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Interactive computer-based simulations as exploratory learning activities.

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INTERACTIVE COMPUTER-BASED SIMULATIONS AS EXPLORATORY LEARNING ACTIVITIES

By

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M.S., Eastern Kentucky University, 2018
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ABSTRACT

INTERACTIVE COMPUTER-BASED SIMULATIONS AS

EXPLORATORY LEARNING ACTIVITIES

Derek McClellan

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Typical college lectures follow a direct instruction framework, where instructors deliver a lecture, followed by an activity. Exploratory learning flips this routine by providing students with an activity prior to instruction. Research suggests that this inversion benefits students' conceptual understanding and ability to transfer their knowledge. The majority of exploratory learning tasks in the literature are problem-solving activities. The current work investigates the use of computer-based simulations during exploratory learning, and whether manipulating the cognitive load of the activity impacts learning. In Experiment 1, undergraduate students (*N*=66) were randomly assigned to explore a simulation-based circuit construction activity prior to instruction (explore-first) or receive instructions on the topic prior to the activity (instruct-first). The learning assessment consisted of conceptual knowledge and transfer of knowledge to a similar topic. Participants in the instruct-first condition scored higher on the assessment than participants in the explore-first condition, and reported lower cognitive load. In Experiment 2, participants received one of two versions of the exploration activity, designed to provide stronger guidance and reduce intrinsic or extraneous cognitive load.

Undergraduate students (N=195) were randomly assigned to one of four conditions based on order (explore-first or instruct-first) and cognitive load reduction type (intrinsic load reduction or extraneous load reduction). Participants in the intrinsic load reduction conditions scored at an equal level on conceptual knowledge, and higher on transfer, compared to participants in the extrinsic load reduction conditions, regardless of order. Across both experiments, participants in the explore-first conditions reported motivational benefits (higher curiosity and higher perceived knowledge gaps). Yet the instruct-first approach led to higher learning, suggesting that these components are not enough for effective exploratory learning, even when reducing intrinsic cognitive load through guidance. Simulation environments may be too complex for students to effectively explore the deep problem features that otherwise provide conceptual advantages.

Keywords: *exploratory learning, interactive simulations, educational technology, cognitive load, STEM education*

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CHAPTER I: INTRODUCTION

Science, technology, engineering, and mathematics (STEM) undergraduate classes typically follow a *direct instruction* framework, consisting of a lecture, and sometimes a subsequent practice activity (Stains et al., 2018). This instructor-centered approach places the teacher as a locus of knowledge, and students as passive recipients of knowledge (Hovey et al., 2019), consequently lowering student agency (Zeiser et al., 2018) and engagement in the classroom (Hovey et al., 2019). Some pedagogical research challenges this framework, advocating for students to become more active agents in the learning process through constructivist methods. In contrast to traditional tell-then-practice instruction, constructivist methods task students with constructing their own knowledge through trial-and-error experiences (Prince, 2004; Schwartz et al., 2011).

Exploratory learning is a constructivist-inspired method that reverses the typical classroom routine, providing students with an activity prior to receiving instructions on the to-be-learned topic (DeCaro & Rittle-Johnson, 2012). Exploratory learning activities often task students with solving novel problems (Kapur, 2012). Such problems can take a variety of forms, such as providing 'real-world' physics problems students must invent solutions to (Schwartz et al., 2011), or intentionally ill-defined mathematics questions (Kapur, 2010).

Though exploratory learning activities are usually completed independently, some level of scaffolding can be provided through contrasting cases (Bego et al., 2023; Schwartz et al., 2011), prompts (Holmes et al., 2014), or partially completed worked examples (Newman & DeCaro, 2019; Schwartz & Martin, 2004). These activity-first approaches are researched under several terms, including problem-solving by invention (Loibl et al., 2017), preparation for future learning (Schwartz & Martin, 2004), and productive failure (Kapur, 2014). For the purposes of this work, all such activity-first approaches will be referred to as *exploratory learning* (DeCaro & Rittle-Johnson, 2012; Weaver et al., 2018).

By combining exploration with a learning resource (e.g., instructions), exploratory learning is designed to avoid the problems that pure discovery learning is commonly criticized for—namely, that exploring without instruction can cause confusion and rehearsal of erroneous problem-solving solutions (Mayer, 2004). This reversed instructional sequence is intended to correct misconceptions acquired during the exploration process (Schwartz & Bransford, 1998). Furthermore, unlike pure discovery learning methods, learners need not arrive at a correct solution for exploration to be deemed a success, as research suggests that the quality of solutions while exploring does not hinder future learning (Kapur, 2016). Contrarily, through exploratory learning, students seldom arrive at the canonical solutions on their own (Kapur, 2012). Despite the quality of students' solutions, research shows that through 'productive failure', students still benefit from exploration when it is paired with subsequent instruction (Loibl & Rummel, 2014b).

Research shows that exploratory learning can result in higher conceptual understanding of material (Kapur, 2016; Loibl & Rummel, 2014a) and comparable procedural and fact-based learning compared to instruct-first approaches (DeCaro & Rittle-Johnson, 2012; Loibl & Rummel, 2014b; Newman & DeCaro, 2019; Weaver et al., 2018). By providing students with more generalized domain knowledge, exploratory learning better prepares students to transfer their knowledge when learning new concepts (Schwartz & Martin, 2004). The conceptual benefits of exploratory learning have been demonstrated across multiple STEM domains, including elementary and middle school mathematics (e.g., DeCaro & Rittle-Johnson, 2015; Kapur, 2010; Kapur, 2011), college-level physics (e.g., Hofer et al., 2018; Schwartz et al., 2011; Weaver et al., 2018), chemistry (e.g., DeCaro et al., 2022), biology (e.g., Chowrira et al., 2019; Halmo et al., 2020), and statistics (e.g., Newman & DeCaro, 2019; Schwartz & Martin, 2004).

