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Adaptivity or agency? Educational technology design for conceptual learning of materials science

Nutnicha Nigon¹ | Julie D. Tucker¹ | Thomas W. Ekstedt^{2,3} |
 Brandon C. Jeong⁴  | Dana C. Simionescu⁵ | Milo D. Koretsky^{3,6} 

¹Mechanical, Industrial, and Manufacturing Engineering, Oregon State University, Corvallis, Oregon, USA

²Chemical, Biological, and Environmental Engineering, Oregon State University, Corvallis, Oregon, USA

³Chemical and Biological Engineering, Tufts University, Medford, Massachusetts, USA

⁴Chemical and Biomolecular Engineering, University of Illinois, Urbana-Champaign, USA

⁵Ecampus, Oregon State University, Corvallis, Oregon, USA

⁶Department of Education, Tufts University, Medford, Massachusetts, USA

Correspondence

Milo D. Koretsky, Chemical and Biological Engineering, Tufts University, Medford, Massachusetts, USA.
 Email: Milo.Koretsky@tufts.edu

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Abstract

As the use of computers in education increases, adaptive learning platforms are becoming more common. However, these adaptive systems are typically designed to support acquisition of declarative knowledge and/or procedural fluency but rarely address conceptual learning. In this work, we developed the Crystallography Adaptive Learning Module (CALM) for materials science to provide students a tool for individualized conceptual learning. We used a randomized quasi-experimental design comparing two instructional designs with different levels of computer-provided direction and student agency. Undergraduate students were randomly assigned to one of two different instructional designs; one design had students complete an individualized, adaptive path using the CALM ($N=80$), and the other gave students the freedom to explore CALM's learning resources but with limited guidance ($N=85$). Within these two designs, we also investigated students among different cumulative grade point average (GPA) groups. While there was no statistically significant difference in the measure of conceptual understanding between instructional designs or among the groups with the same GPA, there is evidence to suggest the CALM improves conceptual understanding of students in the middle GPA group. Students using CALM also showed increased participation with the interactive learning videos compared to the other design. The number of videos watched in each instructional condition aligns with overall academic performance as the low GPA group received the most assigned supplements but watched the least videos by choice. This study provides insight for technology developers on how to develop educational adaptive technology systems that provide a proper level of student agency to promote conceptual understanding in challenging STEM topics.

KEYWORDS

computer adaptive learning, concept questions, conceptual learning, materials science education, student agency

1 | INTRODUCTION

Advanced Personalized Learning has been identified by the National Academy of Engineering as one of 14 Grand Challenges for Engineering for the 21st century [72]. Coupled to the development and availability of educational technology, this approach envisions learners interacting with technology tools that can diagnose their learning needs and provide appropriate resources, thereby producing better outcomes than traditional instruction [26]. However, building such adaptive systems is difficult, time-consuming, and costly [32, 68]—especially for challenging learning outcomes needed for the 21st century, like the development of conceptual understanding (as opposed to acquisition of declarative knowledge or procedural fluency). Another body of research has addressed the relationships between student agency (SA), motivation, and engagement [5, 57]. Importantly, intelligent adaptive tutors often use predesigned guided logic. This approach places agency in the tool, not the learner, which might detract from the learner's engagement.

This research aims to contribute to the knowledge gap around adaptive technology-supported conceptual learning in materials science. We frame this issue as having two distinct parts—the resources available to the learner and how they are deployed. In this study, we examine the latter by examining conceptual understanding in a challenging subject in materials science—crystallography. We use a split design experiment where students in the same course are randomly assigned into one of two instructional designs. Both designs have access to the same learning resources; in the *adaptive feedback (AF)* design, a computer mostly determines how students are directed to those resources while in the *SA* design, students more freely chose for themselves the resources they need to learn. We then measured their conceptual understanding and engagement. Additionally, as overall academic performance can play a role in student motivation and behavior in learning [16, 79], such adaptive support may be more impactful for lower-performing students. To explore this issue, we differentially examine responses based on the students' cumulative GPA. This study contributes to the conversation as to how to efficiently develop and implement educational technology systems to effectively develop conceptual understanding in challenging STEM topics.

2 | BACKGROUND

Woolf [90] argues we are currently at an inflection point in education, driven by three components: artificial intelligence (AI), cognitive science, and the internet. As

AI becomes more powerful and accessible, researchers are investigating the opportunities and challenges around implementing AI in education (e.g., [1, 3, 12]). In the case of online and remote delivery, Dogan [23] identified three research themes: “(1) educational data mining, learning analytics, and artificial intelligence for adaptive and personalized learning, (2) algorithmic online educational spaces, ethics, and human agency; and (3) online learning through detection, identification, recognition, and prediction.” (pp. 9–10).

This study compares student cognitive-development behavior when AI is used as an agentic adaptive tool (machine agency) to a case where students act more as their own agents (human agency) with similar available resources in an asynchronous online setting. We focus on how an adaptive technology tool can support the development of conceptual understanding. In this section, we elaborate on the prior research in three core elements related to this study: adaptive learning systems, SA, and the development of conceptual understanding.

2.1 | Adaptive learning systems

Individualizing instructional design with the use of computer programming has been studied in the context of higher education for the last half century [30]. The main goal is to adapt instruction to better support individual differences among students. Learners interact with technology tools that can diagnose their learning needs and provide appropriate resources, thereby producing learning [58]. While adaptive learning has been introduced in different forms over time, there is no consensus on what the foundations of adaptivity are [24]. There are multiple definitions and types of adaptation used in education (e.g., see [2, 33, 61, 90]). Two commonly discussed types of computer-based adaptive learning systems are intelligent tutoring systems (ITSs) and adaptive hypermedia systems (AHSs, [67]). ITSs incorporate the use of AI while AHSs use hypertext (relations among textual elements) and multimedia (relations among elements of any type of media).

Various companies and institutions have developed and integrated tools to support personalized instruction in large in-person and remote classes in higher education [41, 87]. Currently, there are several commercial platforms that incorporate adaptivity and individualized learning as core parts of their system designs such as ALEKS [39], Smart Sparrow [8, 44], WileyPLUS [89], Tutorial Homework Problems [64], zyBooks [13], and Squirrel AI [59, 86]. The development of these platforms, however, requires expertise and resources resulting in financial costs to users or institutions. Moreover, these

tools often focus on procedural knowledge rather than conceptual understanding.

2.2 | SA and engagement

The concept of agency as self-regulation is discussed widely in social cognitive theory. *Agency*, as summarized by Martin [63], is “the capability of individual human beings to make choices and to act on these choices in ways that make a difference in their lives” (pp. 135). In social cognitive theory, human agency and social structure are inseparable—that agency is influenced from both social and physiological systems [4, 5]. While undergraduate students may be expected to have a good degree of self-regulatory capability (based on Martin’s definition of Agency), they may not make full use when positioned as agents to their own learning. Therefore, researchers have emphasized the importance of promoting SA in not only early grade classrooms [84] but also in higher education [37] as it enriches their learning.

While there is consensus that agency is tied to learning, this concept is operationalized in ways that are context-dependent. For example, Reeve and Tseng [74] emphasize the need for students’ *agentic engagement*—their “constructive contribution into the flow of the instruction they receive” (pp. 2)—as the fourth element of engagement. In addition to students’ behavioral, emotional, and cognitive engagement [28, 40, 70], Engle and Conant [25] view students’ agency in terms of having the *authority* to define and make progress on disciplinary problems. Others frame it as *epistemic agency* where students are provided with freedom to build knowledge of their own and of their choosing [18, 66]. In terms of engineering education, Svihla et al. [81] focus on *framing agency*—“the various actions designers take to understand, define, and bound the (capstone design) problem” (pp. 96), while Schimpf et al. [76] identify themes related to agency as students navigate through open-ended modeling problems. In this study, we use SA to refer to students’ opportunities to choose among available resources to develop conceptual understanding.

