would perform a series of experimental labs focused on nanomaterials synthesis and characterization. Through these labs, students practice writing experimental protocols in addition to gaining technical skills related to materials synthesis and processing. During the COVID pandemic, in-person laboratory sessions for MatSci 160 could not be conducted; it was impossible to send lab kits for students to work with gold nanoparticles or silicon nanowires, for example. Given these restrictions, I shifted the focus of MatSci 160 to serve as the introductory course in our laboratory series at Stanford University (introductory course in the capstone series at Northwestern University). The broader goal was to train students to propose their own experimental investigations in materials science and engineering and build expert-level cognitive abilities *before* stepping foot in the laboratory.

Four new RDC learning outcomes (LO-C to LO-F) were established to support this goal that mapped directly to our department-level learning outcomes for the undergraduate curriculum. The revised course learning outcomes prepared students to:

- LO-A. Describe various techniques used to synthesize nanomaterials and justify their use
- LO-B. Explain how to characterize important properties of nanomaterials
- LO-C. Summarize the important objectives, methods, findings, and conclusions of a scientific report
- LO-D. Perform a literature search on a nanomaterials topic that interests you
- LO-E. Identify an important research question or gap in scientific knowledge
- LO-F. Design a logical set of experiments aimed at answering a specific set of scientific questions

Lectures in MatSci 160 focused on introducing students to real examples in nanomaterials synthesis and characterization (LO-A & LO-B). Laboratory sessions were replaced with weekly writing assessments and discussion sections, allowing students to individually and collaboratively work towards the four RDC learning outcomes (LO-C to LO-F). Each weekly writing assessment, termed "Prelabs" to inspire students to think of these assessments as preparation for laboratory-based activities, included various readings and 4-5 short answer questions that introduced concepts related to the RDC learning outcomes (examples provided in supporting information). In discussion, students reflected on their Prelab responses and worked collaboratively through additional case studies and example problems related to the topics introduced. In Week 7, students gave short presentations (5 min) to their peers to practice communicating important gaps in scientific and engineering knowledge and receive feedback. Table 2 shows the list of discussion topics and associated RDC learning outcomes. Principles of backwards course design were used to map the RDC learning outcomes to discussion topics and Prelabs [12].

Table 2: MatSci 160 discussion topics and associated RDC learning outcomes

Week	Discussion Topics	Expected RDC Learning Outcomes
Week 1	Scientific Method, Reading Scientific Articles	C
Week 2	Comparative Statistics	F
Week 3	Design of Experiment (Full Factorial Design)	F
Week 4	Design of Experiments (Fractional Factorial Design)	F
Week 5	Analyzing Data, Creating Figure Plans	C
Week 6	Identifying Research Gaps	CDE
Week 7	Communicating Research Gaps	CDE
Week 8	Scientific Writing, Broader Impacts and Intellectual Merit	EF
Week 9	Research Ethics	C

Laboratory reports were replaced with three formative assessments that prepared students to accomplish expert-level cognitive tasks that ultimately allow materials scientists and engineers to establish a research or design objective and create a plan to accomplish it. The goal of each assessment was to break down this expert-level process into smaller steps, asking students to (1) design an effective experiment, (2) construct a scientific argument, and (3) propose their own research or design project (supporting information).

The first two assessments (A1 and A2) focused on specific examples in nanomaterials synthesis and characterization introduced previously in lecture. A1 and A2 required students to create their own experimental plan and protocol for an identified objective, where A2 was designed to be more open-ended than A1. A2 also incorporated tasks related to providing scientific evidence covered in Weeks 4-6 in discussion. The teaching team provided significant written feedback after each assessment and I met individually with each student to review their feedback. Admittedly, this is likely not scalable to institutions or programs with large class sizes, but other feedback mechanisms including peer-to-peer review could be easily implemented to ensure students are able to review and reflect on their work.