Mechanisms of Exploratory Learning

Exploratory learning is thought to benefit students' learning through several mechanisms. When attempting to solve novel problems without prior instruction, learners rely on relevant knowledge they already possess (Kapur, 2012; Schwartz & Bransford, 1998). Activating prior knowledge facilitates the formation of connections between new and existing schema, allowing for stronger integration of novel information (Sweller et al., 1998). With this integration, students may also gain new perspectives and correct misconceptions (Ohlsson, 1996). Through the activation of prior knowledge, exploratory learning better prepares students for future learning, as prior knowledge may help students interpret the information during instruction (Schwartz & Martin, 2004). Retrieving and applying existing schemas can also facilitate knowledge transfer (i.e., applying learned knowledge to a novel but relevant problem; Kapur, 2014; Schwartz & Martin, 2004).

Activating prior knowledge encourages students to reflect on what information they do and do not already understand, improving their *metacognitive awareness*

(Glogger-Frey et al., 2015). Direct instruction may sometimes lead to passive engagement (Chi & Wylie, 2014), risking students becoming overconfident in their own understanding, and forming an 'illusion of understanding' (Bjork, 1994; Szpunar et al., 2014). Inaccurately perceived fluency can lead to less time restudying material, resulting in poor long-term retention (Dunlosky & Rawson, 2012). During exploratory learning, students often find that their current understanding does not lead them to successful solutions, consequently raising their awareness of gaps in their knowledge (Glogger-Frey et al., 2015). Awareness of such flaws fosters a 'need to know', heightening curiosity to learn successful solutions (Lamnina & Chase, 2019) and increases motivation to better understand material (Loibl et al., 2017). This increased motivation improves learners' engagement when learning through subsequent instructions (Loibl & Rummel, 2014b). Awareness of knowledge gaps is critical to successful exploratory learning, as failing to raise metacognitive awareness prior to instruction limits the benefits of exploration (Loibl et al., 2020; Nachtigall et al., 2020).

Exploratory learning helps students focus their attention on the deep structure of information through identifying key problem features (Chi et al., 2016). Exploration provides opportunities for learners to observe, interpret, reflect, and test multiple strategies to assess the relationships between a problem's variables (DeCaro & Rittle-Johnson, 2012; Glogger-Frey et al., 2015; Schwartz & Martin, 2005). This trial-and-error allows students insight into which approaches work, but also why certain strategies are effective or ineffective based on a problem's structure (Chin et al., 2016).

Introducing exploration activities in the classroom breaks the normal lecture routine. Furthermore, exploration activities task students to work with materials they may have no prior experience with. For these reasons, exploratory learning has the potential to be a frustrating and cognitively demanding experience for some students (Kapur, 2014). Despite potential frustrations, exploratory learning can result in equal (Glogger-Frey et al., 2015; Kapur, 2014; Newman & DeCaro, 2019) or greater (Weaver et al., 2018, Experiment 1) situational interest compared to direct instruction. These findings suggest that even though exploratory learning activities are challenging, their inclusion does not hinder student interest and motivation.

Despite their advantages, there are challenges to implementing exploration activities in classrooms. Designing exploration activities can be a time and resource demanding endeavor for instructors. Furthermore, for exploration to be productive, materials should be difficult enough to challenge students, without being so difficult that they lose motivation and disengage (Kapur, 2014). Appropriate difficulty of a learning activity is necessary for learners to achieve a *flow state*, characterized by the learner experiencing high concentration, and feeling optimally challenged yet confident about their ability to succeed (Rheinberg et al., 2003). An activity that balances task difficulty with a learner's knowledge should heighten the learner's attention and perceived fluency (Engeser & Rheinberg, 2008).

Balancing the difficulty of exploration may be discouraging to instructors who are new to designing exploratory learning activities. One solution is to look to existing educational resources as possible exploration activities. Computer-based simulations are promising resources for two reasons. First, simulations are already designed for students to learn in an exploratory manner (De Jong & Van Joolingen, 1998). Second, there is a growing body of literature supporting their effectiveness when implemented as classroom activities (e.g., Adams et al., 2015; Chamberlain et al., 2014; Roll et al., 2014).

Simulations as Exploratory Learning Tools

Implementing computer-based simulations as exploration activities, as opposed to pen-and-paper activities, might offer pedagogical and research advantages. This work will use the term *simulation* to refer to interactive simulations specifically designed for graphical visualized representations of processes, situations, and systems (Moser et al., 2017). Such simulations have applications across many different disciplines, even outside of academia, including healthcare and military training (Koh et al., 2010).

Use of simulations has become increasingly common within STEM disciplines, as they can demonstrate complex real-world phenomena (Jimoyiannis & Komis, 2001; Moser et el., 2017). Effective simulations are designed to represent scientifically authentic events, allow students to engage in scientific inquiry by testing hypotheses, and are tailorable to students' interests and ability levels (Blake & Scanlon, 2007; Moser et al., 2017). Simulations are also increasingly accessible, with a growing number of computer-based simulations freely available online through sources like the University of Colorado Boulder's physics education technology (PhET) online library (Wieman et al., 2008).