While agency cannot be forced by other people, it can be influenced by the learning context to achieve a particular purpose [20]. Allowing students to have freedom (or power) to make their own choices can be seen as putting them in a position where they can strengthen their agency [48]. With intentionality, forethought, self-regulation, and self-efficacy, agentic students are able to better regulate, control, and monitor their own learning [16] resulting in greater engagement [5] and leading to stronger academic performance. Reeve and Tseng [74] found that course grades correlated with self-reported

SA. Similarly, Spence et al. [79] reported positive correlation between GPA and students’ achievement striving factor scale (self-evaluated behaviors and attitudes such as “takes schoolwork seriously” and “puts more effort compared to other students”).

We distinguish students’ agentic engagement [48, 73, 74] from their behavioral, emotional, and cognitive engagement [28, 40, 70]. While they represent different aspects, they are correlated [74]. Students who develop their agency (e.g., become aware they can control their own choices) tend to engage more in their activities [5, 43]. However, measuring students’ agentic elements (autonomy, choice, and freedoms) or affective factors (such as motivation) is not easy and commonly done with self-reported questionnaires [16, 38, 48] or field notes from classroom observations [74]. In this study, we examine two instructional designs where students have differing opportunities for agency and then collect their behavioral engagement data.

2.3 | Development of conceptual understanding

For over half a century, researchers have explored pedagogical strategies to promote students’ conceptual understanding. Shavelson et al. [78] proposed four types of scientific knowledge: declarative (knowing that), procedural (knowing how), conceptual (knowing why), and strategic (knowing when, where, and how). The importance of conceptual understanding (to the level of “why”) and the ability to connect knowledge is that it gives students flexibility to solve ill-structured [42] and new complex problems that they have not seen before but are common in engineering practice.

For core engineering topics, activities and assessments should focus on achieving knowledge beyond declarative and procedural; here, we focus on conceptual understanding [77]. Researchers have addressed the development of conceptual understanding using different theoretical stances. One common stance identifies *misconceptions* as coherent, robust, and resistant to change [14, 65]. Researchers then focus on ways to identify and repair or replace misconceptions with the correct concepts, such as the work by Krause and colleagues [56] in materials science. In contrast, another stance emphasizes connecting fragmented pieces of knowledge with one another to develop conceptual understanding [21, 22]. In this case, partial understanding that is not canonically correct can be considered as containing useful resources for students to engage in sense-making, which leads to conceptual understanding [11, 35].

There has been an extensive expansion of pedagogical practice within science and engineering focused on

developing conceptual understanding [77]. Concept-based questions have been used in various fields, for example, mechanics [9, 19], physics [7, 27, 88], electrical circuits [80], thermodynamics [29, 80, 85], chemistry [52], and materials science [46, 53, 75]. Other tools have also been explored and implemented in engineering classes such as written explanations [47, 49], reflection surveys called muddy/most interesting points [45, 51, 54, 55, 62], and interactive hands-on simulations [6, 10, 17]. Before the study reported here, we utilized the written explanations as a tool to capture student reasoning to develop the concept questions reported in this study. We have also developed and incorporated reflection surveys, interactive activities, and a simulation in our learning module (see the section CALM Design).

Despite the growing acknowledgment of the importance of conceptual understanding [80] and the preponderance of studies addressing pedagogical practices to promote conceptual learning, adaptive learning tools have focused mainly on declarative and procedural knowledge [41]. We found only three recent studies in STEM areas that combined the use of research-based concept question assessments together with adaptive platforms: health science [15], electronics [32], and physics [91, 92]. Adaptive learning strategies have also begun to be explored in material science and engineering; however, no concept-based questions were integrated into their design [24].

The degree of SA should also be considered in instructional designs for promoting conceptual learning. It is important to understand how designs that allow different levels of SA influence engagement and learning—especially for groups with different overall academic performance [36]. Still, limited research has been done studying levels of SA and GPA in activities that focus on conceptual understanding. For example, one study [60] in a flipped classroom environment reported a surprising result that when they designed their in-class session to promote less SA (when instructors led or facilitated activities and when decisions on tasks were made by instructors or jointly made with students), students were able to perform better on tests. Another study [82] in a game-based environment found that a proper amount of guidance (in the middle between promoting no guidance and highly directed instruction) led to the highest learning gains. The tests used in these studies, however, were mostly focused on declarative and procedural knowledge and not conceptual understanding.

This study seeks to investigate the role of instructional design on student engagement and development of conceptual understanding in a challenging topic in materials science—crystallography. In a split design

experiment, we compare two different technology-based instructional designs for asynchronous learning. The first design case provides more deliberate feedback and supplemental instruction through the newly developed Crystallography Adaptive Learning Module (CALM) that includes concept questions, interactive learning resources, an interactive simulation, and other components. The second design case provides students access to the same set of resources as the first case but allows them more agency to select which resources to use and when. In addition, we are interested in exploring whether there is a correlation between overall academic performance, engagement, and conceptual learning. The results from this research will benefit researchers and educators who focus on studying conceptual learning, SA, adaptive learning technology, and instructional design. Benefits also expand to computer-based educational software developers working to upgrade and expand this CALM to other topics as well as those working on other similar technological tools and across disciplines and settings, with the common goal—promoting conceptual understanding.

2.4 | Research questions

This research study investigates how the way that learning resources are available to students influences their level of engagement and performance on conceptual understanding. Using a split design, we compared students between the two instructional designs: the SA design and the *adaptive feedback* (AF) design. While students in both instructional designs received similar learning resources, the way they were made available to the students differed. Students in SA design were allowed to navigate the provided resources freely without any specific guidance while those in AF design were guided to each resource within the CALM. We also compared students in three *cumulative GPA* groups (high/middle/low) to represent their overall academic performance. Specifically, we addressed the following research questions:

1. Based on their performance on the summative concept-question assessment, is there any significant difference regarding students' conceptual understanding in materials science between the AF and SA instructional designs? How does development of conceptual understanding relate to students with respect to cumulative GPA groups?
2. How does the level of students' engagement differ among different instructional designs and cumulative GPA groups? For the AF design, how did the number of assigned videos relate to the GPA groups?

3 | THE CALM DESIGN

In this section, we present the components of the CALM that students in the AF design completed. The students in the SA design had access to the same resources but were not directed through any particular path. The CALM was crafted with the goal of improving students' conceptual understanding. The tool addresses one of most challenging topics in materials science—crystallography—and incorporates a nonlinear, adaptive instructional design. Three core *knowledge constructs* were included: crystal structures, atomic packing factor, and theoretical density. The CALM component sequence diagram is shown in Figure 1 along with short descriptions and the terms that students saw in the module within parentheses. Through adaptive hypermedia rule-based functions, each of the CALM components was designed to support students in advancing from declarative and procedural knowledge toward conceptual understanding, following Shavelson et al.'s [78] framework. Concept questions with multiple-choice (MC) assessments for the three knowledge constructs were developed by following guidance from Shavelson and Huang [77] and [7]. The paths that learners follow is adaptive based on their previous responses and the difficulty level (DL) of the questions. Although the CALM developed and used in this work is focused on a specific topic, the design framework is meant to be adaptable and expand the use to other topics in materials science and other STEM subjects.

