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ARTICLE

Flipping a simulation before instruction can improve students' learning, interest and perceived competence

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Abstract

Background: Using simulations in science instruction can help make abstract topics more concrete and boost students' understanding.

Aims: The current research examined whether using a simulation as an exploratory learning activity before an accompanying lecture has additional learning and motivational benefits compared to a more common lecture-then-simulation approach.

Samples: Participants (Experiment 1, $N = 168$; Experiment 2, $N = 357$) were undergraduate students in several sections of a first-year chemistry course.

Methods: Students were randomly assigned to explore a simulation on atomic structure either before a lecture (explore-first condition) or after the lecture (instruct-first condition). In Experiment 1, the simulation activity time was limited (15 min) and the activity varied in whether self-explanation ('why') prompts were included. In Experiment 2, the activity time was lengthened (20 min), and only 'why' prompts were used. After the activity and lecture, students completed a survey and posttest.

Results: In Experiment 1, students in the explore-first condition scored lower on posttest conceptual knowledge scores and reported lower curiosity compared to students in the instruct-first condition. Scores for basic facts and transfer knowledge, and self-reported situational interest, self-efficacy, and competence, were equal between conditions. No effects of prompt condition were found. In Experiment 2, with longer activity time, the results reversed. Students in the explore-first condition scored equally on basic facts and higher on conceptual knowledge and transfer measures,

while also reporting higher curiosity, situational interest, self-efficacy, competence, and cognitive engagement.
Conclusion: When properly designed, placing simulations before—rather than after—lecture can deepen learning, motivation, and competence.

KEYWORDS
exploratory learning, motivation, productive failure, science education, simulation

INTRODUCTION

Students in science, technology, engineering, and mathematics (STEM) courses often struggle to go beyond rote problem solving to understand the underlying concepts (Hunter et al., 2021; Peperkorn et al., 2024; Watson et al., 2020). Such understanding is especially difficult because much science knowledge, such as in chemistry, is represented abstractly, at macroscopic, submicroscopic, and symbolic levels (Gilbert & Treagust, 2009). To make these concepts more concrete, educators often use simulations (Moore et al., 2013; Peperkorn et al., 2024). A number of studies demonstrate benefits of using simulations in STEM, including improvements in students' learning (e.g., Smetana & Bell, 2012; Watson et al., 2020) and engagement (e.g., Josephsen & Kristensen, 2006).

The current work adds to this simulation research by asking how using the same simulation activity either before or after an instructor's lecture might impact learning and motivational outcomes. We theorize that providing the simulation before lecture, rather than after, promotes more constructivist learning processes. With constructivist methods, students take a more active role in creating their own knowledge (Alfieri et al., 2011). Although simulations are often used with constructivist teaching methods, such methods often require revamping an entire course approach (e.g., inquiry learning; Moore et al., 2013; Peperkorn et al., 2024). By simply adding a simulation before a typical lecture, instructors may support students' engagement and understanding without completely revamping their teaching materials. Thus, this method may be readily adopted in classrooms, with important results.

Simulations in science classrooms

The use of simulations as pedagogical tools has increased in recent years, with the evolving use of technology in classrooms (Price et al., 2019). Simulations take many forms but can be generally defined as virtual, interactable, graphical representations of processes, situations and systems (Moser et al., 2017). Many simulations are designed for exploration in classroom settings and are intended to be paired with direct instruction to achieve a variety of learning goals (e.g., Roll et al., 2014).

Using simulation-based activities has been shown to benefit academic performance in fields such as physics (Batuyong & Antonio, 2018; Rutten et al., 2012), biology (Verawati et al., 2022), and chemistry (Josephsen & Kristensen, 2006; Watson et al., 2020), compared to using traditional lectures alone. Simulations have also been shown to boost motivation and engagement beyond typical instruction (Mallari & Lumanog, 2020). Incorporating simulations into flipped-classroom models (Wu et al., 2021) and inquiry-based learning models (Roll et al., 2014) has been shown to improve long-term knowledge retention.

Simulations are advantageous for student learning in multiple ways. Simulations allow students to visualize and manipulate components that would be impossible using real world tools (e.g., rearranging the electrons of an atom; Moore et al., 2014). Simulations also allow for dynamic, autonomous, real-time feedback based on how learners explore (Moore et al., 2013; Podolefsky et al., 2010). Simulations often have built-in, customizable scaffolding, allowing exploration to be tailored based on the prior knowledge and experience of learners (Moore & Perkins, 2018). Simulation interfaces may be comparable to those of some video games, creating a gamified experience and potentially increasing student interest (Ozcan et al., 2020).

Simulations can also offer logistic advantages for instructors. Many simulations are easily accessible and usable across platforms (Perkins et al., 2014). For example, organizations such as PhET—University of Colorado Boulder have designed a library of freely accessible simulations, covering topics from most STEM domains (https://phet.colorado.edu). The accessibility of simulations allows educators to demonstrate science concepts that would otherwise be infeasible due to the cost of laboratory equipment (Finkelstein et al., 2005). Exploring concepts via simulations can be as effective, or more effective, than using comparable real-world tools (Finkelstein et al., 2005).

Though simulations have been found to be effective and accessible learning tools, more research is needed to identify how to incorporate simulations into classrooms to promote student learning (Chamberlain et al., 2014; Peperkorn et al., 2024). For example, simulations could be used to help students consolidate information after instruction. Alternatively, simulations could be used as exploratory learning about a new topic prior to instruction. This simple switch in sequencing may have marked impacts on how students engage with and learn the material.

Exploratory learning before instruction

A growing area of research is examining the conceptual and motivational benefits of exploring a new topic prior to receiving instruction. *Exploratory learning before instruction* flips the typical lecture-then-practice routine of traditional university instruction (e.g., DeCaro & Rittle-Johnson, 2012; Weaver et al., 2018). This constructivist-inspired method motivates students to begin creating their own knowledge, preparing them to learn from the subsequent instruction (Schwartz et al., 2011; Schwartz & Bransford, 1998; Schwartz & Martin, 2004). Though exploring a new topic often leads to errors, these errors help students' conceptual development, resulting in *productive failure* (Kapur, 2012, 2014, 2016). This explore-then-instruct sequence is described by several research areas, including productive failure (e.g., Kapur, 2016), inventing to prepare for future learning (e.g., Schwartz et al., 2011; Schwartz & Martin, 2004) and problem-solve-instruct methods (e.g., Loibl et al., 2024). As do others, we describe this explore-instruct sequence using more general terminology reflecting that students do not always fail during exploration, and not all exploration activities involve problem solving (cf. Bush et al., 2023; DeCaro & Rittle-Johnson, 2012; Weaver et al., 2018).