Simulations are popular tools for guided discovery and inquiry-based research, as they allow learners to explore domain-specific concepts by granting virtual tools to investigate and manipulate visualized models (De Jong & Van Joolingen, 1998). Simulation-based learning has been found to be more effective than traditional instruction alone (Akpan & Andre, 2000; Chen, 2010; Hagemans et al., 2013; Sarabando et al., 2014;

Trundle & Bell, 2010; Zacharia & Olympiou, 2011). Direct instruction paired with a subsequent simulation activity (i.e., instruct-first approaches) has been found to help students overcome prior misconceptions (Jimoyiannis & Komis, 2001).

Simulations can be effective replacements for expensive or difficult to obtain laboratory equipment. Finkelstein and colleagues (2005) found that learning about electrical circuits via a simulation can result in stronger learning outcomes compared to learning with comparable real-world laboratory equipment. Simulations also offer the advantage of modeling concepts that are too small to observe (e.g., atomical structures, neuron action potentials; see DeCaro et al., 2022; Jones et al., 2005), or are otherwise unrealistic (e.g., exploring the conservation of energy by skateboarding in earth's gravity compared to Jupiter's gravity; see Trey & Khan, 2008).

Much of the existing research investigating the use of simulations stems *from inquiry-based learning* research. Like exploratory learning, inquiry learning is a constructivist-inspired method, wherein students construct their own understanding throughout the learning process (Kuhlthau & Maniotes, 2015). Students engaged in inquiry-based learning are given a carefully scaffolded series of problems, and are asked to make sense of them, often independently or in groups. Inquiry-based learning differs from exploratory learning in its structure, as inquiry-based learning is a more open-ended process, and subsequent instruction is not necessarily provided to students (Ernst et al., 2017). Consequently, the two approaches may activate different cognitive mechanisms by which they benefit learning (Song & Kapur, 2017).

Inquiry-based learning research by Roll and colleagues (2018) demonstrated that using interactive simulations can improve conceptual understanding, as well as encourage positive attitudes towards the material. Research has also shown that simulation-based learning can facilitate activation of prior knowledge and help students with low prior knowledge perform at a similar level to students with high prior knowledge (Roll et al., 2014; Roll et al., 2018). Despite the popularity and effectiveness of simulations as inquiry-based learning tools, to our knowledge, few studies have examined the use of computer-based simulations as exploratory learning activities (see Chin et al., 2016; DeCaro et al., 2022). More research is needed to determine the effectiveness and best practice for pairing simulations with instructions (e.g., whether simulations should be accessed prior to or after instruction, how much scaffolding is necessary for simulation-based exploration to benefit instruction).

Many interactive simulations share characteristics with commonly used pen-and paper exploratory learning activities, as they provide problem spaces for testing multiple hypotheses, strategies, and solutions (Kapur, 2016; Moser et al., 2017). However, simulations can offer real-time, adaptive feedback to learners while they explore (Podolefsky et al., 2010). Such feedback can dynamically reveal successes and failures, based on learner input. Feedback can also be more granular, showing progression towards or away from a desired goal (Roll et al., 2014). This feedback pairs well with the mechanisms thought to be responsible for the benefits of exploratory learning, as it can act as an additional source of information highlighting learners' knowledge gaps.

Another advantage to implementing simulations as exploratory learning activities is that simulations may assist students in discerning relevant problem features. For example, a student learning with a PhET atomic structure simulator might notice all electron particles, once placed, automatically orbit outside of the nucleus. The simulation does not produce this effect when placing protons, or neutrons, highlighting an important difference between these particles. The curation of which features a learner can and cannot interact with, and in what ways, may help highlight critical aspects of the topic.

Beyond pedagogical advantages, there are also technological advantages to using simulations as exploratory learning activities in learning research. By using a logfile or screen recording software, researchers can monitor student strategies during exploration (Perez et al., 2017; Roll et al., 2018). These data allow researchers to examine variables such as a learner's off-task behaviors, pausing to reflect on feedback, how learners incorporate guidance, and the quantity of solutions generated during exploration (Tavares et al., 2013). Advancements have also been made in simulation customizability and interoperability, allowing instructors and researchers to personalize controls, labels, starting parameters, and stimuli presentation (Moore & Perkins, 2018). Such features grant educators the freedom to tailor simulation-based learning to meet their students' needs.

There are challenges to consider when using computer-based simulations as exploration activities. If exploratory learning is not incorporated in a classroom environment with regularity, it is possible that students will become frustrated by the idea of breaking from their normal classroom activities to do unfamiliar problem-solving tasks (Lopatto et al., 2020). Effectively guided simulation-based learning may alleviate these problems, as simulation-based learning can elicit students' situational interest (Adams et al., 2008a; Yaman et al., 2008). Such interest, if sustained, is thought to improve attention to task-relevant information and conceptual learning (Hidi & Renninger, 2006), as well as help students persist when material is challenging (Rounds & Su, 2014).

Simulations can be rich with detail, giving learners an abundance of information to process while they learn (Jones et al., 2005; Lehtinen & Viiri, 2017; Zacharia & Olympiou, 2011). Thus, some simulations may be too demanding for some students (Marshall & Young, 2006). The cognitive load experienced by the student while learning from the simulation should be considered when implementing simulations as exploratory learning activities. It is likely that some level of scaffolding is necessary to balance the complexity of the simulation and help students focus on relevant information without prior instruction.