The module begins with an initial video to spark a student's interest in the topic. This video is short (3 min) and connects their experience with materials in their daily life with the content. Then, the student is presented with a choice for a second, interactive video. Three different lengths are available with a suggestion: students who feel confident about the material after reading the book can select the shorter video while students who feel uncertain can select a longer, more detailed video. Pop-up, low-stakes questions are embedded in all three videos. Students receive explanations related to the questions they just answered as they continue watching. While working on each of these questions, the student can navigate back in the video to review any related content but must submit a response before they can move forward.

Next, the module guides students to answer three conceptually based formative assessment question pairs. These question pairs first ask the student to respond to a conceptually challenging multiple-choice question. Based on their answer, a follow-up "Why?" question asks them to identify their reasoning. An example of a why question is shown in Figure 2. If they pick "Other," the question prompts them with a free response box to type their own explanation. These reasoning choices

were developed based on coding of written responses from 133 students in academic terms before the study reported in this paper.

Based on their responses, students may be directed to supplementary video instruction with interactive pop-up questions. The pre-programmed adaptive logic of the CALM (the dotted-line Adaptive Logic block in Figure 1) decides whether the student would be looped back to watch a different initial video, get presented with short supplemental videos, or continue with the next activity. With this approach, students engage in different facets of the same concepts to support their developing conceptual understanding.

In the central activity of the CALM, students are next directed to a hands-on instructional tool—the 3D Crystal Builder (Figure 3, <https://conceptwarehouse.tufts.edu/cw/crystalVL/>) where they complete a corresponding worksheet. The 3D Crystal Builder allows the student to build their own basic crystal structure, atom by atom, before exploring other options of related parameters. For example, they can learn how atomic packing factor or density changes with changes in atomic weight or radius. The worksheet acts as a step-by-step guide to support the student in using the simulation, connecting declarative and procedural knowledge from prior activities in the tool, and prompting conceptual thinking to further understand the relationship among parameters.

Students then evaluate themselves and compare their self-evaluation with their actual performance from the previous CALM activities in the formative report (Figure 4). They can also provide comments or suggestions to their instructor if they would like any additional support. The comparison primes the next learning task, the resources review page where the student can review all available learning resources (three interactive lectures, five interactive supplemental videos, and the hands-on simulation), including videos that were not directly assigned to them.

The module ends with an adaptive summative assessment (Figure 5) to measure their conceptual understanding providing questions of different DL [71]. The adaptive logic guides the student to a harder or an easier question based on their previous answer as indicated with "Y" as a correct answer or "N" as an incorrect answer in the figure. The competency levels of the three knowledge constructs are then calculated and combined with the formative report information and presented to the student in a summative report. Analytics from both the formative and summative assessments allow the student to observe their own learning progress and notice areas that need more attention, as well as allow the instructor to gauge the distribution of understanding in the entire class.

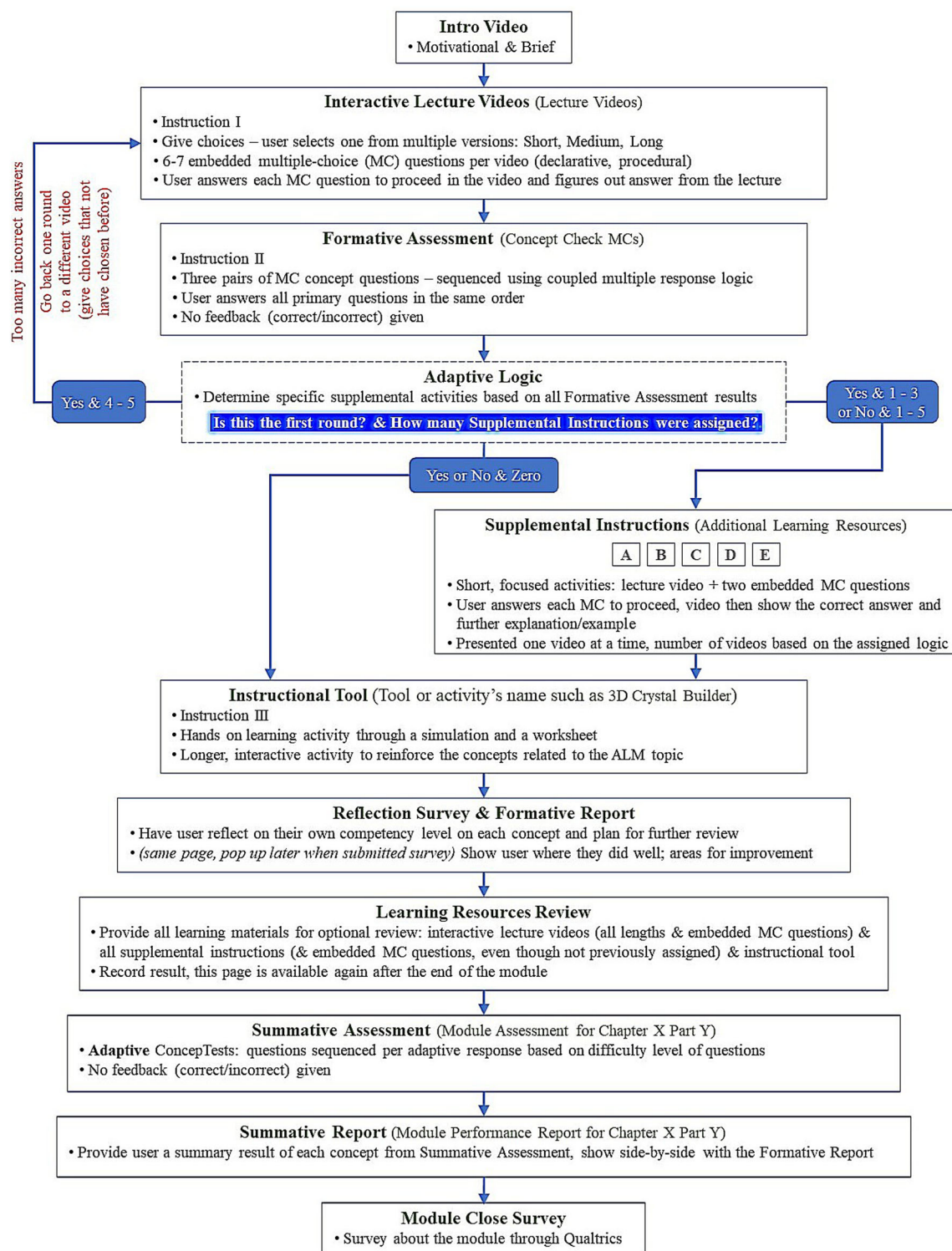


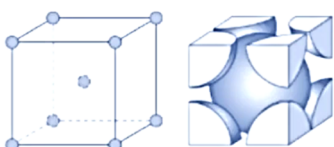
FIGURE 1 The CALM component sequence diagram, (in parentheses are terms that students see in the module).

Lastly, the student is asked to complete a survey; the first part is shown in Figure 6. There is no time limit for any of the tasks besides the due date for completion of the whole module. The resources review page remains available after they have completed the CALM for future use in the course.

4 | METHODS

We focus the scope of this study on undergraduate students in an asynchronous online format of an introduction to materials science course during the week when they were learning crystallography. We used a quasi-experimental

Both Iron and chromium have a body centered cubic (BCC) structure at room temperature. Iron's atomic weight is larger than chromium, but its atomic radius is smaller than chromium. Which element has a higher density for its BCC structure?



body centered cubic (BCC)

Iron has a higher density
 • **Chromium has a higher density.**
 Neither. The density for iron and chromium are approximately equal.