Research shows that exploring before instruction can be more beneficial than the reverse order (i.e., instruction then practice) on measures of conceptual understanding (Darabi et al., 2018; Loibl et al., 2017; Sinha & Kapur, 2021). Exploring can also lead to higher knowledge transfer than direct instruction methods—preparing students to apply what they know when learning subsequent material (Bego et al., 2022; Schwartz & Martin, 2004). Knowledge of basic facts and procedures does not typically differ between explore-first and instruct-first conditions, as exploratory learning targets deeper conceptual understanding (Kapur, 2016). These general outcomes extend across a variety of STEM domains, including biology (Chowrira et al., 2019; Halmo et al., 2020), mathematics (DeCaro & Rittle-Johnson, 2012; Hieb et al., 2021; Kapur, 2014; Loehr et al., 2014), physics (Bego et al., 2022; DeCaro et al., 2023; Weaver et al., 2018), psychology (Schwartz & Bransford, 1998), and statistics (Kapur, 2012). However, not all studies show benefits of exploring first (Chase & Klahr, 2017; Fyfe et al., 2014; Loibl et al., 2020; Nachtigall et al., 2020). Therefore, it is important to examine both when and why exploring before instruction benefits learning.

When students explore a new topic, they first consider what they already know, connecting this prior knowledge with the newly encountered information (Loibl et al., 2017; Newman & DeCaro, 2019). In doing so, learners become more aware of what they do, and do not, know—raising their awareness of their own knowledge gaps and motivating them to fill those gaps (Glogger-Frey et al., 2015; Loibl & Rummel, 2014). As students search the new problem space, they begin to discern various patterns and hypothesize about which features might be important (DeCaro & Rittle-Johnson, 2012; Kapur, 2010; Schwartz et al., 2007). They may also become curious to learn more (Loibl & Rummel, 2014).

Pairing this exploratory learning process with direct instruction afterwards helps to resolve these knowledge gaps, correct misconceptions and fulfil students' desire to learn more (Kapur, 2012). Students also create deeper conceptual structures, integrating their prior exploration experiences with the new information (Loibl & Rummel, 2015; Newman & DeCaro, 2019; Schwartz et al., 2007).

However, exploring before instruction can increase cognitive load (Ashman et al., 2020; Chen & Kalyuga, 2020; Fyfe et al., 2014; Newman & DeCaro, 2019). Students might not focus on the most important features (Velić & DeCaro, 2025). Exploratory learning activities should be designed to be challenging but not overwhelming and have multiple possible solution approaches but also some guidance (DeCaro, Bego, Thompson, & Velić, 2024; DeCaro, Bego, Velić, & Newman, 2024; Kapur, 2016).

Exploring simulations before instruction

Exploratory learning activities are typically designed as worksheets with problems to solve (e.g., Bego et al., 2022; Kapur, 2016; Loibl & Rummel, 2014). For example, exploration activities often require students to invent or generate solutions to math or science problems (e.g., Kapur, 2012; Schwartz et al., 2011). Few studies have incorporated virtual simulations as tools for exploration (Moser et al., 2017)—none in large, authentic classroom settings or with chemistry topics. Saba et al. (2023) found that a biology simulation-based activity given prior to, rather than after, instruction resulted in comparable conceptual learning and greater knowledge transfer for undergraduate students. Chin et al. (2016) found benefits for simulation-based exploratory learning when covering concepts in statistics with middle-school students. However, Chase and Klahr (2017) found no benefit of exploring before instruction for young children learning the control-of-variables strategy in experimental design. Klahr and Nigam (2004) found that exploring the control-of-variables simulation before instruction led to lower learning outcomes than receiving instruction before the simulation. Some argue that the null or negative results of these latter two studies were due to their use of an extensive pretest that was similar to the exploration activity. This pretest may have essentially provided an exploration experience in all conditions (Newman & DeCaro, 2019). Others suggest that the topic was too complex for young learners to benefit from exploring (Saba et al., 2023).

When using simulations as exploratory learning activities, the complexity and abundance of the simulation features are important to consider (Moore & Perkins, 2018). As many simulations are open-ended exploration spaces, they are often accompanied by some instructor-provided scaffolding. This guidance may take the form of a worksheet with probing questions or problems to solve (Roll et al., 2014). Providing learners with a brief explanation for how simulations work, as well as thought-provoking questions or problems, may narrow learner attention to specific simulation features that are key to learning (Sweller et al., 2019).

In addition to learning benefits, exploring using simulations has the potential to support students' motivation, including their curiosity, interest, and sense of self-efficacy/competence. According to Self-Determination Theory (Deci & Ryan, 2000), learners are more motivationally and cognitively engaged when learning is more self-directed (Ryan & Deci, 2020). This engagement can be found in situational interest and intrinsic motivation, in which learning material is considered enjoyable, captivating or stimulating (Glogger-Frey et al., 2015; Hidi & Renninger, 2006). Curiosity can also increase, which leads learners to want to learn more. Both simulations and exploratory learning have been shown to impact interest and curiosity (e.g., Bush et al., 2023; Watson et al., 2020; Weaver et al., 2018), though not always (e.g., Bego et al., 2022; Newman & DeCaro, 2019). In addition to increased autonomy or agency, learners also face and overcome their own challenges. Self-determination theory suggests that learners might increase their perceptions of competence or self-efficacy when engaging in self-directed learning, with intellectual and procedural support or scaffolding to ensure effective engagement with the material (Niemiec & Ryan, 2009). Few studies have tested this idea in the exploratory learning literature (cf. Loibl & Rummel, 2015).

Research examining the use of simulations as exploration activities has the potential to impact both research literatures. Exploration activities typically include problems to solve, yet similar learning mechanisms may underlie exploring with simulations. Simulations are typically used in inquiry learning or as consolidation after lecture. Simply changing the order of activity and instruction may change the way learners approach the information, deepening their resulting understanding. Combining simulations with exploration might also increase motivational and self-efficacy factors associated with students' willingness to persist in educational contexts (Chemers et al., 2011; Findley-Van Nostrand & Pollenz, 2017).

CURRENT RESEARCH

The current studies experimentally compared the use of a PhET atomic structure simulation as an exploration activity before lecture-based instruction (*explore-first condition*) to the same activity given after instruction (*instruct-first condition*), in large enrolment, introductory, undergraduate chemistry courses. Using the same activities in both conditions, and manipulating only the order of the simulation and instruction, allowed us to determine the causal impact of using the simulation as exploration versus consolidation. Thus, this research not only goes beyond simply examining whether simulations are effective but also investigates how they might be effectively used (Chamberlain et al., 2014; Peperkorn et al., 2024). This work extends the limited number of prior studies on exploring before instruction using simulations to large undergraduate classroom settings and to easily accessible, online simulations completed on students' own devices.

During exploration, students were given a worksheet including brief written instructions on how to operate the simulation and questions to answer using the simulation (e.g., Add another proton (two in total) to the nucleus, is this an atom? What is the name of the element?). Before (instruct-first condition) or after (explore-first condition) completing the simulation activity, the course instructor provided an in-class lecture on atomic structure.

