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NSF-IUSE: Multiple/Single Representations and Scaffolding Design in Technology-enhan Semiconductor Learning: A Pilot Crossover Study

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Abstract

This empirical work-in-progress paper examines the impact of two technology-enhanced learning tools, an interactive visualization with multiple representations and explicit scaffolding and a simulation tool with single representation and implicit scaffolding, on students' conceptual understanding and affective outcomes in semiconductor physics. This domain is known for early conceptual difficulty that often limits student progression into advanced coursework and the semiconductor workforce. Using a crossover design, 20 undergraduate electrical engineering students engaged with both tools and completed pre and post-assessments of conceptual knowledge, perceived understanding, interest, and motivation. A semi-structured focus group was analyzed using thematic analysis to capture students' learning experiences. The findings reveal that while both tools supported students' cognitive and affective processes, one primarily fostered foundational understanding for novice learners, whereas the other one enabled deeper exploration for more experienced students. Although limited by sample size and short duration, the results suggest that aligning tool design with learners' developmental stage may support both learning and motivation. Overall, this study demonstrates how instructional design features shape students' engagement with complex engineering content and underscores the importance of adaptive technology-enhanced learning environments.

Keywords: simulation, visualization, representation, scaffolding, conceptual, affective

Despite strong national demands for semiconductor expertise [1], semiconductor physics and microelectronics remain among the most challenging topics for students. These topics are fundamental for advanced coursework and serve as a key entry point into the semiconductor workforce. Because traditional instruction is often centered on mathematical formulism [2], learners often struggle with the invisible and highly abstract nature of semiconductor phenomena and develop persistent misconceptions [3]. While recent efforts on technology-enhanced visualizations have shown promise in improving student motivation, interest, and low-cognitive outcomes such as recall and recognition [4], [5], few studies examine misconceptions and more high-level conceptual understanding–a problem that contributes directly to the early conceptual bottleneck in microelectronics learning [6].

Learning is an iterative process shaped by the interplay among learners' behavioral, cognitive, and affective factors and their dynamic interactions with learners' mental models and the learning environment (INTERACT model) [7]. Affective factors, such as interest, confidence, and motivation can sustain engagement with challenging engineering learning tasks [8]. Instructional cues and scaffoldings embedded in the learning environment can support cognitive development and encourage positive affective responses [9].

A growing body of work has employed technology-enhanced learning environments in semiconductor physics education, including interactive visualizations, simulations, games, and virtual/mixed reality. These studies suggest that such tools make complex, abstract concepts more accessible and support both conceptual learning and affective outcomes [2], [4], [5]. However, less is known about how specific design features of these tools shape learning. Design characteristics such as representation choices, the form of scaffolding, the degree of learner control, and interface usability may influence both how students construct knowledge and how they experience the learning process.

To address this gap, we compare two technology-enhanced tools for semiconductor learning: LearnQM and nanoHUB. LearnQM (https://learnqm.gatech.edu) is an interactive visualization tool that provides explicit, step-by-step guidance and uses multiple linked representations. In contrast, nanoHUB (https://nanohub.org/resources/moscap) is an interactive simulation tool that relies more on implicit guidance and offers greater learner controls for manipulating simulation parameters.

Guided by multimedia learning theory, we focus on two design features: (1) multiple versus single representations and (2) explicit versus implicit scaffolding. Learning may be supported when phenomena are presented through multiple complementary representations (Multimedia principle) [10], particularly when information is introduced in learner-paced steps (Segmenting Principle) [10]. For example, pairing an energy-band diagram with a real-space depiction of electron motion can help students reconcile misconceptions about the relationship between energy changes and electron movements. At the same time, when the concepts are highly complex, presenting a single representation, paired with interactive controls to vary parameters and observe outcomes, may reduce nonessential processing and help learners focus on key relationships (Coherence principle) [10]. These considerations suggest a potential tradeoff between supporting essential sense-making and increasing cognitive demands.