The Role of Cognitive Load

In order to learn, students must process information in working memory; however, working memory capacity is limited in how much information can be processed at once (Mayer & Fiorella, 2014). Educators must be mindful of *cognitive load* (i.e., the amount and types of demand on working memory) when selecting and designing learning materials. Presenting too much concurrent information comes at the risk of overburdening working memory capacity (Cowan, 2010). According to the triarchic theory of cognitive load (Sweller, 2005), and the cognitive load theory of multimedia learning (Mayer & Moreno, 2003), load imposed on working memory can be classified into three categories: extraneous, intrinsic, and germane processing. Each load type utilizes working memory resources differently and should be considered when appraising the appropriateness of an instructional method.

Intrinsic cognitive load refers to the number, and complexity, of elements that are essential for accurate comprehension of concepts (Van Merrienboer & Ayres, 2005). Intrinsic cognitive load depends on the nature and connectivity of the material, rather than the instructional method used to deliver the information (Brame, 2016; Sweller, 2016). Intrinsically demanding materials are those which have several elements that must be processed within working memory to obtain a full understanding (DeLeeuw & Mayer, 2008; Van Merrienboer & Ayres, 2005). The term *element interactivity* (Sweller, 1994) is often used to define the degree of complexity of those elements, as well as their interactions. Highly complex topics, like those often covered in STEM courses, possess an abundance of interacting elements, making them especially challenging for students with low relevant prior knowledge (Mutlu-Bayraktar et al., 2019).

Extraneous cognitive load refers to resources used when learners engage in processing information that does not support the formation of relevant schema (DeeLeeuw & Mayer, 2008). Extraneous load is elicited by the ways in which information is delivered, and is high when the learning materials include distracting or irrelevant information that impedes processing of the target content (e.g., distracting sounds, imagery, confusing instructions, poorly configured layouts, an abundance of text; Brame, 2016). Cognitive load is additive—regardless of the type of cognitive load, all load within the same sensory modality draws from the same pool of shared resources (Sweller, 1998). If sufficient encoding is to occur, the total load cannot exceed the available working memory resources (Sweller, 2011). As working memory resources are allocated to process superfluous information, resources available to process relevant information are limited (Orru & Longo, 2019), making extraneous load a hindrance to forming new schema.

Germane cognitive load, or generative processing, is load devoted to cognitive processes that are necessary to form robust schema (Sweller, 1994). Whereas extraneous load is considered interference, germane load is effective load, as germane processing promotes learning (Kalyuga, 2011). Some researchers have reconceptualized germane load as a direct function of intrinsic load, rather than as an independent source of load, arguing that germane load is comprised of the resources learners devote to address the interactivity stemming from task difficulty (Jiang & Kalyuga, 2020). Such arguments do not account for the possible inverse relationship between intrinsic and germane load, as an overwhelmingly complex task (e.g., high on intrinsic load) leaves little room for the deeper processing that is characteristic of germane load (Kalyuga, 2011).

If intrinsic and extraneous loads leave adequate working memory resources, germane load allows better organization and elaboration through linking information with existing schema (Gerjets & Scheiter, 2003). Germane load is also a function of learner characteristics, with higher levels of motivation and prior knowledge leading to better integration of schema (Cook, 2006).

Cognitive Load and Exploratory Learning

There is ongoing debate regarding Cognitive Load Theory's (CLT) applicability to the mechanisms of exploratory learning. A criticism of constructivist-inspired methods is that learners experience high cognitive load (Kirschner et al., 2006). When students are tasked with independently inventing solutions to novel problems, they often produce errors and allocate their attentional resources to superfluous details or incorrect solutions (i.e., sources of extraneous cognitive load; Kapur, 2016). This procedure comes at the expense of allocating those resources to germane information and successful strategies (Sinha & Kapur, 2019). These notions put cognitive load theory at odds with the exploratory learning benefits found throughout literature.

Attempting to resolve this discrepancy, Kalyuga and Singh (2016) argue that the goal of exploration is to prepare students for future learning through motivating and engaging the learner. The framework of CLT assumes that the goal of a learning activity is to immediately acquire domain-specific schemas. By this reasoning, because students are not expected to discover the canonical solution while exploring, CLT is not relevant to exploratory learning. Despite this claim, there is a growing body of literature suggesting that cognitive mechanisms are at least partially responsible for the benefits of exploratory learning (Kapur, 2010; Schwartz & Martin, 2004), and that cognitive load plays a role in successful exploration (Kapur, 2014; Newman & DeCaro, 2019).

When element interactivity (i.e., intrinsic load) is high, instruct-first methods may result in better conceptual learning and knowledge transfer compared to explore-first methods (Ashman et al., 2020). Even though exploratory learning may increase students' cognitive load (Kapur, 2014; Toh & Kapur, 2017), it is possible that much of this mental effort could be beneficial for learning. If attention is divided between task relevant information and extraneous information, engagement may suffer (Vesga et al., 2021), but this problem extends beyond motivation. Without focusing on relevant problem details, learners may fail to encode key problem features, and may not perceive gaps in their knowledge, leading to poorer schema acquisition during subsequent instruction (Newman & DeCaro, 2019). If most working memory processes are devoted to acquiring key problem features throughout exploration, then this load could be classified as germane (i.e., the learner is processing information relevant to the to-be-learned concept). Consistent with this idea, Newman & DeCaro (2019) found that use of worked examples during exploration (i.e., a means of reducing extraneous load) improved conceptual understanding and knowledge transfer.