The final assessment (A3) was designed as a mock NSF-style proposal, intended for students to showcase their RDC skills and practice their ability to think like an expert-level materials scientist and materials engineer. A3 is similar to the research proposal students submit for the NSF Graduate Research Fellowships Program, with a few key differences related to scope (intellectual merit was more broadly defined to include both scientific and engineering problems) and broader impacts (less emphasis on student impact, more emphasis on societal impact). Unlike A1 and A2, A3 required students to come up with their own objective as well as their plan to accomplish it. Additionally, A3 introduced students to the goals of technical writing, the NSF evaluation criteria (intellectual merit and broader impacts), and strategies for effective communication. These topics were covered in a few lectures and in Weeks 7-9 in discussion. A3 was also specifically scaffolded through Prelabs 6-8.

Methods

After designing and implementing MatSci 160, I sought to measure the impact of the course design on student ability, metacognition, and self-perception. Since MatSci 160 was developed as the introductory laboratory course at Stanford University, I decided to focus on student metacognition and self-perception for this study. The goal was to determine if students perceive growth in RDC learning outcomes during MatSci 160 and an improved ability to accomplish expert-level cognitive tasks, even though it is not considered a “hands-on” course. Directly measuring student ability in achieving these RDC learning outcomes requires a longitudinal study through the entire course series, which is currently ongoing.

To measure student metacognition, students completed weekly self-assessments that were included in each Prelab assessment. The benefits of using self-assessment as a learning tool were explained to students at the beginning of the course. All self-assessments were optional, but strongly encouraged. Students were asked to identify which RDC learning outcomes they worked on in that particular Prelab. Students were also asked to self-identify any new skills developed and any fascinating or challenging concepts through free-response questions (supporting information).

To measure student self-perception, students completed diagnostic surveys before, during, and after the course to collect broader information at key checkpoints. Pre-course surveys were administered before the first day of the course, mid-course surveys were administered after students submitted A1, and post-course surveys were administered in the last lecture (just before students submitted A3). Each survey asked students to rate their ability to achieve the RDC learning outcomes using 5-point Likert-scale questions (supporting information). All self-assessments and surveys were incorporated into formal course assessment (although not required) and qualified for exempt status through the Institutional Review Boards at Stanford University and Northwestern University.

Results and Discussion

In total, 70 students enrolled in MatSci 160 across the four iterations of the course. Students completed self-assessments, pre-course surveys, and post-course surveys in all four iterations (Table 3). Students completed mid-course surveys in all iterations except F23-SU.

Table 3: Survey responses in MatSci 160

Instructor Term	Kumar S24-NU	Yan F23-SU	Kumar F22-SU	Kumar F21-SU	Totals
Enrollment	16	18	13	23	70
Pre-Course Survey Responses	16	17	13	23	69
Mid-Course Survey Responses	16	0	11	22	49
Post-Course Survey Responses	14	16	12	21	63

Student Self-Assessment

Table 4 shows the compiled self-assessment responses from all MatSci 160 students, with the total response rate for each self-assessment shown on the right. Students were able to select any of the learning outcomes they felt they had practiced during that week's Prelab. Learning outcomes that were selected by at least 66% of respondents are highlighted to help visualize the outcomes that were selected by a supermajority of students. G indicates students responding, "I didn't work on any of these learning outcomes".

Table 4: Summary of Prelab self-assessment responses on RDC learning outcomes

Week	Discussion Topics	Expected RDC Learning Outcomes	A	B	C	D	E	F	G	Responses (Rate)
Week 1	Scientific Method, Reading Scientific Articles	C	67%	39%	92%	15%	27%	5%	2%	66 (94%)
Week 2	Comparative Statistics	F	16%	12%	28%	26%	2%	86%	5%	43 (61%)
Week 3	Design of Experiment (Full Factorial Design)	F	5%	2%	23%	26%	5%	86%	2%	57 (81%)
Week 4	Design of Experiments (Fractional Factorial Design)	F	4%	5%	7%	25%	5%	89%	4%	55 (79%)
Week 5	Analyzing Data, Creating Figure Plans	C	37%	30%	89%	21%	9%	19%	4%	57 (81%)
Week 6	Identifying Research Gaps	CDE	32%	57%	70%	68%	70%	11%	0%	47 (67%)
Week 7	Communicating Research Gaps	CDE	55%	45%	70%	52%	85%	6%	0%	33 (47%)
Week 8	Scientific Writing, Broader Impacts and Intellectual Merit	EF	20%	26%	40%	60%	70%	54%	6%	50 (71%)
Week 9	Research Ethics	C	2%	2%	40%	9%	13%	2%	47%	45 (64%)