We also examine the type of scaffolding embedded in the tool. Explicit scaffolding provides step-by-step instructions and procedures that structure how learners interact with the tool, helping them focus on one concept at a time and address target misconceptions through a predefined sequence. In contrast, implicit scaffolding is embedded in the tool's interface and interactivity, guiding learners through instructional cues and interactive features without requiring them to follow linear steps. This approach offers greater learner autonomy and supports exploration, for example, manipulating multiple parameters and observing outputs in real time. However, the same flexibility may overwhelm learners who have not yet developed key foundational concepts.

In this pilot study, we focused on the INTERACT model's cognitive and affective components in relation to learning environment features. The study was guided by the following research questions: (1) How do students' conceptual and affective outcomes change after engaging with technology-enhanced learning tools? (2) Do these outcomes differ between students who used LearnQM and those who used nanoHUB? and (3) How do students describe and compare their learning experiences with the two tools?

Methodology

Study Design, Data Collection, and Procedure

The study used a randomized experimental crossover design. Participants first completed a pretest assessing their prior conceptual knowledge and affective dimensions. They were then randomly assigned to one of two tools and engaged with the assigned tool for a one-hour self-learning session using a learning activity sheet. One week later, participants completed a posttest that repeated the knowledge and affective measures. These posttest scores therefore reflect outcomes from the first assigned tool (prior to crossover). Participants then used the alternate tool. After all participants had experienced both tools, the research team conducted a 20-30 minute semi-structured focus group to elicit in-depth feedback on comparisons of learner experiences with the two tools.

Participants and Context

Participants were students enrolled in two electrical engineering classes (beginning and beginning-intermediate) at a university in the U.S. Southeast during Spring 2025. Twenty students completed both surveys and learning activities: For the first learning session, 11 students were randomly assigned to LearnQM (Group A) and 9 students to nanoHUB (Group B).

Measures

Conceptual outcome was measured using 12 knowledge items aligned with five learning objectives and developed by several subject-matter experts. Affective outcomes were measured using 13 items on a five-point Likert scale, including five items assessing perceived understanding of the topic, three assessing interest in the topic, and five assessing motivation to continue studying the topic. Internal consistency reliability was estimated using KR-20 for dichotomously scored knowledge test and Cronbach's α for the Likert-type affective scales: the knowledge test showed acceptable reliability (KR-20: pre = .66; post =.74), and the affective scales showed good reliability: Understanding (pre α: .80; post α: .84), Interest (pre α: .92; post α: .84), and Motivation (pre α: .88; post α: .87).

Analysis

As part of the preliminary analysis, item analysis based on classical test theory was conducted: items were revised to be within acceptable ranges, with additional analysis planned as more data are collected. Quantitative analyses included descriptive statistics and correlations to describe patterns in conceptual knowledge and affective dimensions. Due to the small sample size, nonparametric statistics were used. Wilcoxon signed-rank tests were used to examine pre-post changes. To compare group differences between students who used the two tools, Quade's rank ANCOVA was performed with pretest scores as the covariate.

For qualitative data, two researchers used a two-cycle coding approach: inductive coding, followed by axial coding. In the second cycle, codes were organized into three themes from the INTERACT model (Domagk et al., 2010): cognitive, affective, and learning-environmental components. Interrater reliability was substantial (Cohen's $k = .79$).

Results

Conceptual Learning Outcomes

The mean knowledge scores increased from pretest ($M = 2.65$) to posttest ($M = 3.55$). However, variability remained high at both time points (pretest: $SD = 2.39$; posttest: $SD = 2.67$), suggesting substantial differences existed in prior knowledge that persisted after instruction. With weak correlation between pre and posttest ($r = .03$), pretest scores were essentially unrelated to posttest scores, indicating that students' relative standing changed from pre to post. However, the overall pre–post change was not statistically significant ($W = 32.0$, $p > .05$, $r = 0.61$). Between-group comparisons (Table 1) indicated no statistically significant difference on conceptual understanding between Group A (LearnQM) and Group B (nanoHUB) after adjusting for pretest scores.