Why? Which of the following statements best supports your reasoning? (choose at least one)

- ☐ Because both a smaller atomic weight and a larger atomic radius increase density.
- ☐ Because a smaller atomic weight increases density has a higher effect than a larger atomic radius that decreases density.
- ☐ Because a larger atomic radius increases density has a higher effect than a smaller atomic weight that decreases density.
- ☐ Because only a smaller atomic weight increases density, and density does not relate to the size of the atoms.
- ☐ Because only a larger atomic radius increases density, and density does not relate to the weight of the atoms.
- ☐ Other

FIGURE 2 An example of the formative assessment with the question “Why?” after picking an answer.

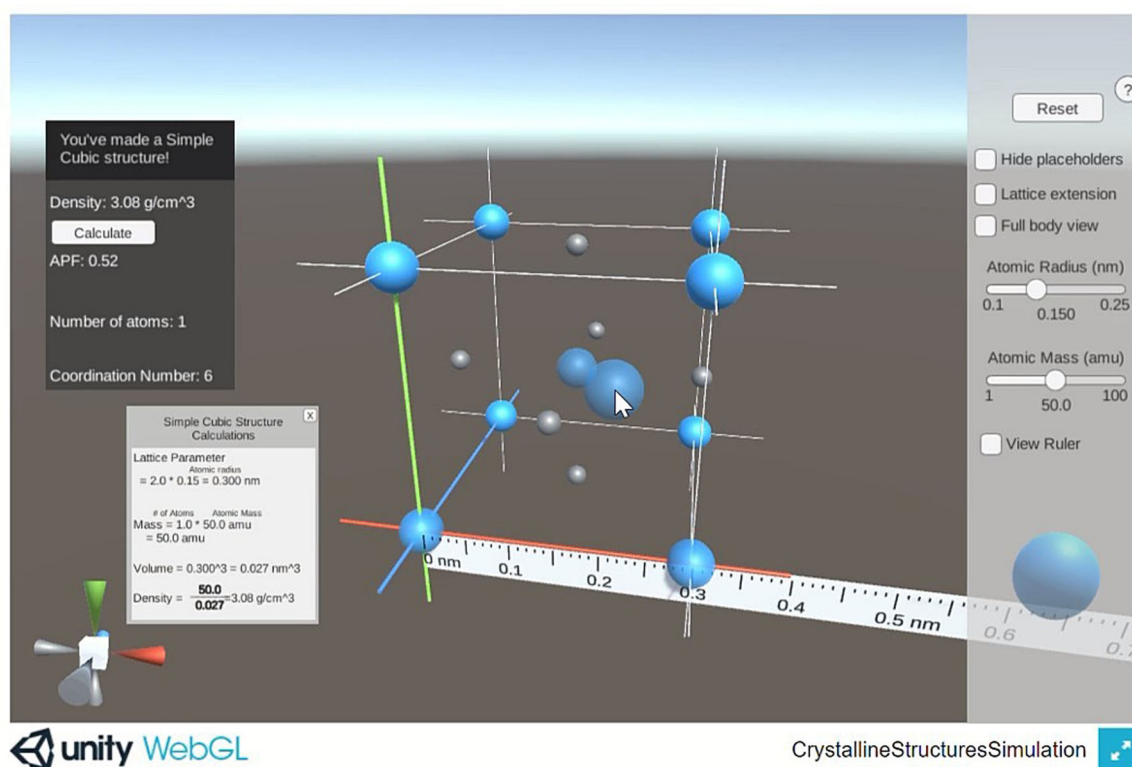


FIGURE 3 A sample screenshot of the newly developed 3D Crystal Builder simulation.

randomized split design to determine the influence of instructional design (AF vs. SA) and overall academic performance (as measured by cumulative GPA) on conceptual learning and student engagement.

4.1 | Participants and setting

We collected data from the asynchronous online setting of the introduction to materials science course at a large

Formative Report			
For the Chapter 3 Part 1 concepts listed below, you have...	demonstrated Mastery through Concept Check Multiple Choices.	received training through Additional Learning Videos.	evaluated your competence as ...
Crystal structure [Chapter 3.2 - 3.4 and 3.7]		X	Exceeds basic competency
Atomic packing factor and close-packed structure [Chapter 3.4 and 3.12]	X		Meets basic competency
Density [Chapter 3.5]		X	Below basic competency
Next			

FIGURE 4 An example of a formative report in the CALM.

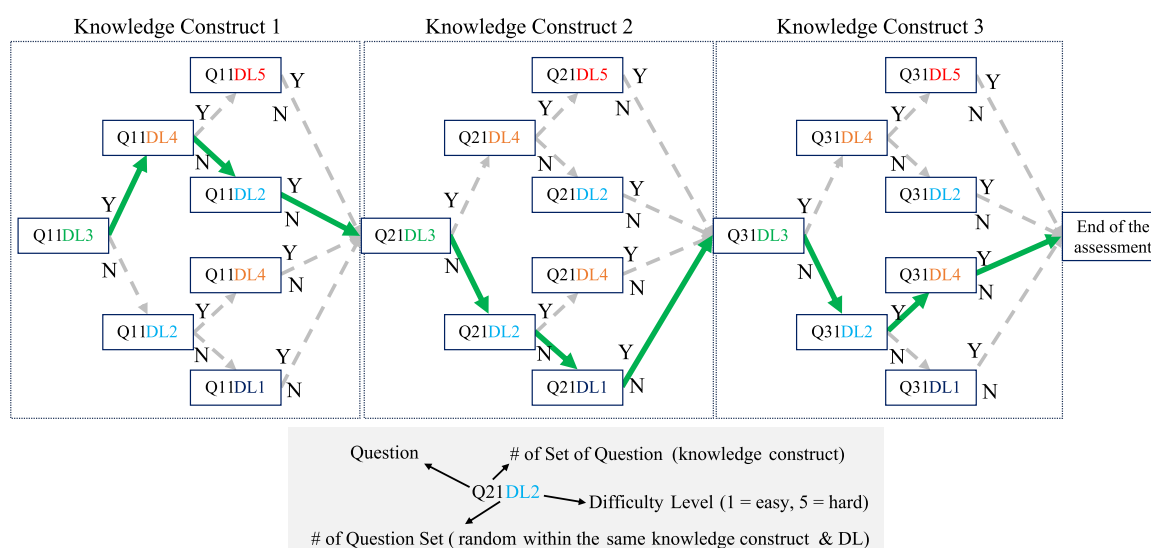


FIGURE 5 The summative assessment adaptive logic. Solid green arrows show a sample student path. Dashed gray arrows show other possible paths. Correct and incorrect responses indicate with “Y” and “N”, respectively. (adapted from Nigon et al. [71]).

public university as a convenience sample. Data were collected over six consecutive academic quarter-terms (including a summer term) from winter 2022 to spring 2023. During the week when crystallography was covered (Week 2), students were randomly divided to complete two instructional designs: the AF design and the SA design. They experienced the same curriculum at all other times. Students completing the AF design went through the CALM using the adaptive logic shown in Figure 1. Students completing the SA design had the freedom to visit and work on or skip any component of the CALM and could choose the order they completed each component. The absence of the assigned individual feedback logic also meant that they were not assigned to a specific supplemental instruction based on their formative assessment performance; however, they had access to those resources if they chose. In addition, the students

completing the AF design received two feedback reports that the SA design only received one.