Overall, student responses closely match the intended learning outcomes and exactly match the RDC learning outcomes in all but two discussions (Week 7 and Week 9). This suggests that students recognize the structure of the designed course and its intended outcomes. In Week 7, students strongly indicate practicing how to summarize scientific reports (LO-C) and identify important research questions (LO-E), which was necessary for their short presentations given in that week's discussion. Students were also expected to perform a literature search to identify research gaps, but this was also incorporated in Week 6, which saw a higher student response for LO-D. In Week 9, students reviewed and discussed ethical case studies in nanomaterials design, focusing on data manipulation and designing reproducible experiments. This was an important culminating topic to consider in conjunction with the other expert-level cognitive tasks. However, students did not map this Prelab to any of the RDC learning outcomes, suggesting revisions might be needed to express ethical considerations in LO-C.

Additionally, students self-reported many skills developed each week which mapped closely to the RDC learning outcomes. These self-identified skills predominantly included reading strategies for technical reports, experimental strategies and guidelines, identifying technical problems that are relevant and unanswered, and effectively explaining ideas and objectives via technical writing. Students also occasionally identified being able to recall concepts covered in previous Prelabs and discussions and an ability to connect ideas from week to week. Students also consistently identified difficulty in acquiring and synthesizing new information, especially in weeks connected to LO-C (Weeks 1, 5, 6, and 7). This is likely expected among students with limited practice or exposure to scientific and technical reports and emphasizes the importance of teaching technical reading strategies rather than assuming students can acquire new information.

Pre-, Mid-, and Post-Course Surveys

As shown in Table 3, student participation varied in our diagnostic surveys. Out of 70 students, 45 completed all three of the pre-, mid-, and post-course surveys. Figure 1 shows the change in self-perception of the 45 students who completed all three surveys. Comparing pre-course and post-course surveys, students reported a 20%, 13%, 42%, and 35% increase in their comfort-level with LO-C, LO-D, LO-E, and LO-F, respectively. Using paired, two-tailed t-tests, student responses between all three checkpoints were analyzed statistically (Tables 5-7). Students reported a statistically significant difference in all comparisons except for LO-D between the pre-course and mid-course survey, although the p-value (0.0779) is close to the conventional significance level of $\alpha = 0.05$. Survey responses were also compared across sophomores, juniors, seniors, and masters-level students (supporting information, Table S1-S3). For all learning outcomes, there were no significant differences in self-perception between student levels, indicating that the perceived growth was similar across students with varying backgrounds and preparedness levels.