Table 1. Between-Group Comparisons Adjusted for Pretest (Group A: LearnQM, Group B: nanoHUB).

	Group	**Pretest *M* (*SD*)**	**Posttest *M* (*SD*)**	**Quade's Rank ANCOVA**
Knowledge	A ($n = 11$)	2.55 (2.34)	3.55 (2.30)	F (1, 17) = 0.20, p = 0.66,
	B ($n = 9$)	2.78 (2.59)	3.56 (3.21)	partial $\eta^2 = 0.012$
Understanding	A ($n = 11$)	2.69 (0.79)	2.85 (0.81)	F (1, 17) = 0.49, p = 0.49,
	B ($n = 9$)	3.00 (0.56)	3.13 (0.42)	partial $\eta^2 = 0.028$
Interest	A ($n = 11$)	3.88 (0.78)	3.76 (0.78)	F (1, 17) = 0.06, p = 0.81,
	B ($n = 9$)	3.59 (0.62)	3.44 (0.73)	partial $\eta^2 = 0.004$
Motivation	A ($n = 11$)	4.07 (0.64)	4.13 (0.62)	F (1, 17) = 0.94, p = 0.35,
	B ($n = 9$)	3.40 (0.48)	3.38 (0.60)	partial $\eta^2 = 0.052$

Affective Learning Outcomes

Participants began with moderate perceived understanding (Pre-Understanding: $M = 2.83$, $SD = 0.70$) and relatively high interest and motivation (Pre-Interest: $M = 3.75$, $SD = 0.71$; Pre-Motivation: $M = 3.77$, $SD = 0.66$). Affective scores were largely stable from pre (Pre-Understanding: $M = 2.83$, $SD = 0.70$; Pre-Interest: $M = 3.75$, SD = 0.71; Pre-Motivation: $M = 3.77$, $SD = 0.66$) to post (Post-Understanding: $M = 2.98$, $SD = 0.66$; Post-Interest: $M = 3.62$, SD = 0.75; Post-Motivation: $M = 3.79$, $SD = 0.71$). Wilcoxon tests indicated no statistically significant pre-post changes for Understanding ($W = 41.0$, p > .05, $r = 0.35$), Interest ($W = 16.50$, p > .05, $r = -0.35$), and Motivation ($W = 42.50$, p > .05, $r = 0.06$). Consistent with the knowledge results, Quade's rank ANCOVA results (Table 1) showed minimal group effects across the affective outcomes after adjusting for pretest scores.

Qualitative Feedback from Focus Group

The focus group offered deeper insights into students' experiences with the tools (Table 2). Overall, participants perceived both tools as valuable and helpful for conceptual learning but for different purposes: the LearnQM tool was viewed as supporting foundational understanding, particularly for novice learners, whereas nanoHUB was appreciated as enabling deeper exploration and reinforcing concepts for advanced learners. Participants reported positive experiences with both tools and shared increased motivation to learn more about the topics. Participants also reported that LearnQM has an enjoyable interface with detailed visualizations and immediate interactivity. However, they noted limited user control and reported that the step-by-step format could feel slow, with no option to skip ahead. In contrast, participants reported that nanoHUB had technical issues and that, without immediate feedback or explanations after parameter changes, it was difficult to determine whether their actions were correct or how to interpret the results.

Table 2. Themes that Emerged from the Focus Group.