Supporting Exploratory Learning

Though explore-first approaches to learning have sometimes been shown to be effective with minimal guidance (e.g., Kapur, 2008), providing support may still alleviate unnecessary cognitive load. Several methods of reducing cognitive load during exploration have been tested. Contrasting cases have been found to be an effective means of focusing learners' attention on specific problem features by reducing the amount of processed information (Bego et al., 2023; Schwartz & Martin, 2004). However, contrasting cases may only support exploration beyond instruct-first approaches when learners are guided to use them during problem-solving (Loibl et al., 2020). Other studies have found metacognitive prompts (Holmes et al., 2014; Kalyuga & Hsu, 2019) and self-explanation prompts (Fyfe et al., 2014) to be effective scaffolding during exploration. The nature of the prompts may influence the effectiveness of exploratory learning, as studies that used prompts probing conceptual knowledge have led to more effective learning (e.g., Holmes et al., 2014).

Worked examples (i.e., problems with solutions already prepared and available to the learner), have been found to reduce working memory demand by narrowing the number of possible strategies and streamlining attention to critical problem features, facilitating attention towards germane information (Sweller et al., 1998). Evidence suggests worked examples are an effective form of guidance for reducing cognitive load (Kirschner et al., 2006). Some studies have found worked examples to be an effective tool for guided exploration, resulting in better conceptual learning (Glogger-Frey et al., 2015; Newman & DeCaro, 2019, Studies 1 & 3) and reduced cognitive load (Glogger-Frey et al., 2017; Kalyuga & Hsu, 2019) when compared to learning from unguided exploration. Other studies have found no significant differences when comparing exploration guided by worked examples to no guidance exploration (Likourezos & Kalyuga, 2017; Newman & DeCaro, 2019, Study 2).

Simulations and Cognitive Load

When designing activities for simulation-based learning, it is important to consider cognitive load from three angles: 1) guidance provided by the instructor with the goal of facilitating conceptual inquiry (Adams et al., 2008a), 2) feedback embedded within the simulation design (e.g., visual cues to draw student attention to germane features, or dynamically demonstrate to students that they have made an error; Roll et al., 2014), and 3) how simulation features (e.g., interface, buttons, sliders, options, and modes) are designed (Moore & Perkins, 2018).

Optimally designed simulations allow for more robust scientific inquiry and minimize extraneous load, while still offering enough complexity to allow opportunities for germane processing (Adams et al., 2008b). How information is delivered by a simulation is critical for managing working memory resources. For example, pairing relevant words and visuals together reduces extraneous load (i.e., *spatial contiguity principle*, see Mayer & Fiorella, 2014). When left to explore on their own, students are likely to explore the most salient features within a simulation. Activity design can take advantage of this tendency by highlighting the most important problem features within the simulation, minimizing attention drawn to less relevant features (i.e., *signaling*, see Mayer & Fiorella, 2014). Successful simulations teach by visualizing information, rather than describing details in text (Adams et al., 2008c).

Guidance and Simulation-Based Learning

The type and amount of guidance necessary for implementing simulations as exploratory learning activities is not well known. Most studies implementing simulations use them as inquiry learning tools (e.g., Roll et al., 2014; Roll et al., 2018), and do not manipulate the order of instructions to determine whether simulations are appropriate for exploratory learning. Even though simulations are often designed to provide dynamic feedback, most simulations are not imbedded with intrinsic objectives or goals for students, and typically rely on the help of instructor activities or guidance for added context (Holmes et al., 2014).

Without context, student interest and attention are not driven by learning goals and are instead driven by the simulation features (Wieman et al., 2010). As such, student engagement can be minimal. Students who receive no guidance during simulation-based learning tend to interact with the most salient simulation features, regardless of conceptual relevance (Adams et al., 2008b). With no guidance, the extraneous load induced by the simulation's design is critical to success, as it is common for students to disengage if they cannot navigate the simulation on their own (Adams et al., 2008a).

The level of guidance that is most appropriate may largely depend on the characteristics of the learner. Interactions between some learner characteristics (e.g., prior knowledge, motivation), and simulation-based inquiry learning, are well studied (e.g., Manlove et al., 2007; Roll et al., 2018). Inquiry-based learning research has found that pairing simulations with strong, direct support (e.g., reflection prompts, visual aids, compare-and-contrast examples) can improve learning, especially when learners already possess high levels of prior knowledge (Roll et al., 2018).

It is uncertain whether simulation-based exploratory learning requires similar guidance compared to using simulations in other ways. Some researchers argue that the goal of exploration is not the initial acquisition of domain-specific knowledge (Kalyuga & Singh, 2015), but is instead to activate prior knowledge, bring awareness to knowledge gaps, and highlight critical problem features to prepare for future learning (Schwartz & Martin, 2004). Furthermore, exploratory learning includes an additional learning resource (i.e., subsequent instruction) to assist in schema consolidation and correcting misconceptions; learners need not necessarily acquire knowledge from exploring the simulation alone (Kapur, 2016). These design features would suggest that using simulations as exploratory learning tools would require less formal structure than in other contexts.