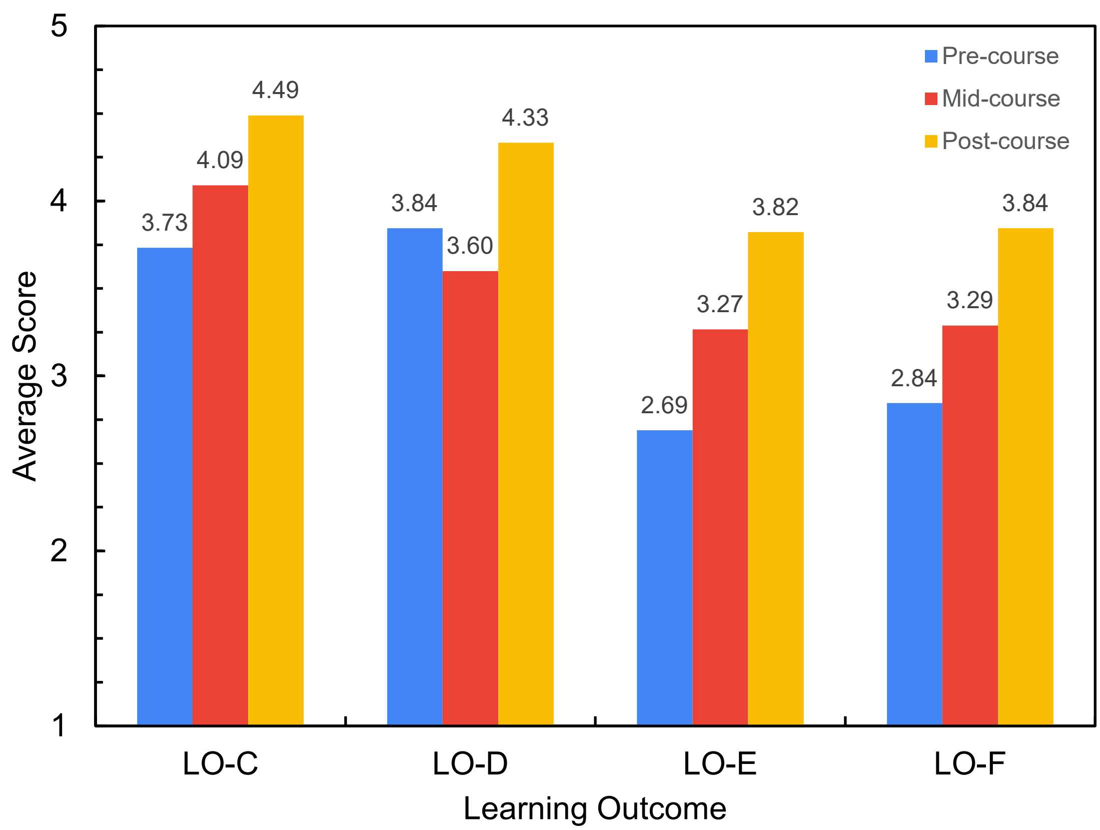

Figure 1: Average self-perception of RDC learning outcome achievement at pre-, mid-, and post-course checkpoints

Interestingly, this change in LO-D was the only observed decrease in self-perception. Students rated LO-D, their ability to perform a literature search on a scientific topic, the highest among the four learning outcomes in the pre-course survey, yet saw a nearly statistically significant decrease midway through the course. As shown in the supporting information (Table S3) students across all undergraduate levels reported a decrease in their self-perception of their achievement in LO-D from their pre- to mid-course survey, while masters-level students reported no change.

This appears to be consistent with the illusion of explanatory depth, a cognitive bias that describes a person's belief that they understand a topic with far greater precision and detail than in reality, which is not remedied until that person is asked to explain that topic [13]. Students believe that they are able to perform a successful literature search until they are actually asked to do so. This indicates the importance of LO-D and its connection to LO-C, expert-level cognitive tasks that are often considered assumed knowledge by instructors, but in reality are difficult tasks for undergraduate students. By the end of the course, students rated LO-D much higher, which suggests that students can be trained to acquire new information when given practice in performing these tasks. In contrast to LO-D, students rated LO-E and LO-F much lower in the pre-course survey, which is expected given the position of MatSci 160 in the curriculum. Increases in self-perception were significant in both learning outcomes at both checkpoints, indicating that students experience continued growth in these areas throughout the course.