We also examined two potential boundary factors that could impact whether exploring a simulation before instruction is effective. We tested whether prompting students for conceptual self-explanations during the simulation impacted learning outcomes (i.e., 'why' questions or not; Experiment 1). We also examined whether time on task—providing less (Experiment 1) or more (Experiment 2) time on the simulation—changed the pattern of results. In both studies, we assessed three types of learning outcomes (basic facts, concepts and transfer), all important to learning chemistry. We also included survey measures of motivation (i.e., interest, curiosity), perceived self-efficacy/competence and cognitive load. If cognitive load is too high, it can undermine students' ability or willingness to work on an activity (Chen & Kalyuga, 2020; DeCaro, Bego, Thompson, & Velić, 2024; DeCaro, Bego, Velić, & Newman, 2024).

Research questions

We investigated four primary research questions:

RQ1: Does using a chemistry simulation to explore atomic structure before instruction (explore-first condition) result in higher conceptual knowledge and transfer of knowledge, and equal fact-based learning scores, compared to receiving instruction prior to exploration (instruct-first condition)? (Experiments 1 and 2).

RQ2: Does the explore-first condition increase students' motivation (i.e., interest, curiosity) and self-efficacy/competence compared to the instruct-first condition? (Experiments 1 and 2).

RQ3: Does the type of prompting question (i.e., why-question prompts vs. no why-question prompts) provided during exploration impact conceptual and transfer learning outcomes? (Experiment 1).

RQ4: Does reducing/extending the time provided for simulation-based exploration impact learning or survey outcomes? (Experiment 1 vs. Experiment 2).

Hypotheses

H1: Consistent with previous research suggesting that an explore-first approach benefits conceptual knowledge and transfer (cf. Loibl et al., 2017; Schwartz & Martin, 2004; Sinha & Kapur, 2021), we hypothesized that students in the explore-first condition would score higher on conceptual and transfer items. Most prior exploratory learning studies use problem-solving tasks, and thus also assess procedural knowledge (e.g., ability to solve mathematics or physics problems; Loibl et al., 2017). Like the basic facts taught in the current study, the problem-solving procedures are directly taught in the lesson and require a lower level of conceptual engagement. Because the benefits of exploring before instruction are specific to sense-making processes, we predicted that there would be no significant difference between conditions on basic fact items (Kapur, 2016).

H2: Based on previous findings, we hypothesized that students in the explore-first condition would report equal or higher situational interest (Glogger-Frey et al., 2015; Kapur, 2014; Weaver et al., 2018), curiosity (Glogger-Frey et al., 2015) and cognitive load (DeCaro, Bego, Velić, & Newman, 2024; Newman & DeCaro, 2019; Velić & DeCaro, 2025), compared to students in the instruct-first condition. Perceived self-efficacy has not been measured in exploratory learning studies, but prior research has shown that self-efficacy improves with active learning (Ballen et al., 2017). Prior research has found no difference in perceived competence between explore-first and instruct-first conditions (Loibl & Rummel, 2015). We expected that self-efficacy and competence would be equal or higher in the explore-first compared to instruct-first condition.

H3: Research suggests that 'why' questions can better probe students' conceptual thinking (Melhuish et al., 2024). Such elaborative interrogation can help students connect prior knowledge with new information (Dunlosky et al., 2013). We predicted that students who completed worksheets with 'why' questions would be especially likely to benefit from exploratory learning, scoring higher on conceptual and transfer items. However, an alternative possibility is that such questioning is redundant with processes already occurring during exploration, and therefore would have no added benefit. The latter was found by DeCaro and Rittle-Johnson (2012), in a study examining children's learning mathematics from exploring before instruction.

H4: We expected to find benefits of exploring before instruction in both Experiments 1 and 2. In Experiment 1, students were given 5 min less time to work on the simulation activity than in Experiment 2. Examining whether this procedural change impacted the results allowed us to test an important potential boundary to these effects, namely whether explore-first benefits can be diminished when students are given insufficient time on the activity.

All data and materials for both experiments are available on the Open Science Framework (OSF) at https://osf.io/8bmfw/?view_only=e1bb6f74889941d3834b52fe3b3eb087.

EXPERIMENT 1

Method

Participants

Participants ($N = 168$; age $M = 18.85$, $SD = 2.38$; gender: 37.5% women, 52.3% men, 0.60% nonbinary, 9.5% no response) were undergraduate students at a Midwestern US metropolitan university who were enrolled across two sections of an introductory chemistry course taught by the same professor.

TABLE 1 Class session phases as a function of condition.

Instruct-first condition	Explore-first condition
Lecture (15 min)	Simulation activity (15 min)
Simulation activity (15 min)	Lecture (15 min)
Survey (5 min)	Survey (5 min)
Posttest (10 min)	Posttest (10 min)

Participants were included in the study if they attended class on the day of the experiment and completed the simulation activity, posttest, and survey. Additional students were excluded from analyses for arriving late to class and missing part of either the lecture or activity ($n = 3$) or for illegible handwriting on the posttest ($n = 1$).

Materials and design

Class sessions were divided into four phases: lecture, simulation activity, survey and posttest. A 2 (*order condition:* instruct-first, explore-first) × 2 (*prompt condition:* why-prompt, no why-prompt) between-subjects design was used. All materials were the same between order conditions, but the order of the lecture and simulation activity was switched (see Table 1). Students randomly assigned to the *instruct-first condition* ($n = 103$) first received a lecture on atomic structure, followed by the simulation activity. Students in the *explore-first condition* ($n = 65$) completed the simulation activity, followed by the lecture. Sample sizes were uneven due to attendance on the days of the study. During the simulation activity, students were also randomly assigned to the why-prompt or no why-prompt conditions. After completing both lecture and activity, students in all conditions completed the survey, then the posttest.

Simulation activity

For the *simulation activity*, students used their own devices to explore the *Build an Atom* Physics Education Technology (PhET) interactive simulation (https://phet.colorado.edu/en/simulations/build-an-atom) (Figure 2). During the activity, students completed a guided worksheet. The worksheet provided brief instructions on how to operate the simulation, along with guided questions (e.g., 'Place a neutron in the nucleus (total of 2). What is the name of the element? What is the mass number?'). Two different versions of the worksheet were provided for students in each condition. These versions were identical except that, in the *why-prompt condition*, learners were asked to provide explanations for some of their answers (e.g., 'why or why not?'). Six explanation prompts were given. Worksheets are provided in Appendix S1 (Figure 1).

Lecture

During the *lecture*, the instructor explained key concepts of atomic structure through direct instruction accompanied by presentation slides. The instructor introduced basic concepts of atoms, atomic structure, isotopes and atom identity.

Survey

The survey assessed motivation and other perceptions regarding the learning activities students had just completed. Students were informed that their responses would not be identifiable by the instructor. Except for the cognitive load item, subscale items were interleaved, and students were asked to indicate their agreement with statements on a 5-point Likert scale (1 = *Strongly Disagree*, 5 = *Strongly Agree*). Survey scales reported here were given in addition to other scales that were part of a larger study examining different research questions not relevant to the current study.