However, simulations are often rich with information from extraneous and germane resources, so it is still likely that simulation-based exploratory learning would benefit from appropriate scaffolding. Just as research suggests that contrasting cases help focus attention to deeper problem features when problem-solving (Loibl et al., 2017; Schwartz & Martin, 2004), educators can use relevant simulation features to narrow learners' attention to critical problem features, concepts, and relationships, leading to higher germane processing and improved conceptual understanding.

Current Research

The objectives of this research were to investigate (a) whether simulations can be effectively used as exploratory learning activities, (b) how the intrinsic cognitive demand of these activities affects learning strategies and outcomes, and (c) whether guidance is necessary to improve learning when implementing these activities. It is important to examine the type of guidance students require to successfully explore simulations for two reasons. First, simulations have built in guidance in the form of dynamic feedback (Lehtinen & Viiri, 2017; Roll et al., 2014), so care must be taken that students are not overwhelmed with an abundance of information from multiple sources. Additionally, exploratory learning entails adding a set of instructions following exploration (Kapur, 2012), so support should be designed to ensure information is presented in a way in which key ideas can be integrated together, rather than result in redundant or superfluous processing (Mayer & Fiorella, 2014; Sweller, 2011).

Existing research on simulation-based learning has examined how implementing guidance during simulation activities can improve learning (Roll et al., 2014, 2018). However, these studies did not include direct instruction either before or after their simulation activities. Recent research has examined instructional order (DeCaro et al., 2022), but has done so without manipulating the type of guidance provided to students during exploration. The current work expands on prior simulation-based research by investigating how instructional order (i.e., completing the simulation activity before or after instruction), and the intrinsic cognitive load of the material, can affect conceptual understanding and knowledge transfer.

Experiment 1 addressed the first research question, by examining how instructional order affects learning. We investigated whether using a computer-based physics simulation as an exploratory learning activity prior to conceptual instruction (explore-first) yielded benefits compared to exploring the same simulation-based activity after instruction (instruct-first). The simulation provided students the necessary components to construct virtual circuits, as well as tools to measure the current and voltage of these circuits. All participants were provided with an activity worksheet to complete while exploring the simulation (see Appendix A). Analogous to pure invention methods of exploratory learning (Schwartz & Martin, 2004), only minimal guidance was provided to participants while they explored the simulation (i.e., few conceptual reasoning questions were posed, no explanatory tables or diagrams were displayed, no reflection prompts were provided). The worksheet included a stated objective (i.e., "use the simulation to explore how voltage, current, and the brightness of the light bulbs depends on 1) the number of light bulbs in the circuit, and 2) the arrangement of light bulbs in the circuit). The worksheet included questions and scenarios for participants to explore using the simulation (e.g., which bulb do you think will be the brightest?; how could you hook up a battery and 2 light bulbs so that the least amount of current flows through the battery?) but did not include guidance of scaffolding to facilitate successful completion of these problems.

Because some research suggests that activity review is necessary to prepare for future learning from a learning resource (Loibl et al., 2017), after the exploration and instruction phases were both completed, participants reviewed the solutions to the exploration activity worksheet. To assess whether exploring prepared participants for future learning and knowledge transfer, participants then viewed video material on a similar but unexplored topic. Survey items assessed participants' perceptions of the learning activities, including self-reported cognitive load, perceived knowledge gaps, perceived flow, curiosity about the learned material, and interest/enjoyment. Finally, participants completed a learning assessment, measuring their conceptual knowledge of the taught physics topic, and how well they could transfer their knowledge to the unexplored video material.

Based on previous literature revealing the benefits of exploratory learning, we hypothesized that participants in the explore-first condition would score higher on conceptual items (i.e., questions that probe knowledge covered by the activity and instruction) and transfer items (i.e., questions that are similar, but not identical content to concepts covered by the activity and instruction) than students in the instruct-first condition. Based on previous research, we also predicted that participants in the explore-first condition would report higher levels of perceived knowledge gaps (Glogger-Frey et al., 2015), flow (Kapur, 2012), curiosity (Loibl et al., 2017), and equal or higher levels of interest/enjoyment (Kapur, 2014; Weaver et al., 2018, Experiment 1). Based on prior literature, we also predicted that participants in the explore-first condition would report equal or higher levels of cognitive load (Newman & DeCaro, 2019).

Experiment 2 addressed the remaining research questions regarding intrinsic cognitive demand of exploratory learning activities and whether guidance is necessary when implementing these activities. A 2 (instructional order: explore-first, instruct-first) × 2 (load reduction: intrinsic load, extraneous load) between-subjects design was used. As in Experiment 1, participants were randomly assigned to either complete the simulation activity before instruction (explore-first) or receive instructions prior to completing the simulation activity (instruct-first).

We predicted that cognitive load imposed by the simulation activity would be reduced in two ways, varying across condition. In the intrinsic load reduction condition (ILR), the intrinsic demand of the activity was reduced by breaking down the activity into smaller problem sets (e.g., pairwise comparisons of circuit components instead of comparing multiple circuits at once). By breaking the activity down into steps, the number of interacting elements participants must concurrently hold within working memory was reduced. Beyond this manipulation, participants in the ILR condition received a level of guidance comparable to participants in Experiment 1.

A second condition, the extraneous load reduction condition (ELR), addressed cognitive load by embedding partially completed worked examples into the activity worksheet. The format of questions was similar to Experiment 1 but included some steps to correctly solve the worksheet problems. The intention was to reduce extraneous cognitive load experienced by the participants, as prior research suggests that worked examples are an effective way to focus students' attention to key problem features and correct solutions, allowing them to allocate working memory resources to constructing schema (Sweller, 2004).