Table 5: Changes in self-perception of RDC learning outcome achievement between pre-course and mid-course checkpoints

RDC Learning Outcome	Mean (SD) Pre-Course	Mean (SD) Mid-Course	df	T-Score	P-Value	Effect Size (d)
LO-C	3.73 (1.05)	4.09 (0.79)	44	2.276	0.0278	0.39
LO-D	3.84 (1.04)	3.60 (0.91)	44	1.805	0.0779	0.25
LO-E	2.69 (0.90)	3.27 (0.89)	44	3.922	0.0003	0.65
LO-F	2.84 (0.95)	3.29 (0.94)	44	3.246	0.0022	0.48

Table 6: Changes in self-perception of RDC learning outcome achievement between pre-course and post-course checkpoints

RDC Learning Outcome	Mean (SD) Pre-Course	Mean (SD) Post-Course	df	T-Score	P-Value	Effect Size (d)
LO-C	3.73 (1.05)	4.49 (0.59)	44	4.480	5.25E-05	0.89
LO-D	3.84 (1.04)	4.33 (0.88)	44	2.981	0.0047	0.51
LO-E	2.69 (0.90)	3.82 (0.89)	44	6.788	2.34E-08	1.26
LO-F	2.84 (0.95)	3.84 (0.98)	44	7.416	2.82E-09	1.04

Table 7: Changes in self-perception of RDC learning outcome achievement between mid-course and post-course checkpoints

RDC Learning Outcome	Mean (SD) Mid-Course	Mean (SD) Post-Course	df	T-Score	P-Value	Effect Size (d)
LO-A	3.80 (0.76)	4.16 (0.56)	44	3.917	0.0003	0.54
LO-B	3.69 (0.82)	4.24 (0.77)	44	5.380	2.72E-06	0.69
LO-C	4.09 (0.79)	4.49 (0.59)	44	3.903	0.0003	0.57
LO-D	3.60 (0.91)	4.33 (0.88)	44	5.880	5.07E-07	0.82
LO-E	3.27 (0.89)	3.82 (0.89)	44	3.953	0.0003	0.62
LO-F	3.29 (0.94)	3.84 (0.98)	44	4.432	6.13E-05	0.57

Conclusion

Overall, this work demonstrates that expert-level cognitive tasks related to problem development, experimental design, and technical communication can be practiced outside of a traditional "hands-on" engineering course. Using a scalable framework, four research, design, and communication (RDC) learning outcomes are implemented into a single materials science and engineering course that can be positioned at the beginning of a laboratory or capstone course sequence. These RDC learning outcomes engage students to "think like an engineer" and have a positive impact on student metacognition and self-perception. Further work is needed to perform longitudinal studies to see if this approach leads to improvements in student ability in further laboratory or capstone coursework. Additionally, studies should be implemented to determine if this approach prepares students with transferable skills more equitably than in traditional laboratory and capstone courses.

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Supporting Information

A. Prelab question examples (portions of Prelabs)

Week 1:

Online Article: Pain, E. (2016) How to (seriously) read a scientific paper. *Science*, DOI: 10.1126/science.caredit.a1600047.
Link here: https://www.science.org/careers/2016/03/how-seriously-read-scientific-paper

1. What are some useful strategies for reading a scientific paper? Include at least three strategies mentioned in the article that you already use or would like to implement.
2. What resonated with you in the "What do you do when there is something you don't understand?" or "Do you ever feel overwhelmed reading papers, and how do you deal with that?" sections? Write about a topic that stood out to you as being important.

Week 2:

1. Suppose you were in charge of running a self-assembled monolayer deposition process. You noticed that some of your films have visible defects, so you want to investigate how to improve the uniformity of the deposited SAMs.

    a. Come up with 2-3 design factors that you would like to study. Explain your choices.
    b. Can you think of any nuisance factors that may arise? Would these factors be controllable or uncontrollable?

Week 5:

Primary Article 1: Sau, T. K. and Murphy, C. J. (2004) Seeded high yield synthesis of short Au nanorods in aqueous solution. *Langmuir, 20* (15), 6414-6420.

1. We will first be looking at how the message depicted by figures in **Primary Article 1** match with the authors' intended objective.

    a. First, before reading through the paper, look at all the figures and tables. Summarize the main findings of each figure in a short bullet point list with one bullet point for each figure. **Hint:** You may find that reading the text that references each figure provides useful context
    b. Now, read through the abstract and conclusion. Does the explanation of your analysis of the figures/tables match with the author's written message? What discrepancies exist between the figures and the explanation in text?