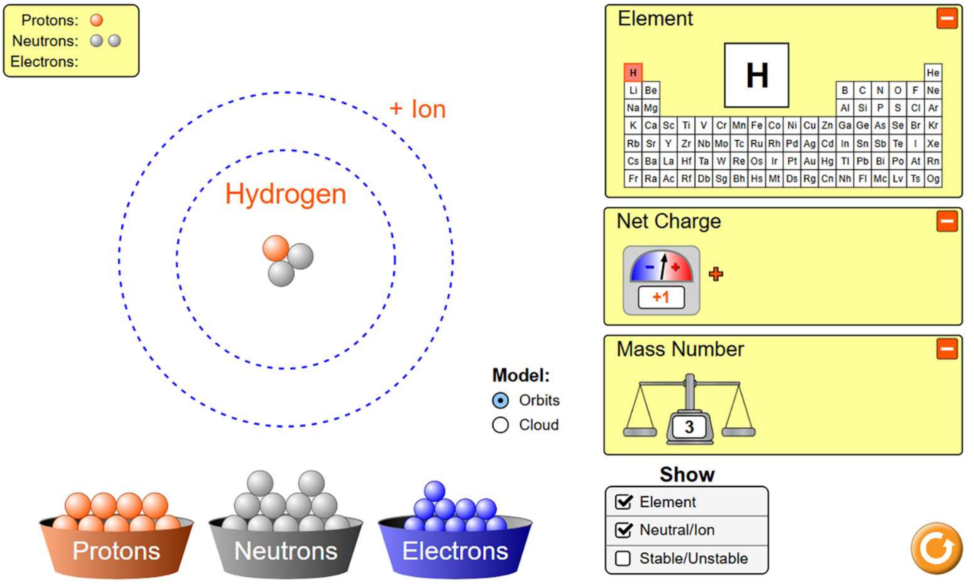

FIGURE 1 Build an atom PhET simulation. Students can change the number and types of particles in the atom. The element name, net charge and mass number are displayed, providing feedback as students explore. (*Source:* https://phet.colorado.edu/en/simulations/build-an-atom).

Students were asked to rate their *mental effort* as a more general measure of cognitive load used in prior exploratory learning studies (DeCaro, Bego, Thompson, & Velić, 2024; DeCaro, Bego, Velić, & Newman, 2024; Newman & DeCaro, 2019; Velić & DeCaro, 2025). This measure is consistent with Kalyuga and Singh's (2016) suggestion that exploration activities impact 'the intensity of cognitive activity involved in achieving a specific goal of the task' (p. 848). The Mental Effort Rating Scale (Paas, 1992) includes one item ('In completing the learning activities I invested…'), rated on a scale from 1 (*very, very low mental effort*) to 9 (*very, very high mental effort*). The remaining survey scales are listed in Appendix S2. Students rated their perceived *self-efficacy* and *competence* using items adapted from Findley-Van Nostrand and Pollenz (2017) and Sheldon et al. (2001) (e.g., *Now that I've completed today's activities, I feel confident in my ability to learn this topic; Thanks to today's learning activities, I feel more competent in this topic area*). *Situational interest* was assessed using items adapted from Rotgans and Schmidt (2014) (e.g., *I think this topic is interesting*). *Curiosity* was assessed using items adapted from Naylor (1981) (e.g., *I wanted to know more about what I was working on*). Items from these scales were interspersed with each other and with other measures given as part of another study. Mental effort, situational interest, and curiosity items have been used in prior exploratory learning research (DeCaro, Bego, Thompson, & Velić, 2024; DeCaro, Bego, Velić, & Newman, 2024; Glogger-Frey et al., 2015; Newman & DeCaro, 2019). The self-efficacy and competence scales were adapted and shortened from longer existing scales, due to limited classroom time. This method has the potential to reduce reliability of the scales, but provided an initial test of the impact of exploration on these constructs, and these items have been used in prior research (DeCaro, Bego, Thompson, & Velić, 2024).

Finally, students provided demographic information, including a question assessing students' reported prior knowledge on the topic ('Before you completed the materials today, how much did you know about these specifics topics?' 0 = *Not at all* to 4 = *Very much*). This item has been used in prior research to determine whether self-reported prior knowledge was equivalent between conditions, ensuring random assignment (Newman & DeCaro, 2019; Velić & DeCaro, 2025).

Posttest

The posttest included 12 questions developed by two chemistry professors involved in the study, consistent with a call for a more ecologically valid approach to research materials (Chowrira et al., 2019).

The posttest targeted three knowledge types. Knowledge of *basic facts* was assessed with facts directly taught in the lecture (6 items, 6 points possible; $\alpha = .90$; e.g., 'What is the name of a particle that has no charge?'). *Conceptual knowledge* items assessed understanding of the underlying principles of atomic structure (6 items, 10 points possible; $\alpha = .52$, e.g., 'Why is the atom a neutral entity?'). The *transfer* item assessed students' ability to extend the principles learned to answer a novel question on a related topic (1 item, 2 points possible; i.e., 'What is the charge of an ion that has 12 protons and 13 electrons? Explain your answer.'). All posttest items required short answer responses. All items and scoring rubric are in Appendix S3.

Procedure

Students were enrolled in two sections of an introductory chemistry course taught by the same instructor in a large lecture hall in a 50-minute session. The course included primarily first-semester students and was required for students across a variety of majors (e.g., chemistry, engineering). Students were randomly assigned to conditions and asked to attend class on one of two separate days of the study. Students assigned to attend the Wednesday session participated in the instruct-first condition, and students assigned to the Friday session completed the explore-first condition. The two worksheet types were interleaved, and students were randomly assigned to prompt conditions by which worksheet they received.

The instructor began class by informing students that the class activities were part of a research study on student learning and that the assignments would not be included in their course grades. Students were told that it was okay if they did not know the answers to the activities, and to try their best. Students in the instruct-first condition first received the lecture (15 min), followed by the simulation activity (15 min). In contrast, students in the explore-first condition first completed the simulation activity, followed by the lecture. On the activity, students were told they could work together or alone; most worked alone. Students in both conditions then used their devices (i.e., computers or cell phones) to complete the survey (5 min). Finally, students were instructed to put their computers and notes away and complete the posttest, which was referred to as a 'practice test' (10 min). At the end of the semester, students were emailed with information about the study and given the option to withdraw their data from analyses. All study procedures were approved by the university Institutional Review Board (#20.0415).

Results

Prior knowledge

Students' reported prior knowledge did not differ between the instruct-first ($M = 3.42$, $SE = .09$, 95% CI [3.24, 3.60]) and explore-first order conditions ($M = 3.57$, $SE = .12$, 95% CI [3.32, 3.81]), $F < 1$, $p = .350$, $\eta_p^2 = .01$.

Posttest

We analysed posttest scores using a 2 (*order condition*: instruct-first, explore-first) × 2 (*prompt condition*: why-prompts, no why-prompts) between-subjects ANOVA for each subscale separately. For the *basic facts* scale, no main effect of order condition, $F < 1$, $p = .717$, $\eta_p^2 = .00$, prompt condition $F(1, 164) = 3.06$, $p = .082$, $\eta_p^2 = .02$, or interaction, $F < 1$, $p = .720$, $\eta_p^2 = .00$, were found (see Table 2, Figure 2).