The tasks were available to students through the Concept Warehouse platform [29, 50] except the end of the module survey that was completed using Qualtrics. All tasks, including the survey, were graded based only on participation except for one task, the summative assessment, where correctness mattered. In each academic term, tasks were available for students in each participant group over a similar time window, varying from 4 to 7 days, and students worked at their own pace. Discussion boards were available but separated for each instructional design during this week of the study. Students were allowed to use any outside resources or post questions on their group's discussion boards, but they were asked not to work on the tasks side by side with their peers.

What features of this module helped you learn the most? Please describe.

I

What was the most challenging part of this module? Please describe.

(a)

Please indicate the extent to which you agree with each of the following statements from your experience with this module.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I needed to think conceptually.	☐	☐	☐	☐	☐
I needed to reason through the content.	☐	☐	☐	☐	☐
I learned to correct my mistakes.	☐	☐	☐	☐	☐
The interactive learning portions helped me to better understand the concepts.	☐	☐	☐	☐	☐
The module contains clear language and I understood what was being asked or what to do.	☐	☐	☐	☐	☐
The interface was easy to interact with and navigate.	☐	☐	☐	☐	☐
After completing this module, I have gained confidence in my progress and performance.	☐	☐	☐	☐	☐
I felt my time invested was worth it relative to other ways I might learn the content (e.g., read	☐	☐	☐	☐	☐

(b)

FIGURE 6 An example of part of the end of the module survey with (a) open-ended questions and (b) Likert scale questions.

All students that enrolled in the asynchronous online course were invited to participate, and the data used come only from those who consented (IRB-2020-0775) and completed the summative assessment task. The number of participants by academic term is shown in Table 1. Ninety percent of students who provided their consent for both instructional designs completed their summative assessment. Participants were mostly undergraduate students in their junior or senior year pursuing a mechanical engineering degree.

4.2 | Measures

The summative assessment task was used as a measure of conceptual understanding of the three knowledge

constructs. Each student encountered three questions for each knowledge construct but the second and third questions differed based on the correctness of the previous question as shown in Figure 5. All three knowledge constructs used the same scoring chart shown in Table 2. The scoring is progressive where students who answered more difficult questions receive higher scores, for example, a correct answer from DL1 was assigned 1 point while DL5 was assigned 5 points. The score from the three knowledge constructs were added together (maximum score at 36) as a measure of conceptual understanding of crystallography.

Student cumulative GPA at the end of the academic term was obtained from the registrar. The 165 participants were divided into three *cumulative GPA* groups (high, middle, and low) with about 55 students per group, as

TABLE 1 Number of participants (*N*), separated based on instructional designs and by academic term.

Academic term	Instructional design					
	AF			SA		
	Enrolled ^a	Provided consent	Completed task ^b	Enrolled ^a	Provided consent	Completed task ^b
Two	18	13	11	19	12	10
Three	24	20	17	25	22	20
Four	24	16	15	24	18	17
Five	17	11	11	16	12	11
Six	24	20	18	24	16	15
Total	134	88	<i>N</i> = 80	133	92	<i>N</i> = 85

^aAt the beginning of Week 2.^bCompleted the summative assessment task. Used these data in the analysis reported in this study.**TABLE 2** Scoring criteria for each knowledge construct where a higher score is given for questions at a higher difficulty level (DL). The summative assessment score is shown for all possible paths a student can take (column DL).

DL for each question ^a and student response ^b	Number of correct answers	Summative assessment score ^c
3N → 2N → 1N	0	0
3N → 2N → 1Y	1	1
3N → 2Y → 4N	1	2
3Y → 4N → 2N	1	3
3Y → 4N → 2Y	2	5
3N → 2Y → 4Y	2	6
3Y → 4Y → 5N	2	7
3Y → 4Y → 5Y	3	12

Note: This table shows a scoring criteria per one knowledge construct—a student encounters three questions of the same concept. The summative assessment of the CALM has three knowledge constructs.

^aDL1 = easiest to DL5 = hardest.^bCorrect and incorrect responses indicate with “Y” and “N,” respectively.^cSummative assessment score calculated from DL 1 = 1 point, ..., DL5 = 5 points.

shown in Table 3. The range of GPAs was not equal among groups as listed in the second column on the table; for example, the “Low” GPA group is the widest.

As a proxy for engagement, we counted the number of videos that students watched based on the completion of the pop-up questions. Although students in AF design were assigned to videos one by one (except for the review page before the summative assessment, see Figure 1), the CALM did not force them to complete the video before they could move on. The results were compared between

TABLE 3 Number of participants in each performance group for all participants in each of the instructional designs.

Cumulative GPA group	Range of cumulative GPA	Instructional design		
		AF	SA	Total
High	3.56–4.00	29	26	55
Middle	3.15–3.55	24	30	54
Low	2.00–3.14	27	29	56
Total	4.00	80	85	165

both instructional designs (SA and AF) and among the three cumulative GPA groups. The number of assigned videos for students in AF design was also collected.

4.3 | Trustworthiness

To justify that the instruction was at the appropriate DL, we solicited students' perceptions through several five-point Likert scale items after they completed the module. Eighty-six percent of students from the AF design and 84% from the SA design reported that the module was neither too challenging nor too easy. Thus, most students believed that they were appropriately challenged. Another Likert scale question asked students their perception that the instruction asked them to “*think conceptually*.” Ninety-four percent from the AF design and 91% from the SA design reported affirmatively (agree or strongly agree). These survey data support the adequacy of the module's difficulty as well as the fact that students view this module as conceptually oriented based on their prior experiences.

4.4 | Data analysis

To answer research question 1, the means of the summative assessment scores from the two instructional designs were tested using the Welch two-sample t -test, assuming a normal distribution due to the large sample sizes (Table 1). Their variances were confirmed using a Fisher's F test (F -test of equality of variances). Among the six design-and-GPA groups, the centers of the summative assessment scores were analyzed using Kruskal–Wallis rank sum test (nonparametric analysis of variance) due to the smaller sample size for each group (Table 3) and the assumption of normality being suspect. Bartlett's test was used to test their variances. For post hoc analysis, Dunn's test was chosen with the p -values adjusted using the Bonferroni correction.

All statistical analyses in this research were performed in Rstudio [83] using a significance level of $\alpha = .05$. We treat all data as independent within groups as well as between all groups since students would not take two courses simultaneously. This assumption is tenuous for students who re-enrolled, as their overall academic performance would likely have changed somewhat; however, this exception only applies to a small number of students and so does not noticeably impact the analysis. For research question 2, the number of videos that students completed were compared across groups. The number of assigned videos for the AF design were compared among cumulative GPA groups. These data were compared visually, analyzed using Kruskal–Wallis rank sum test, and discussed in descriptive statistics.

5 | RESULTS

This section describes the results that address each of the research questions.

5.1 | Conceptual understanding

Distributions showing the summative assessment scores (see Table 2) between the AF and SA designs are shown in Figure 7. The mean score (the X mark in the box plot) for the AF design is 22.6 with a standard deviation of 6.68. The mean score for the SA design is 21.6 with a standard deviation of 6.06. A Welch's t -test shows that there is not strong evidence that the difference between means is statistically significant ($t(159) = 1.02$, $p = .309$), and a Fisher's F test indicated there is no significant difference in variances ($F = 1.21$; $p = .381$). This result suggests that different instructional designs in this study—using a directed adaptive path that guides students through activities or an agentic path that makes resources available without specific direction—may not be an important factor toward conceptual learning of crystallography topics when considering all the students. However, looking at Figure 7a, the AF design, interestingly, has a higher third quartile and median (top and middle horizontal lines on the boxes, respectively) and the SA design has one lower outlier (the dot at the bottom). The histograms show more students that scored 24 and higher in the AF design compared to the SA design, which suggests a possibility that the difference in instructional designs may support certain groups of students.