The goal of Experiment 2 was to set up two potentially more optimal explore-first conditions, to compare to two instruct-first conditions that use the same activity and instructions (in reverse order). An objective of Experiment 2 was to establish preliminary guidelines for implementing computer-based simulations as exploratory learning activities. With these preliminary guidelines, future research can further examine and expand upon the design features that are beneficial to learning.

Like Experiment 1, Experiment 2 used survey items assessing participants' perceptions of the learning activities: perceived knowledge gaps, flow, curiosity, and interest/enjoyment. Experiment 2 assessed self-reported cognitive load, but also employed an additional instrument to discriminate between the three types of cognitive load (Klepsch et al., 2017; Leppink et al., 2013).

The manipulations used in Experiment 2 were intended to reduce cognitive load relative to participants in Experiment 1. Compared to students in the instruct-first conditions, we predicted that participants in the explore-first conditions would score higher on conceptual and transfer items. We predicted that participants in the ELR and ILR conditions would score comparably on conceptual items. We also predicted that participants in the ELR would perform lower on transfer items compared to participants in the ILR conditions. Prior literature suggests that worked examples are effective at focusing student attention to problem features, thus, reducing extraneous cognitive load (Sweller, 2004). Such forms of strongly directed guidance can lead to less freedom during simulation learning, resulting in students fixating on only the prescribed instructions (Adams et al., 2008a).

Consistent with previous literature, we predicted that participants in the explore-first conditions will report higher perceived knowledge gaps, perceived flow, curiosity, and equal or higher interest/enjoyment than participants in the instruct-first conditions. We predicted that participants in the explore-first conditions would report equal or higher cognitive load than participants in the instruct-first group, but that the type of cognitive load reported would vary based on the load reduction condition (ELR or ILR). Consistent with our design intentions, we hypothesized that participants in the ELR condition would report significantly lower extraneous load, but significantly higher intrinsic load, than participants in the ILR condition.

Beyond examining learning outcomes, Experiments 1 and 2 used video recording software to capture how learners explored the simulation. Though studies have investigated student strategies during exploration (e.g., Kapur, & Bielczyz, 2011), this work used a different method to look at how those solutions inform preparation for future learning. Analyzing video footage allows researchers to investigate how specific student approaches facilitate learning (e.g., construction using more circuit components, formal testing through measurement tools, taking more time to reflect on feedback, and going beyond activity tasks).

In Roll et al.'s (2018) prior research, students who received guidance with simulations were more likely to engage in formal testing (i.e., using the tools provided by the simulation to obtain objective data), whereas unguided students were more likely to engage in informal testing (i.e., constructing pieces within the simulation to observe feedback provided by the simulation). Pausing and resetting the simulation were equal across conditions. If we consider instructions as comparable to directive guidance, we can predict that students who receive instructions prior to the activity will engage in more formal testing, whereas participants who complete the activity prior to instruction may engage in less formal observation. We predict that pausing and resetting the simulation will be equal across conditions. Given that we are manipulating the order of these instructions, it is possible that these findings will not be consistent with prior inquiry-based findings. An alternative prediction is that students who explore the simulation first would show increased use of all these approaches, as prior research shows that exploration leads to increased generation of strategies (Kapur, 2008).

Theoretical and Practical Implications

The current research will link the exploratory learning and computer-based simulation literatures and begin to identify the boundary conditions for implementing simulations as exploratory learning tools in real classrooms. There are a lot of variables to consider when determining how to best use an educational intervention (e.g., participant attitudes, perceptions, characteristics). This research takes steps towards identifying when and why this intervention may work. One goal of this work is to form a theoretical and empirical starting point for a body of literature which outlines the conditions necessary for educators to use simulations to enrich student learning through exploratory learning. As suggested by previous literature, there are conditions for which exploration may not be advantageous (e.g., when a task is too intrinsically demanding; Ashman et al., 2020; the material is strictly procedural; Loibl & Rummel, 2014b). If particular kinds of simulations, used in particular contexts, are not optimal as conceptual, exploratory learning tools for particular learning objectives, understanding why may inform their classroom implementation, and future simulation design.

The secondary hypotheses regarding learner perceptions, such as perceived flow, interest, perceived knowledge gaps, and curiosity, will extend our understanding of the motivational mechanisms behind the effectiveness of exploratory learning, and will extend these findings into the domain of computer-based learning.

Finally, capturing student exploration strategies on video will also grant insight into how student strategies are related to successful exploratory learning. If particular behavioral patterns (e.g., engaging in more formal testing or reflection) map onto self-report of increased awareness of knowledge gaps, curiosity, interest, or activation of prior knowledge, we may gain insight into how those mechanisms are affecting student strategies. Understanding when and why students engage with specific simulation features may also be a step towards improving future simulation design.

CHAPTER II: EXPERIMENT 1

Two experiments will assess the level of guidance that is optimal when implementing computer-based simulations as exploratory learning activities. Because the implementation of simulations as exploratory learning activities is relatively new, the goal of Experiment 1 was to obtain a baseline comparison for instruct-first and explore-first conditions in a simulation-based learning task, using only minimal guidance. Experiment 1 tested the design of a minimal guidance exploratory learning worksheet, paired with a PhET physics-based simulation on the topic of circuit construction. The primary measured outcomes were participants' learning on items assessing their conceptual understanding of the conceptual material, as well as learning of transfer items (i.e., items that assess a similar but not identical topic). Experiment 1 also assessed secondary variables of interest that have been found to be associated with exploratory learning or learning from simulations, including cognitive load, perceived knowledge gaps, interest and enjoyment, and curiosity. Experiment 1 also measured perceived flow; a variable found to be associated with improved learning in computer-based simulations (Winberg & Hedman, 2008).