We used planned comparisons to split the sample by prompt condition, to examine the impact of order separately for the why-prompt and no why-prompt conditions. The effect of order was not

TABLE 2 Descriptive statistics for Experiment 1 posttest.

	Explore-first						Instruct-first					
	Why prompts (n = 31)			No why prompts (n = 34)			Why prompts (n = 54)			No why prompts (n = 49)		
	M	*SE*	95% CI	*M*	*SE*	95% CI	*M*	*SE*	95% CI	*M*	*SE*	95% CI
Basic facts	97.85	3.04	[91.84, 103.86]	94.12	2.90	[88.38, 99.86]	97.84	2.31	[93.29, 102.39]	92.18	2.42	[87.40, 96.96]
Conceptual knowledge	34.52	3.47	[27.66, 41.37]	35.29	3.30	[28.75, 41.84]	42.04	2.63	[36.84, 47.23]	42.86	2.76	[37.40, 48.31]
Transfer	59.68	6.40	[47.05, 72.31]	69.12	6.10	[57.06, 81.18]	64.82	4.85	[55.24, 74.39]	67.35	5.09	[57.30, 77.39]

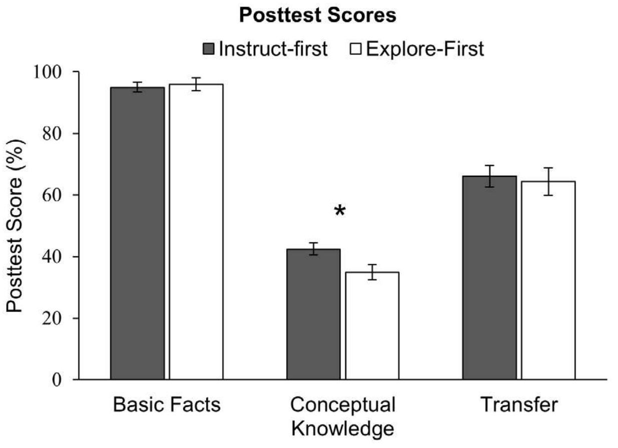

FIGURE 2 Experiment 1 posttest scores as a function of order condition and posttest subscale. Error bars represent ±1 standard error of the mean. *$p < .05$.

significant for either the why-prompt, $F < 1$, $p = .995$, $\eta_p^2 = .00$, or no why-prompt conditions, $F < 1$, $p = .708$, $\eta_p^2 = .00$ (see Table 2).

For the *conceptual knowledge* scale, a main effect of order was found, $F(1, 164) = 6.05$, $p = .015$, $\eta_p^2 = .04$. Contrary to hypotheses, students in the instruct-first condition ($M = 42.45\%$, $SE = 1.91$, 95% CI [38.68, 46.21]) scored significantly higher than those in the explore-first condition ($M = 35.91\%$, $SE = 2.40$, 95% CI [31.17, 39.65]; Figure 2). There was no effect of prompt condition, $F < 1$, $p = .795$, $\eta_p^2 = .00$, or interaction, $F < 1$, $p = .995$, $\eta_p^2 = .00$ (see Table 2).

This pattern of results was the same when examining each prompt condition separately, though the significance was reduced due to the smaller sample size when splitting the sample. There was a trending effect of order for the why-prompt condition, $F(1, 83) = 3.25$, $p = .075$, $\eta_p^2 = .04$, and no why-prompt condition, $F(1, 81) = 2.83$, $p = .096$, $\eta_p^2 = .03$, with higher scores in the instruct-first order (Table 2).

On the *transfer* scale, no significant effects were found for order, $F < 1$, $p = .766$, $\eta_p^2 = .00$, prompt condition, $F(1, 164) = 1.12$, $p = .291$, $\eta_p^2 = .01$, or the interaction, $F < 1$, $p = .542$, $\eta_p^2 = .00$ (Figure 2, Table 2). This was also the case when splitting the sample by prompt condition: why-prompt condition, $F < 1$, $p = .542$, $\eta_p^2 = .00$, no why-prompt condition, $F < 1$, $p = .815$, $\eta_p^2 = .00$.

Survey

Survey data were missing for some students on some subscales. Because there were no effects of prompt condition on the posttest scores, we collapsed across this factor for the survey analyses, for simplicity. Descriptive statistics are shown in Table 3.

For mental effort, no differences were found between instruct-first and explore-first conditions, $F(1, 166) = 2.68$, $p = .104$, $\eta_p^2 = .02$. Scores were somewhat above the midpoint of 5 on the 9-point scale, indicating 'rather high mental effort' in the explore-first condition.

A multivariate analysis of variance (MANOVA) was used to examine the differences between order conditions on the other survey items. There was an overall significant main effect of order, $F(4, 161) = 3.10$, $p = .017$; Wilks' $\Lambda = .928$, $\eta_p^2 = .07$. Examining each scale individually, curiosity was significantly higher in the instruct-first compared to the explore-first condition, $F(1, 164) = 4.71$, $p = .031$, $\eta_p^2 = .03$. No significant differences were found for situational interest, $F < 1$, $p = .639$, $\eta_p^2 = .00$, self-efficacy, $F(1, 164) = 1.71$, $p = .192$, $\eta_p^2 = .01$, or competence, $F(1, 164) = 2.92$, $p = .090$, $\eta_p^2 = .02$.

TABLE 3 Descriptive statistics for Experiment 1 survey scales.

	Explore-first			Instruct-first		
	M	*SE*	95% CI	*M*	*SE*	95% CI
Mental effort	6.03	.19	[5.66–6.40]	5.64	.15	[5.35–5.93]
Self-efficacy	4.13	.07	[4.00–4.26]	4.02	.05	[3.92–4.13]
Curiosity	**3.63**	**.08**	**[3.48–3.78]**	**3.84**	**.06**	**[3.72–3.96]**
Competence	3.93	.09	[3.76–4.10]	3.74	.07	[3.61–3.88]
Situational interest	3.86	.08	[3.70–4.02]	3.91	.07	[3.78–4.04]

Note: Bold values denote statistical significance at the $p<.05$ level. Mental effort was measured on a 9-point scale; all others on a 5-point scale.

Discussion

Consistent with hypotheses, the instruct-first and explore-first approaches resulted in equal scores on basic facts that were directly taught in lecture. Inconsistent with hypotheses, students in the instruct-first condition scored significantly higher than students in the explore-first condition on conceptual knowledge items. No difference was found for knowledge transfer to a new, related item. Students in the instruct-first condition also reported higher curiosity than those in the explore-first condition. All other survey results were equal between order conditions.

One observation made during the sessions was that students did not have time to finish the learning activity. This observation is consistent with the finding that students scored a little above the midpoint on the mental effort item in both conditions, around the 'rather high mental effort' point (6 on a 9-point scale). Given the complexity of the simulation environment, it is possible that 15 min was an insufficient amount of time for students to explore critical conceptual features. The amount of time provided for exploration activities varies greatly throughout the literature, and no two simulations are identical in this respect. However, studies showing benefits for simulation-based learning sometimes provide more than what we allowed during Experiment 1 (Roll et al., 2014, 25 min for exploration). With additional time provided during the simulation activity, it is possible that students would be better able to discern conceptually relevant problem features, deepening their learning.