The summative assessment scores of the three cumulative GPA groups among the two instructional designs is shown in Table 4. A Kruskal–Wallis test indicates a significant difference of at least two centers of the module assessment score, $\chi^2(5) = 26.4$, $p < .001$. Post hoc comparisons using Dunn's test with a Bonferroni adjustment found a statistically significant differences ($p < .025$) between three pairs of the high and low cumulative GPA groups of the same instructional design and across the two

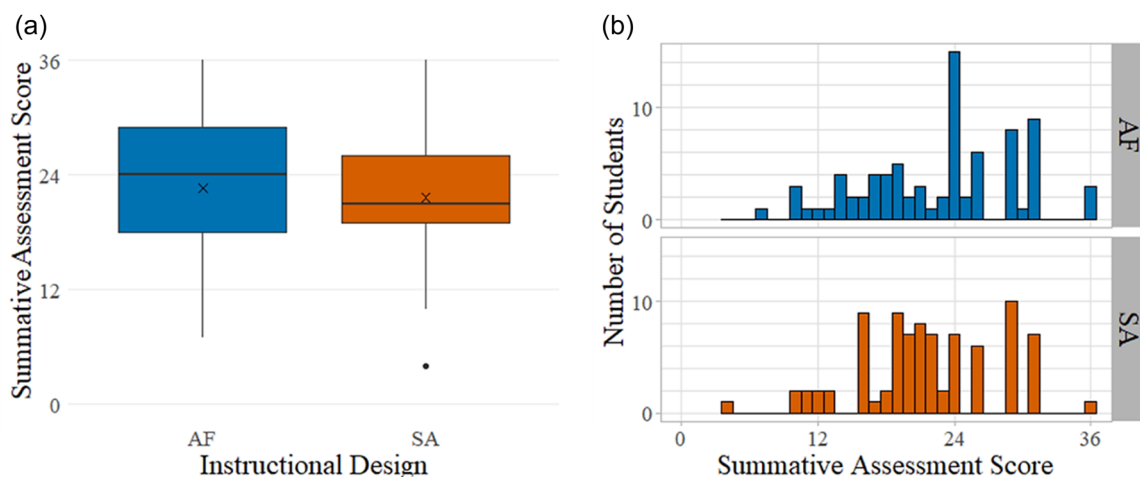


FIGURE 7 (a) Box plots and (b) histograms of the summative assessment score from all three knowledge constructs between the two instructional designs.

TABLE 4 Number of participants (n), means (M), standard deviations (SD), and Kruskal–Wallis rank sum test in summative assessment scores of the three cumulative GPA groups and the two instructional designs.

Cumulative GPA group	Instructional design						$\chi^2(5)$	p
	AF			SA				
	n	M	SD	n	M	SD		
High	29	24.7	5.28	26	25.4	4.63	26.4	<.001
Middle	24	23.8	6.97	30	21.2	4.81		
Low	27	19.4	6.43	29	18.7	6.42		

Note: Bartlett's test indicated there is no significant difference in variances (Bartlett's K -squared = 7.44; p = .190).

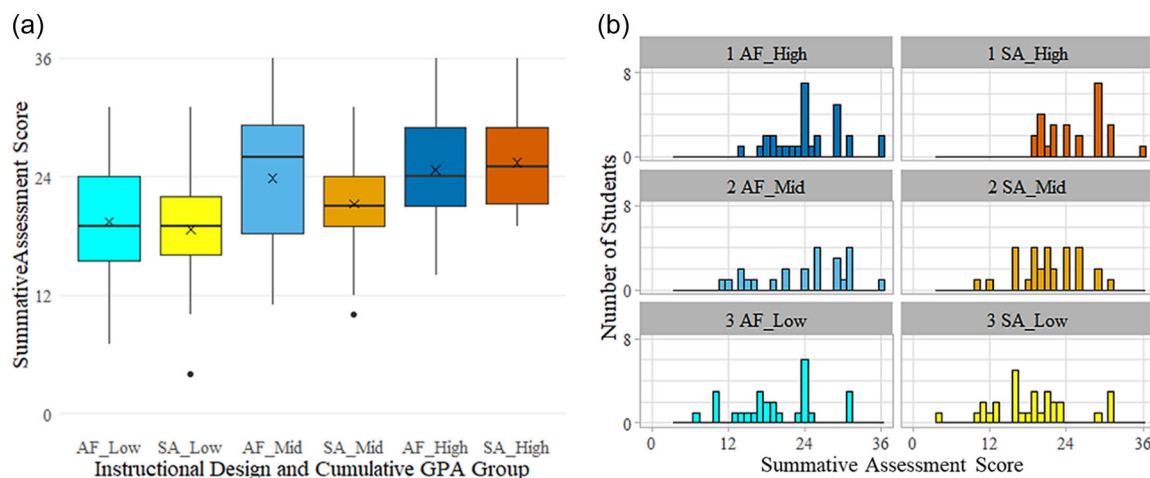


FIGURE 8 (a) Box plots and (b) histograms of the summative assessment score (three knowledge constructs) between the three cumulative GPA groups and the two instructional designs.

designs (except AF-low and AF-high) and one extra pair between the AF-mid and the SA-low groups. None of the other comparisons were significantly different, including all three pairs comparing the same GPA groups between different instructional designs.

The distributions of the score across instructional design and cumulative GPA groups are shown in Figure 8. Inspection of these plots shows that the AF using CALM may differentially help students in the middle GPA group (labeled AF_Mid). Again, the third quartile and median (top and middle horizontal lines on the boxes, respectively) of the AF_Mid group are higher than the third quartile of the SA_Mid group and these values as well as the mean for the AF_Mid lie in a range similar to the high-GPA groups. While we cannot make definitive claims, these results are intriguing and suggest the lack of significance may be due to statistical power with $n < 30$.

5.2 | Engagement

To further explore potential differences between the AF and SA designs, we next relate student engagement with

the provided learning resources, focusing on the number of videos watched. Figure 9 shows the percentage of students that were assigned or had completed a given number of videos. For the AF design, the number of assigned videos (gray dotted bars), the number of completed videos from the assigned path (dark blue bars), and the number of extra videos completed “by choice” as they reviewed for the summative assessment (light blue striped bars) are shown. All students were assigned to at least one interactive lecture video at the start (as shown in Figure 1); thus, the number of assigned videos (gray dotted bar) is at 100% for one video. The adaptive logic (the box with dotted line in Figure 1) could either loop the student back to another round of interactive lecture or provide up to five additional supplemental videos, which resulted in a maximum number of assigned videos up to seven. The number of all videos completed for the SA design before working on the summative assessment is shown in orange-striped bars; all of these are *by choice*. Although all eight videos were provided on the review page for both designs, the CALM did not record when students re-watched the video for review if they had previously watched it. Therefore, the actual number of *by*