B. Formative assessment examples (portions of assignments)

A1:

For this assignment, our goal is to develop a mixed-monolayer alkanethiol SAM on gold via micro-contact printing (μCP) with tunable surface properties. Your objectives are:

1) Identify at least ten experimental factors that could influence the two responses below. Include a brief explanation for why each factor might affect one or both responses.

   Response 1: SAM surface coverage (we want to maximize this)
   Response 2: SAM surface free energy (we want to be able to tune this)

2) From your list of factors, choose three that you want to test. Explain why you think these are important. (ie. Why will these have an impact on surface coverage and surface free energy? Why are they the most important factors to consider?)

   Hint: one factor should be related to the composition of the mixed-monolayer SAM!

A2:

1) Design an initial screening experiment. Create a table showing your factors, levels, responses, replicates, and number of experiments and answer the following questions below your table:

   a. How did you select your factorial design (full vs. fractional, number of levels)? Provide a rationale for your choice based on the time and resources needed for your experiment.
   b. How did you select your levels for each factor?
   c. Do you expect any interactions between your chosen factors?
   d. How do you plan on minimizing effects due to confounding?

2) Create a detailed protocol for nanowire growth and device fabrication. Include the following details:

   a. Materials selection – briefly describe (5-7 sentences) the final architecture of the solar cell and list the materials used for the substrate, current collectors, semiconductor (absorber), dopants, and any electron or hole transport layers.
   b. Substrate patterning – describe in detail (2-3 paragraphs) the methods to clean and pattern the substrate via nanoimprint lithography (NIL).
   c. Nanowire growth – describe in detail (2-3 paragraphs) the methods to grow the NWs via chemical vapor deposition (CVD).
   d. Device fabrication – briefly describe (5-7 sentences) how the final NWSC will be assembled.
   e. Characterization methods – briefly describe (5-7 sentences) how you will measure your responses.

   Identify all experimental factors you will hold constant. Identify any nuisance variables (either controlled or uncontrolled) that you expect could influence either of the chosen responses. How will you address these potential nuisance variables?

C. Self-assessment questions

1. For this week's Prelab, how would you rate your level of conceptual understanding of the assigned readings? [Likert scale 1 (did not understand at all) to 5 (fully understand)]
2. What new skill(s) did you gain or improve upon in this week's Prelab? [free response]
3. What learning outcomes do you feel like you worked on in this week's Prelab? Select all that apply. [Describe various techniques used to synthesize nanomaterials and justify their use; Explain how to characterize important properties of nanomaterials; Summarize the important objectives, methods, findings, and conclusions of a scientific report; Perform a literature search on a topic that interests you; Identify an important research question or gap in scientific knowledge; Design a logical set of experiments aimed at answering a specific set of scientific questions; I didn't work on any of these learning outcomes]
4. What was one topic you found fascinating from the reading? [free response]
5. What was one topic you found challenging from the reading/Prelab? [free response]
6. Do you have any other questions for the instruction team? [free response]

D. Pre-course, mid-course, and post-course survey questions

All on Likert scale 1 (not comfortable at all) to 5 (extremely comfortable)

1. Do you feel comfortable describing various techniques used to synthesize nanomaterials?
2. Do you feel comfortable explaining how to characterize important properties of nanomaterials?
3. Do you feel comfortable reading a scientific paper and summarizing the important objectives, methods, findings, and conclusions?
4. Do you feel comfortable performing a literature search on a topic that interests you?
5. Do you feel comfortable identifying an important research question or gap in scientific knowledge?
6. Do you feel comfortable designing your own set of experiments to answer a particular scientific question?

E. Pre-course, mid-course, and post-course survey analysis across student levels

Table S1: Comparison in self-perception of averaged RDC learning outcome achievement across student levels. Comparisons are performed via an unpaired t-test with p-values (degrees of freedom) reported in each cell.