Prompting students to provide conceptual explanations while using the simulation did not result in higher conceptual knowledge in either condition. Prior research suggests that elaborative interrogation (i.e., asking 'why' questions) deepens the connections students make between old and new knowledge, strengthening learning and memory for these topics (Dunlosky et al., 2013). It is possible that we would have found a benefit for the why-prompt condition with more time to explore. Without sufficient time, students might not have been able to fully engage in the question prompts. However, DeCaro and Rittle-Johnson (2012) compared explore-first conditions with and without a self-explanation prompt and also found no differences. Exploring before instruction benefited conceptual understanding overall, regardless of whether students self-explained or not. It is likely that exploring promotes sense-making processes, with or without explicit prompts to do so (DeCaro, Bego, Velić, & Newman, 2024). We did not examine this question further in Experiment 2, instead using only the why-prompt worksheets during the simulation activity and focusing on the main research questions regarding order of simulation and instruction.

EXPERIMENT 2

Experiment 2 further assessed the potential benefits of exploring a simulation before instruction by examining whether providing more time to explore would improve learning. As in Experiment 1, students either completed a simulation-based activity before (explore-first condition) or after instruction (instruct-first condition). The simulation activity was identical to the one used in

Experiment 1, except that all versions of the activity worksheet included 'why' questions, and students were given an additional 5 min to complete the activity. The survey used in Experiment 2 also added items assessing active, constructive, and interactive engagement. These items were based on ICAP theory, which predicts learning outcomes based on students' level of engagement. Interactive engagement is considered the highest level, and passive engagement the lowest of the four (Chi et al., 2018; Chi & Wylie, 2014). *Interactive engagement* involves engaging in constructive dialogue with one or more partners. *Constructive engagement* requires students to generate new knowledge beyond what is provided to them. *Active engagement* includes rote practice, manipulating, or rehearsing information. *Passive engagement* involves passively receiving information from a lecture or reading, without otherwise cognitively engaging. Because all students engaged in a simulation activity, we presumed they were engaged to a higher degree than passive and therefore did not measure this level. The cognitive engagement measure was adapted from prior items and therefore was used only as an exploratory measure in this study.

We predicted that, given additional time, students in the explore-first condition would demonstrate higher conceptual knowledge and transfer compared to students in the instruct-first condition, while scoring equally well on fact-based items. We also predicted that students in the explore-first condition would report equal or higher cognitive load, situational interest, curiosity, self-efficacy and competence. Prior exploratory learning research has not assessed active, constructive, and interactive cognitive engagement. We were interested in whether students would be more engaged, and at a higher level, in the explore-first condition.

Methods

Participants

Participants ($N = 357$; age $M = 18.91$, $SD = 2.39$; gender: 44.5% female, 50.7% male, 0.8% nonbinary, 0.3% gender fluid, 3.6% no response) were undergraduate students from the same university and course as in Experiment 1, enrolled across two different semesters. Students in one semester were enrolled across two course sections and randomly assigned to condition in the same way as in Experiment 1. Due to restrictions in the course schedule, students in the second semester were randomly assigned based on which of two course sections they were enrolled in (i.e., one course section was randomly assigned to receive the explore-first condition, and one section received the instruct-first condition). Students were included in the study if they attended class on the day of the experiment and turned in the simulation activity, survey and posttest. Additional students ($n = 5$) were excluded from analyses for arriving late to class and missing content. One additional class section was excluded from analyses because students did not get the full time on the posttest, and many did not finish.

Materials, design and procedure

Students were randomly assigned to the instruct-first condition ($n = 229$) or the explore-first condition ($n = 128$[1]). The lecture and simulation activity were the same as in Experiment 1 except that all students completed worksheets with 'why' prompts, and students were given 20 min on the activity. There were also very slight differences in the activity instructions. We used the same survey questions as in Experiment 1, with two exceptions. First, the self-efficacy items omitted the first part

[1]The second-semester instruct-first class section was larger than the explore-first section, resulting in unequal sample size. In the first semester, students were randomly assigned to condition within each course section, and sample sizes were similar between conditions. The statistical significance of results is the same with and without including the second-semester sample in the dataset.

TABLE 4 Descriptive statistics for Experiment 2 posttest.

	Explore-first			Instruct-first		
	M	*SE*	95% CI	*M*	*SE*	95% CI
Basic facts ($\alpha = .82$)	96.75	1.15	[94.49, 99.00]	96.58	.86	[94.89, 98.27]
Conceptual knowledge ($\alpha = .58$)	**52.58**	**2.04**	**[48.56, 56.60]**	**37.64**	**1.53**	**[34.64, 40.65]**
Transfer	**80.86**	**3.74**	**[73.52, 88.20]**	**61.79**	**2.79**	**[56.30, 67.28]**

Note: Bold values denote statistical significance at the $p < .05$ level.

(e.g., "Thanks to today's learning activities…"). Second, we added three subscales assessing active, constructive and interactive engagement. These items were adapted from McEldoon (2014) and based on Chi et al.'s (2018) ICAP framework (see Appendix S2). The procedure was otherwise identical to Experiment 1.

Results

Prior knowledge

As with Experiment 1, reported prior knowledge was similar between students in the instruct-first ($M = 3.16$, $SE = .06$, 95% CI [3.04, 3.28]) and explore-first ($M = 3.02$, $SE = .08$, 95% CI [2.86, 3.18]) order conditions, $F(1, 345) = 1.99$, $p = .159$, $\eta_p^2 = .01$. This finding suggests that random assignment to condition was successful.

Posttest

Descriptive statistics for the posttest are in Table 4 (see also Figure 3). For the *basic facts* scale, there remained no difference as a function of order, $F < 1$, $p = .908$, $\eta_p^2 = .00$. Conversely, for *conceptual knowledge*, students in the explore-first order condition scored significantly higher than those in the instruct-first condition, $F(1, 355) = 34.30$, $p < .001$, $\eta_p^2 = .09$. *Transfer* scores were also significantly higher for students in the explore-first condition than for those in the instruct-first condition, $F(1, 355) = 16.72$, $p < .001$, $\eta_p^2 = .05$.

Survey

Descriptive statistics for the survey subscales are found in Table 5. Order condition did not impact students' reported mental effort, $F(1, 348) = 1.66$, $p = .199$, $\eta_p^2 = 01$, which was also slightly lower than in Experiment 1 (between 'neither low nor high mental effort' and 'rather high mental effort').

Using a MANOVA for the other four survey scales used in Experiment 1, there was an overall significant order effect, $F(4, 352) = 3.39$, $p = .010$; Wilks' $\Lambda = .963$, $\eta_p^2 = .04$. Examining each individual scale, students in the explore-first order condition gave higher ratings for curiosity, $F(1, 355) = 7.90$, $p = .005$, $\eta_p^2 = .02$, situational interest, $F(1, 355) = 6.69$, $p = .010$, $\eta_p^2 = .02$, self-efficacy, $F(1, 355) = 4.02$, $p = .046$, $\eta_p^2 = .01$, and competence, $F(1, 355) = 10.01$, $p = .002$, $\eta_p^2 = .03$.