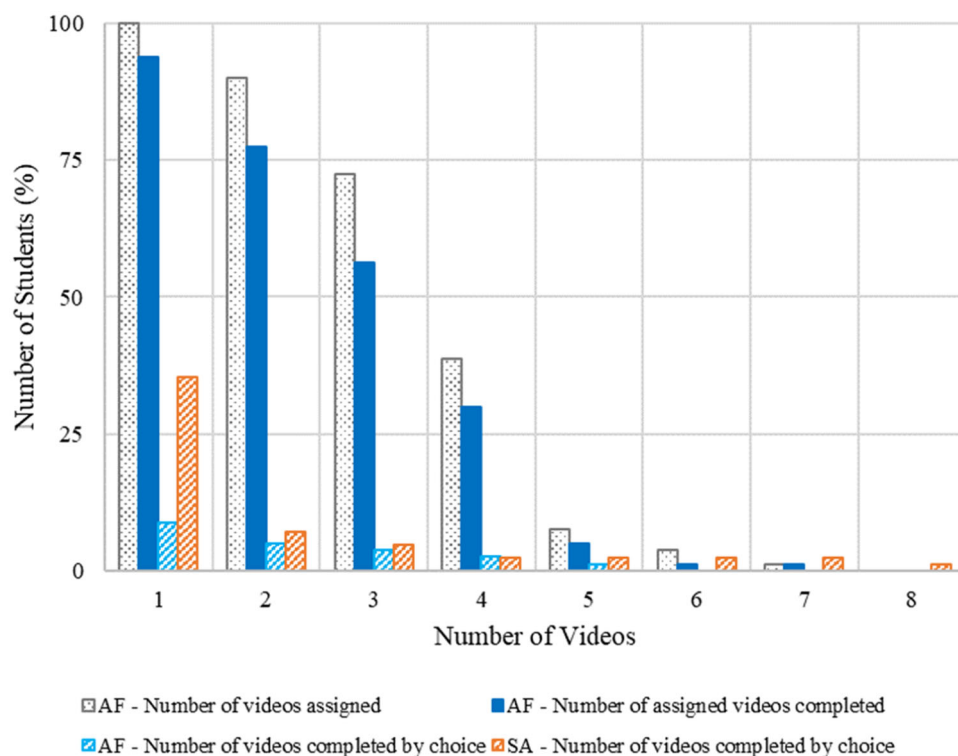


FIGURE 9 Percentage of students in each instructional design versus the number of videos assigned or completed.

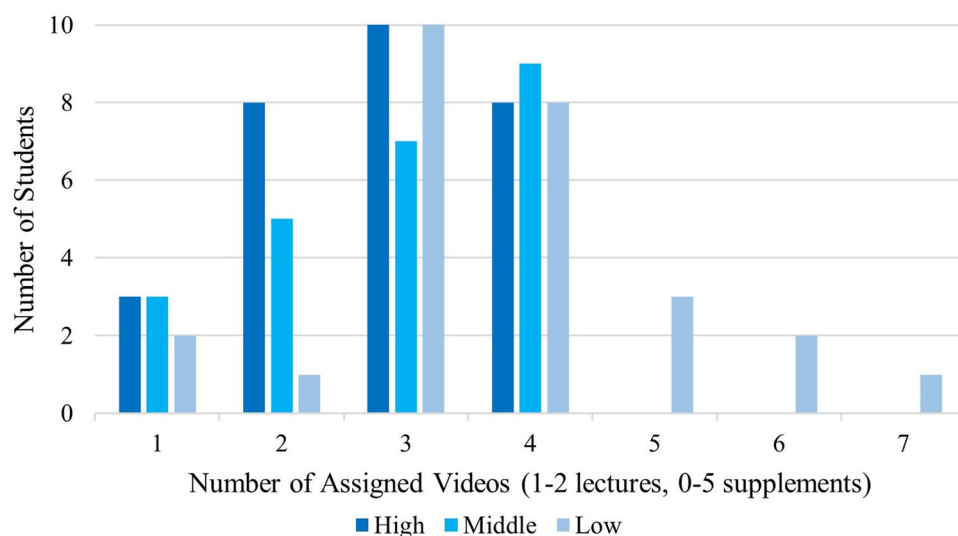


FIGURE 10 Number of students in AF instructional design versus the number of videos that were assigned disaggregated by cumulative GPA.

choice videos watched for both designs may be higher than reported here.

The number of completed *assigned* videos to students in the AF design was much higher (94% for one video, 30% for four videos) than the *by choice* in the SA design (35% for one video, 2% for four videos). More than half (55 students, 65%) of students in SA design did not watch any videos before

working on their summative assessment as compared to only 6% (5 students) from all students in the AF design. Additionally, from individual data, 79% (63 students) in the AF design completed all their assigned videos.

Figure 10 presents the number of videos that were assigned to students in the AF design when disaggregated according to cumulative GPA. The average

TABLE 5 Number of videos students have watched (completed all pop-up questions) between instructional design and cumulative GPA groups.

Instructional design	Cumulative GPA group	Number of videos completed					
		None	1	2	3	4	5 or more ^b
AF assigned	High	2	5	8	8	6	0
	Middle	1	4	6	6	7	0
	Low	2	4	3	7	7	4
AF by choice ^a	High	24	2	1	1	0	1
	Middle	23	0	0	0	1	0
	Low	26	1	0	0	0	0
SA by choice ^a	High	12	12	1	1	0	0
	Middle	18	9	1	1	0	1
	Low	25	3	0	0	0	1

^aFor AF, on the resources review page before working on the summative assessment. For SA, on the resources page counting only videos completed before working on the summative assessment.

^bFor AF, maximum at seven. For SA, maximum at eight.

number of assigned videos for the high, middle, and low cumulative GPA groups are 2.8, 2.9, and 3.7 respectively. Eight students (10%) were assigned to only their first video, and one low-performance student got assigned all possible seven videos (two rounds of lectures and five supplemental videos). In general, the lower the cumulative GPA group, the more videos were assigned with only the low GPA group ($n = 27$) receiving more than four videos.

A Kruskal-Wallis rank sum test showed a significant difference in the number of videos completed across instructional design and cumulative GPA groups, $\chi^2(5) = 87.3$, $p < .001$. Table 5 reports number of videos that students in each instructional design completed when disaggregated by cumulative GPA. For students in the SA design, video engagement strongly correlated to cumulative GPA. For the high GPA group, 14 out of 26 students (54%) watched at least one video. For the middle GPA group, 12 out of 30 students (40%) watched at least one video while the low GPA group only had 4 out of 29 students (14%) watch one video. Only 6 out of 85 SA design students across all three groups (7%) watched more than one video. For students in the AF design, on the other hand, the completion percentage of the assigned videos were roughly the same (79% for high cumulative GPA group; 83% for middle, and 74% for low). We conclude the directed activity of CALM led to greater engagement and more even distribution in video completion. However, mostly students from the high GPA group (5 out of 7 students in the AF design) watched extra videos (by choice) to prepare for the summative assessment.

6 | DISCUSSION

One of the beacons for educational technology is the ability to provide personalized learning for students [72]. However, creating fully adaptive systems is costly and time-consuming and the extent that personalized learning can address development of conceptual understanding in challenging STEM subjects like materials science is unclear. In this study, we addressed these issues by developing the CALM and investigating student engagement and performance on a conceptually based assessment on a challenging topic in materials science through a split design study. Students were randomly assigned to complete one of two instructional designs that provided different levels of automated feedback and SA.

There was no statistically significant difference in the means of the student scores between the two designs (Figure 7). However, when divided into groups of different cumulative GPA (Figure 8), the distributions of the AF design suggest the performance of students in the middle GPA group might have approached or equaled that of the high GPA group. The distributions of student scores in the SA design do not show an equivalent shift. This increase aligns with their engagement. The adaptive design increased the engagement of all students as they completed higher number of videos (Figure 9) possibly leading to the improved conceptual learning performance in the middle GPA AF design (Figure 8). The middle GPA group also received a slightly greater number of assigned videos relative to the high group (Figure 10). While students in the SA design were provided with a resource page where the same videos were

available, they watched far fewer videos than students in the AF design. This might be due to the directed activity of CALM making it more convenient for students to engage as all the learning resources were combined into one continuous lesson.