LearnQM		nanoHUB
Subthemes	Main Themes	Subthemes
• Conceptual understanding through visualization: *"I didn't know exactly what it would look like. ... it was good to just like get a confirmation of the visuals that I had in my mind while I was studying."* • Step-by-step learning that supports gradual conceptual understanding: *"... each step it felt more guided, and it was explained why each thing is being done… it seemed to make a lot more sense."* • Beginner-friendly learning/ fundamental understanding: *"... in terms of learning the basics I did like the LearnQM", "LearnQM was kind of a good way to like get the ball rolling."* • Limited depth due to simplicity: *"... it's simplifying so much that you do lose some of the upper level, like complex equations ..."*	Cognitive	• Clear numerical feedback supports understanding: *"I feel like the nanoHUB tool gives you hard, discrete numbers that you can compare. I thought the comparisons were really nice ... made it clear exactly what is happening."* • Guidance enabled effective use: *"... nanoHUB effectiveness also highly depends on the instructions being given with it, ... Like having a specific set of instructions is really important."* • Useful to check understanding: *"... is good for checking your understanding."* • Allows advanced exploration and in-depth learning: *"... nanoHUB one is more useful, for, like later stage learning.", "if you wanted to go deeper into it out outside of class or something gives you more of an opportunity to do that on your own time. Explore things possibly in more depth.", "nanoHUB tool seems a lot more high-level relative to the other one."*
• Promotes sustained interest across topics, return behavior, and overall motivation: *"... made me more eager to come back.", "I want to go back through, make sure I've got a better understanding."* • Engaging and enjoyable interaction: *"I quite enjoyed it a lot ... I really liked all the visualization tools", "... that was something that amazed me, actually."*	Affective	• Promotes deeper investigation of a specific simulation or task: *"as soon as I finished the nanoHUB stuff, my first thought is okay, I'm really curious to do more with this tool, with this specific simulation I want to do more with it."*
• Detailed visualizations and immediate response: *"the visualization is*	Learning-Environ mental	• Technical barriers (bugs related to login and entering parameters): *"I'm just having issues with putting in the parameters."*

very detailed", "LearnQM is very visual, and it responds very quickly to what you want." • Limited customization and navigability: *"LearnQM one was a little bit restrictive, since it only let you change two parameters.", "I wouldn't say I'm a huge fan of scrolling with the LearnQM lever. It gets a little disorganized."*	• Less-intuitive UI and limited usability: *"... it's not much attention paid to the user experience, just basically like getting results.", "My main critique is just the UI. I think it would be greatly improved, and it will make it much easier to work through..."* • Ambiguous outputs leave learners unsure of correctness: *"I don't know if the graph that I'm getting is correct or not. I'm just getting straight lines. It doesn't really say much."*

Discussion and Conclusion

This study addresses an important and underexplored question in technology-enhanced semiconductor education: how the design of instructional tools shapes both what students learn and how they experience learning. Despite the short intervention, the findings are consistent with prior research showing that technology-enhanced learning with instructional scaffolding can be more effective than text alone [10]. Although not statistically significant, we observed modest conceptual gains and relatively stable affective outcomes, suggesting that even brief engagement with well-designed tools can support conceptual learning.

The different roles students attributed to the two tools highlight the importance of aligning instructional design with learners' developmental stage. LearnQM's step-by-step structure and integrated visual representations appear to support novices by making complex and invisible processes more accessible, consistent with the Multimedia and Segmenting principles [10]. In contrast, nanoHUB's flexibility and parameter control seem better suited for students who already possess some foundational understanding and are ready to explore relationships more independently. This highlights the value of adapting instructional tools to students' knowledge and stage of learning. As learners gain expertise, they may benefit from increased autonomy and opportunities for exploration [11].

In addition, students' affective responses and learning-environmental components were closely tied to their overall learning experiences and perception of the tools. Prior work has shown that positive affective responses play a key role in sustaining engagement and persistence when learning challenging engineering topics [8]. Our findings extend this work by illustrating how interface usability, feedback clarity, and interactivity can either support or hinder these affective processes in semiconductor learning.

Overall, the results suggest that effective technology-enhanced instruction should provide strong conceptual support in the early stages of learning and gradually shift toward more open-ended exploration as students' understanding develops. Although this pilot study is limited in scope, it offers early evidence that thoughtful instructional design, grounded in both cognitive and affective considerations, can help address persistent barriers in semiconductor education. While this study measured delayed post-test outcomes only one week after exposure, future research should examine longer delay intervals to better understand the retention of cognitive and affective outcomes. Additionally, future studies should investigate design features and pedagogical approaches to support diverse student groups, including those with limited prior knowledge, low motivation, and limited reasoning skills.

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