A separate MANOVA was used to examine the effects of order on the three cognitive engagement subscales. Overall, students in the explore-first condition reported higher engagement than students in the instruct-first condition, $F(3, 343) = 3.21$, Wilks' $\Lambda = .973$, $\eta_p^2 = .03$. Of the separate subscales, the order effect was not significant for the active, $F(1, 345) = 1.93$, $p = .166$, $\eta_p^2 = .01$, or constructive subscales, $F(1, 345) = 3.71$, $p = .055$, $\eta_p^2 = .01$. Order was significant for the interactive subscale, $F(1, 345) = 8.09$, $p = .005$, $\eta_p^2 = .02$.

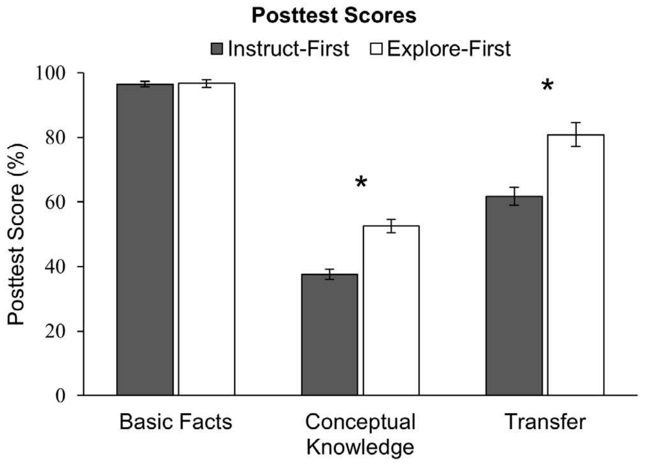

FIGURE 3 Experiment 2 posttest scores as a function of condition and posttest subscale. Error bars represent ±1 standard error of the mean. *$p < .05$.

TABLE 5 Descriptive statistics for Experiment 2 survey.

	Explore-first			Instruct-first		
	M	*SE*	95% CI	*M*	*SE*	95% CI
Mental effort	5.53	.14	[5.25–5.81]	5.30	.11	[5.09–5.51]
Self-efficacy	**4.34**	**.05**	**[4.24–4.43]**	**4.22**	**.04**	**[4.15–4.29]**
Curiosity	**3.76**	**.06**	**[3.64–3.88]**	**3.55**	**.05**	**[3.46–3.64]**
Competence	**3.77**	**.07**	**[3.64–3.90]**	**3.51**	**.05**	**[3.41–3.61]**
Situational interest	**3.90**	**.06**	**[3.78–4.02]**	**3.70**	**.05**	**[3.61–3.79]**
Active engagement	4.18	.05	[4.08–4.28]	4.09	.04	[4.02–4.16]
Constructive engagement	3.81	.06	[3.69–3.94]	3.66	.05	[3.57–3.75]
Interactive engagement	**2.82**	**.08**	**[2.66–2.99]**	**2.53**	**.06**	**[2.41–2.65]**

Note: Bold values denote statistical significance at the $p < .05$ level. Mental effort (cognitive load) was measured on a 9-point scale; all others on a 5-point scale.

Discussion

Consistent with hypotheses, students who explored the simulation before lecture scored higher on the conceptual knowledge and transfer posttest scales than students who completed the simulation after lecture. Knowledge of basic facts was high, and equal between conditions. Students who explored first also reported higher curiosity, situational interest, competence, and self-efficacy. Overall cognitive engagement was also higher, including on the interactive engagement subscale. Thus, exploring first had multiple benefits when students were given additional time on the activity.

GENERAL DISCUSSION

A number of studies demonstrate the learning and motivational benefits of augmenting instruction with simulations (e.g., Chernikova et al., 2020; Smetana & Bell, 2012), including in chemistry education (e.g., Josephsen & Kristensen, 2006; Watson et al., 2020). However, best practices for how to use simulations are less clear (Chamberlain et al., 2014; Moore et al., 2013). We investigated whether providing a simulation before, rather than after, an undergraduate chemistry lecture improved students' learning, motivation, and other factors. We expected that using the exact same learning materials, but switching their order, would change how students approach the learning activities from a cognitive (learning) and motivational standpoint. For example, when the simulation occurs before instruction, students must make sense of what they observe. They may begin to discern important conceptual structures that help them to better understand the meaning of the subsequent lecture (Schwartz et al., 2011; Schwartz & Bransford, 1998). A more traditional instruct-first order might instead be more likely to lead to superficial processing and rote understanding (Freeman et al., 2014; Schwartz et al., 2011). In line with these ideas, we found that completing a simulation-based activity before instruction (i.e., *explore-first* condition), rather than after instruction (i.e., *instruct-first* condition) improved conceptual knowledge and transfer of this knowledge.

However, this benefit only occurred when students were provided sufficient time on the exploration activity (Experiment 2). When the activity time was too short, these learning benefits were reversed (Experiment 1). Research using an explore-instruct sequence does not always find benefits compared to an instruct-first approach. This work identifies an important boundary condition that could help explain prior results as well as continue to develop theory as to why exploration helps. These findings suggest that the activity must be designed so that students have sufficient time to explore, or exploring before instruction could worsen learning outcomes. Without sufficient time, students may be less able to discern the important underlying features (Schwartz et al., 2007). For example, in the chemistry simulation used in this research, students could observe the way certain sub-atomic particles attract and repel each other, whether they can be placed in the nucleus or in the orbitals, whether adding or removing the particles results in an atom, ion or an isotope, and so forth. These were all important observations for building students' conceptual understanding beyond simply hearing this information in a lecture. However, these observations take some time to reflect on and interact with in the simulation. Instructors should be mindful of how long students need to sufficiently explore the problem space.

This idea is supported by comparing the descriptive statistics for mental effort between Experiments 1 (shorter activity time) and 2 (longer activity time). The means for each experiment fell outside of the confidence intervals of the other experiment, suggesting that mental effort was higher in Experiment 1. Prior research has suggested that activities should be designed to be challenging, but not too taxing on students' cognitive resources (Kapur, 2016). Otherwise, the benefits of exploring before instruction could nullify or reverse (Ashman et al., 2020; DeCaro, Bego, Thompson, & Velić, 2024; DeCaro, Bego, Velić, & Newman, 2024; Fyfe et al., 2014; Newman & DeCaro, 2019). Providing more time may have supported students' capacity to engage with, and benefit from, the simulation activity.

The benefits of exploration were specific to assessments of conceptual understanding and transfer of knowledge. Knowledge of basic facts was similar (and high) in both explore-first and instruct-first conditions. These findings suggest that using simulations as exploratory learning tools is most useful when the goal is higher-level sense-making (see Loibl et al., 2024). If instructors wish to teach basic facts, using simulations either before or after instruction will likely have comparable results. These results are consistent with prior research showing that basic problem-solving procedures are typically learned no differently between explore-first and instruct-first conditions (Loibl et al., 2017) but extend such results to basic facts rather than computations.