While 165 students participated in this study, we divided that sample into six sub-groups—having two instructional designs (AF and SA) and three cumulative GPA groups (high, middle, low). Due to the small sample size in these sub-groups ($n < 30$), more data should be collected for students with mid-level cumulative GPAs to determine if the directed activity provided by CALM increases their measured conceptual understanding. There may be a counteracting effect to the directed resources from the CALM as findings from the literature show that SA can benefit learning [82]. We note here that ethical considerations prevented us from comparing learning to a control group, as we did not believe it appropriate to withhold learning resources from students in a naturalistic setting. However, this study could be reproduced in a laboratory setting to see the influence of the resources provided in either instructional design (AF or SA) as compared to textbook and video lecture only, which is common to the other chapters in the course.

While the CALM provides some limited agency (e.g., choice of videos; access to learning resources for review), it may be useful to combine these aspects to promote student conceptual learning, especially for students in lower cumulative GPA groups. Further research is needed to investigate how to more completely incorporate student *epistemic agency*, defined as “students being positioned with, perceiving, and acting on, opportunities to shape the knowledge building work in their classroom community” (pp. 1058, [66]).

Finally, we reflect on the influence of our shifting theoretical stance as we engaged in developing the CALM and conducting this study. We began our initial development of the CALM with the *misconceptions* stance [14, 65]. We focused on identifying misconceptions in students through the formative assessment and sought to develop a tool to repair them through support from the adaptive logic feedback. From this view, student conceptual learning was treated as if the tool guided them to register new ideas and replace any incorrect beliefs they might have. However, when we shifted our theoretical stance to *knowledge in pieces* [21, 22], the idea of guided feedback from the tool also shifted, now being a way to bring resources for students in areas that they have not yet mastered. Thus, the epistemological role of the tool has shifted from representing an authority to diagnose and replace misconceptions to a conversational agent to provide additional ideas that students can use in their thinking. As conceptual understanding is marked by how

that knowledge is connected and organized [31, 69], the process of providing additional pieces of knowledge then is to help students further develop new connections and learn to activate related resources to make sense of the targeted concept [35]. As different theoretical stances in conceptual learning—misconceptions or knowledge-in-pieces—can greatly influence our awareness and objectives in the development and use of such instructional tools, it is important for researchers and educators to understand how their underlying theoretical stances contribute to instructional design decisions [34].

6.1 | Limitations

There are several limitations to this study. This was the first version of the CALM and all components of this complex tool needed to be created from scratch, including the formative and summative concept questions, lecture and supplemental videos with pop-up questions, the interactive 3D Crystal Builder and worksheet, reflection surveys, performance reports, and the adaptive logics. The system will improve with iterative development informed by data such as presented in this study. The scope of the study is limited to one topic in materials science (crystallography), expanding to other topics and subject areas is needed. Data were collected from live asynchronous online classes across six academic quarter-terms where other possible contributing factors may have influenced the results. Further investigating within classes in various formats (such as in-person, hybrid, flip, etc.) as well as classes taught by other instructors and across universities is recommended. The CALM was able to record data only when students first answered each pop-up question in a video. No data were collected if they reviewed any of the previously watched videos. Generally, engineering students tend to perform better on quantitative, procedural-based questions than the qualitatively based concept questions used here [53]. Since cumulative GPA represents performance from students in various courses many of which emphasize declarative and procedural knowledge, the GPA groupings have some limitations to identifying students' preparation to engage in conceptual learning. The summative assessment was based on DL, but refining a set of five questions of ascending difficulty is challenging as reported in previous work [71].

7 | CONCLUSIONS

Research on adaptive learning with the use of computers is growing as well as the emphasis of promoting SA and improving conceptual learning. In this research,

new concept questions and active learning activities were developed and implemented in a newly designed CALM for materials science. The study used a split design experiment to compare between allowing different levels of computer direction or SA through two instructional designs. Students in one design were guided through the CALM on their individualized, directed path, adapted based on the predesigned logic, and students in the other design were provided with resources from the CALM but with no specific guidance providing more SA. Within this comparison, we also investigated among students in three groups of overall academic performance based on cumulative GPA—high, middle, and low. We found that the adaptive module successfully increased student participation in certain activities. There was no statistically significant difference in the final concept-question assessment scores between the two instructional designs nor among the same cumulative GPA groups between these two instructional designs; however, there is some evidence that the CALM potentially supported conceptual learning for students in the middle cumulative GPA group more than the same GPA group in the SA instructional design. Larger sample sizes are needed to draw a definitive conclusion. The low GPA group received the greatest number of assigned supplements and completed the least number of videos by choice. More research should continue to study for further improvement of the current tool as well as expand the development into other topics and disciplines.

REMARK ABOUT THE USE OF GENERATIVE AI IN THIS ARTICLE

We have not used generative AI (such as ChatGPT) to support in writing this article nor used when creating the CALM learning components.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Brandon C. Jeong  <http://orcid.org/0000-0003-4143-2996>

Milo D. Koretsky  <http://orcid.org/0000-0002-6887-4527>

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AUTHOR BIOGRAPHIES



Nutnicha Nigon recently graduated with a PhD in Materials Science from the School of Mechanical, Industrial and Manufacturing Engineering and a minor in Education at Oregon State University, USA. She received B.Eng. and M.Eng. degrees in Metallurgical and Materials Engineering from Chulalongkorn University, Thailand. Her research focuses on conceptual learning and personalized feedback design in engineering.



Julie D. Tucker earned her PhD in Nuclear Engineering at the University of Wisconsin, Madison. After graduation, she spent five years as a Principal Scientist at Knolls Atomic Power Laboratory. In 2013, she joined the School of Mechanical, Industrial, and Manufacturing Engineering at Oregon State University and was recently promoted to Full Professor. Dr. Tucker served as the Materials Science Interdisciplinary Graduate Program Director for five years and recently became the Director for the Design for Social Impact Program. Her research focuses on degradation of materials in extreme environments using both modeling and experimental approaches to gain fundamental understanding of materials performance.



Thomas W. Ekstedt received his BS degree from UC Davis and an MS degree from MIT, both in Electrical Engineering. He is a software developer in the Department of Chemical and Biological Engineering at Tufts University. He is involved in the development of technology-based educational systems, particularly in the areas of concept-based instruction and adaptive learning.



Brandon C. Jeong received his BS in chemical engineering from Oregon State University and is currently pursuing a PhD in chemical engineering at the University of Illinois Urbana-Champaign. During his time as a graduate student, he has received the Mavis Future Faculty Fellowship and the NSF Graduate Research Fellowship honorable mention. His current research implements molecular dynamics polymer simulation to predict force-responsive mechanophore behavior as a pathway toward understanding polymer response to stress on a microscopic scale. In the long term, he intends to use computational methods to provide further mapping between a polymer's microscopic structure and its macroscopic properties.



Dana C. Simionescu received an MA in Linguistics and a PhD in Instructional Technology from Ohio University. She is an Instructional Designer with Oregon State University Ecampus, working with instructors and media specialists to create high-quality online courses.



Milo D. Koretsky received his BS and MS degrees from UC San Diego and his PhD from UC Berkeley, all in Chemical Engineering. He is the McDonnell Family Bridge Professor with a joint appointment in the Department of Chemical and Biological Engineering and the Department of Education at Tufts University. He serves as co-director of the Institute for Research on Learning and Instruction (IRLI). His group works on integrating technology into effective educational practices that promote the use of higher-level cognitive and social skills in engineering problem solving and in promoting change towards motivating faculty to use evidence-based instructional practices.

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