Student Level	Mean (SD) **Pre-Course**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	3.37 (1.09)	N/A	0.5849 (30)	0.9843 (18)	0.9247 (17)
Junior	3.14 (1.20)	0.5849 (30)	N/A	0.6717 (24)	0.6093 (23)
Senior	3.36 (1.03)	0.9843 (18)	0.6717 (24)	N/A	0.9163 (11)
Masters	3.42 (0.97)	0.9247 (17)	0.6093 (23)	0.9163 (11)	N/A

Student Level	Mean (SD) **Mid-Course**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	3.68 (0.81)	N/A	0.5713 (30)	0.9798 (18)	0.7052 (17)
Junior	3.49 (0.99)	0.5713 (30)	N/A	0.6422 (24)	0.4484 (23)
Senior	3.69 (0.87)	0.9798 (18)	0.6422 (24)	N/A	0.7628 (11)
Masters	3.83 (0.74)	0.7052 (17)	0.4484 (23)	0.7628 (11)	N/A

Student Level	Mean (SD) **Post-Course**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	4.44 (0.57)	N/A	0.1260 (30)	0.3898 (18)	0.2465 (17)
Junior	3.96 (0.99)	0.1260 (30)	N/A	0.5772 (24)	0.7860 (23)
Senior	4.19 (0.67)	0.3898 (18)	0.5772 (24)	N/A	0.7764 (11)
Masters	4.08 (0.69)	0.2465 (17)	0.7860 (23)	0.7764 (11)	N/A

Table S2: Comparison in self-perception change of LO-C achievement across student levels. Comparisons are performed via an unpaired t-test with p-values (degrees of freedom) reported in each cell.

Student Level	Δmean (ΔSD) **Pre to Mid**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	0.15 (1.28)	N/A	0.4595 (30)	0.7858 (18)	0.5518 (17)
Junior	0.47 (1.12)	0.4595 (30)	N/A	0.6877 (24)	0.9526 (23)
Senior	0.29 (0.49)	0.7858 (18)	0.6877 (24)	N/A	0.5856 (11)
Masters	0.50 (0.84)	0.5518 (17)	0.9526 (23)	0.5856 (11)	N/A

Student Level	Δmean (ΔSD) **Pre to Post**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	0.85 (1.21)	N/A	0.9274 (30)	0.7855 (18)	0.2253 (17)
Junior	0.89 (1.29)	0.9274 (30)	N/A	0.7331 (24)	0.2105 (23)
Senior	0.71 (0.76)	0.7855 (18)	0.7331 (24)	N/A	0.2253 (11)
Masters	0.17 (0.75)	0.2253 (17)	0.2105 (23)	0.2253 (11)	N/A

Table S3: Comparison in self-perception change of LO-D achievement across student levels. Comparisons are performed via an unpaired t-test with p-values (degrees of freedom) reported in each cell.

Student Level	Δmean (ΔSD) **Pre to Mid**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	-0.15 (0.99)	N/A	0.4297 (30)	0.9825 (18)	0.7558 (17)
Junior	-0.42 (0.90)	0.4297 (30)	N/A	0.4884 (24)	0.3282 (23)
Senior	-0.14 (0.90)	0.9825 (18)	0.4884 (24)	N/A	0.7839 (11)
Masters	0 (0.89)	0.7558 (17)	0.3282 (23)	0.7839 (11)	N/A

Student Level	Δmean (ΔSD) **Pre to Post**	vs Sophomores	vs Juniors	vs Seniors	vs Masters
Sophomore	0.85 (1.28)	N/A	0.1915 (30)	0.5901 (18)	0.3779 (17)
Junior	0.26 (1.19)	0.1915 (30)	N/A	0.5162 (24)	0.8950 (23)
Senior	0.57 (0.53)	0.5901 (18)	0.5162 (24)	N/A	0.5373 (11)
Masters	0.33 (0.82)	0.3779 (17)	0.8950 (23)	0.5373 (11)	N/A