These results resemble those from multiple literatures using an explore-instruct sequence, with largely the same proposed underlying learning mechanisms. However, prior research using this sequence rarely uses interactive simulations. For example, exploration activities from the problem-solve-instruct literature use this sequence with problems to be solved (e.g., Loibl et al., 2024; Loibl & Rummel, 2014). Similarly, activities from the preparation for future learning literature typically ask students to invent solutions to problems (e.g., Schwartz et al., 2011; Schwartz & Martin, 2004). Activities used in the productive failure literature typically require students to generate multiple solutions (e.g., Kapur, 2012, 2014; Trninic et al., 2022). Across these literatures, it is expected that students will likely fail to derive a canonical solution. The process of exploration supports conceptual learning. When using the simulation in the current research, students do not necessarily 'fail,' because they are not solving problems. Yet, they are still likely engaging in sense-making and observation processes. These overarching processes align across these literatures to explain why exploration before instruction is useful. Demonstrating that a different type of activity—outside of problem solving—had similar benefits extends this research more broadly.

Exploring also had motivational benefits when students were given sufficient time to engage with the learning material. Without sufficient time (Experiment 1), students in the explore-first condition reported significantly lower curiosity than students in the instruct-first condition. However, exploring first did not reduce their situational interest, self-efficacy, or competence, nor did reported mental effort increase compared to the instruct-first condition. These findings largely reversed when given more activity time (Experiment 2). Although mental effort remained equal between conditions, students in the explore-first condition reported higher curiosity, interest, self-efficacy, and perceived competence. Some prior studies have found higher curiosity or interest in explore-first conditions (e.g., Bush et al., 2023; Weaver et al., 2018), though not all (e.g., Bego et al., 2022; Newman & DeCaro, 2019).

These results suggest that, when given sufficient time to engage in self-directed learning, the benefits of exploration went beyond learning to support motivation (i.e., interest and curiosity) as well. These results align with Hidi and Renninger's (2006) model of interest development, which suggests that the learning context can initially trigger students' interest and can be maintained through personal involvement in the task. Interest at this stage is externally maintained, and cutting the time to explore short in Experiment 1 likely undermined this process.

Moreover, few studies have examined the impact of exploratory learning on self-efficacy and competence, although these factors have been supported by active learning more generally (Ballen et al., 2017). One possibility is that experiencing, and overcoming, the conceptual challenges of exploratory learning supported students' feelings of efficacy and competence (Ballen et al., 2017). When paired with direct instruction after exploring, students were able to engage in self-directed learning, but also experience guidance to support their competence (Ryan & Deci, 2020). Alternatively, these results might accurately reflect students' knowledge of the topic, given that students in the explore-first condition both reported higher self-efficacy/competence and demonstrated greater learning outcomes. All of these factors (i.e., interest, curiosity, self-efficacy, competence) are associated with students' willingness to persist in educational domains (Chemers et al., 2011; Findley-Van Nostrand & Pollenz, 2017). Thus, the potential benefits of exploring a simulation before instruction may extend beyond the lesson, although more research is needed to directly test this idea.

We also piloted a new measure of cognitive engagement in Experiment 2, developed based on ICAP theory (Chi & Wylie, 2014). Students in the explore-first condition reported higher overall cognitive engagement when accounting for active, constructive, and interactive engagement simultaneously. Examining each subscale separately, all three showed a pattern in this same direction, with statistically significant results for the interactive engagement scale. Interactive engagement is considered the highest level in which students engage in constructive dialogue that enables them to generate new ideas and conceptual connections. Exploring a simulation may help support such constructive dialogue. These findings suggest that the benefits of exploratory learning extend to cognitive engagement as well.

Limitations and future research

The current findings are limited to one specific simulation activity, targeting introductory level concepts. More research is needed to extend these findings to other simulation activities across different topics. Many elements of simulations can be tailored to the needs of each classroom or research setting, so future work might alter the structure or layout of simulations to investigate which simulation features are responsible for fostering motivation and conceptual understanding.

Related to this idea, we compared activity worksheets that included self-explanation ('why') prompts, or not, in Experiment 1. Overall, we found no differences between these prompt conditions. We focused only on order effects in Experiment 2, and used only worksheets with 'why' prompts. Thus, our results do not fully speak to whether these prompts are necessary or helpful during a properly designed simulation activity (i.e., one that gives students sufficient time, and benefits learning). It is possible that these prompts are not necessary, given that students are likely engaging in sense-making processes on their own while exploring (DeCaro & Rittle-Johnson, 2012). However, more work is needed to fully test this idea.

We also included a general measure of cognitive load, operationalized as mental effort, consistent with several other exploratory learning studies (DeCaro, Bego, Thompson, & Velić, 2024; DeCaro, Bego, Velić, & Newman, 2024; Newman & DeCaro, 2019; Velić & DeCaro, 2025). We used this measure to assess whether our exploration activity overly taxed students, and were therefore most interested in this general perception of mental effort. However, cognitive load is often measured as multiple types of load, such as intrinsic and extraneous. Some types of cognitive load can be helpful to learners, whereas other types are not (Sweller et al., 2019). Future research would be useful to determine how different types of cognitive load are impacted during exploration.

CONCLUSION

The current research demonstrated that simulations can be an effective exploratory learning tool in the classroom, broadening our understanding of what sort of activities can be used for exploration. Allowing students to explore a simulation before instruction can deepen their learning, motivation, self-efficacy/competence and cognitive engagement. Exploring with simulations seems to be most effective when the learning goals are conceptual, rather than focused on basic facts. Students must also be given sufficient time to fully engage in these sense-making processes. As conceptual sense-making supports students' greater scientific thinking (Hunter et al., 2021), exploring with simulations is a promising instructional method.

AUTHOR CONTRIBUTIONS

Marci S. DeCaro: Conceptualization; methodology; funding acquisition; resources; investigation; supervision; project administration; writing – original draft; visualization; formal analysis. **Derek K. McClellan:** Investigation; writing – original draft; data curation; visualization. **Ryan Patrick:** Data curation; writing – original draft; investigation; visualization. **Aleeta M. Powe:** Conceptualization; methodology; investigation; writing – review and editing; resources. **Danielle Franco:** Conceptualization; methodology; investigation; resources; writing – review and editing. **Raymond J. Chastain:** Conceptualization; methodology; writing – review and editing; funding acquisition; investigation. **Linda Fuselier:** Conceptualization; methodology; funding acquisition; writing – review and editing; investigation. **Jeffrey L. Hieb:** Conceptualization; methodology; investigation; funding acquisition; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to declare that are relevant to the content of this article.

DATA AVAILABILITY STATEMENT

Data for this article are available at Open Science Framework (OSF) at https://osf.io/8bmfw/?view_only=e1bb6f74889941d3834b52fe3b3eb087.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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