Method

Participants

Undergraduate students (N=66, M_{age}=19.65, SD=2.52, 76% female) participated for research credit in psychology courses. Thirteen additional participants were excluded from analyses for not following the study protocol. Participants were randomly assigned to either explore a physics simulation before instruction (explore-first condition; n=35) or receive instructions prior to exploring the physics simulation (instruct-first condition, n=31).

Materials

This study consisted of multiple phases, the order of which was altered across the two conditions. In the explore-first condition, the order consisted of the simulation activity, instruction, review, assessment, transfer instruction, and transfer assessment. In the instruct-first condition, the order consisted of instruction, the simulation activity, review, assessment, transfer instruction, and transfer assessment. For each condition, survey items were administered after exploration, and once again after the exploration review (see Table 1).

Table 1: Order of Materials for each Condition

Explore-First	Instruct-First
Simulation Activity	Instruction
Instruction	Simulation Activity
Activity Review	Activity Review
Assessment	Assessment
Transfer Instruction	Transfer Instruction
Transfer Assessment	Transfer Assessment

Instruction. Participants watched an 8-min video lecture about circuit construction (https://www.youtube.com/watch?v=x2EuYqj_0Uk&ab_channel=BozemanScience). The lecture described basic circuit components (i.e., wires, batteries, switches, and light bulbs), showed different types of circuits (i.e., series, parallel, and complex circuits), and explained the differences between these different circuit designs in terms of the current they produce.

Simulation Activity. Before completing the simulation activity, participants watched a 2-min video briefly explaining the simulation's controls and features (e.g., how to click and drag objects within the simulation environment). This instruction was to ensure that all participants had at least a basic understanding of how to operate the simulation. Participants were then given access to the simulation. The PhET simulation was on the topic of circuit construction (https://phet.colorado.edu/sims/html/circuit-construction-kit-dc/latest/circuit-construction-kit-dc_en.html). The simulation's interface allows users to construct circuits using various parts (e.g., wires, batteries, light bulbs, resistors), and offers dynamic feedback (e.g., brightness of light bulbs, visualized current speed), based on user input. This simulation was selected due to its use in prior inquiry learning research (Roll et al., 2014; Roll et al., 2018). Participants were then provided with a worksheet consisting of four problems to answer by using the simulation (see Appendix A). The worksheet consisted of four problems, each targeting relevant aspects of circuit construction (e.g., current, voltage). Participants were given 20-min to interact with the simulation.

The method for coding student actions within the simulation were adapted from Roll and colleagues (2018). The following actions were counted: constructing (e.g., adding individual resistors, connecting wires, splitting junctions, etc.); testing (i.e., using the voltmeter and ammeter to test voltage and current); pausing for reflection (i.e., not using any simulation functions for longer than 15 seconds), and resetting (i.e., using the reset button to remove all components and start from scratch). Actions that did not change the circuit or test the circuit (e.g., zooming) were ignored.

Activity Review. After participants completed both the simulation activity and instruction phases, participants were provided the answers to the four worksheet problems on the computer and were instructed to carefully review each explanation. Each explanation was accompanied by visual aids in the graphical interchange format (GIF), showing the correct circuit layouts and measured current.

Survey. Survey items were administered once after the simulation activity, and again after the activity review. Cognitive load was measured using the Mental Effort Rating Scale (Paas, 1992). Participants rated the amount of mental effort they spent on the activity by responding on a scale from 1 (*very, very low mental effort)* to 9 (*very, very high mental effort*). Participants also rated their prior knowledge on the topic from 1 (*Not at all*) to 4 (*Very much*).

All other survey items were intermixed and rated on a 5-point Likert scale (1=*Strongly Disagree*, 5=*Strongly Agree)*. To measure interest and enjoyment, items were adapted from Ryan (1998) (3 items, e.g., "I found this learning activity interesting"; $\alpha = 0.88$; Weaver et al., 2018). Perceived knowledge gaps were measured using 4 items adapted from Flynn and Goldsmith (1999) (e.g., "Compared to most other people, I know less about this topic"; $\alpha = 0.87$). Curiosity was measured using items adapted from the Melbourne Curiosity Inventory (Naylor, 1981) (6 items, e.g., "I feel like seeking information about what I just worked on"; $\alpha =0.80$). Perceived flow was measured using 7 items from the Flow Short Scale (Rheinberg et al., 2003). These flow items were separated into two factors: fluency of performance (4 items, e.g., "The right thoughts/movements occurred of their own accord", α=.74), and absorption by activity (3 items, e.g., I was totally absorbed in what I am doing", α=.84).

Conceptual Knowledge Assessment. The conceptual knowledge assessment consisted of 14 multiple-choice items adapted from Roll and colleagues (2014). These items assessed learning of the taught concepts (i.e., circuit construction, different types of circuits, and current; e.g., "Comparing circuits B and D, which circuit has the brightest light bulbs?", "Comparing light bulbs A and B, which light bulb has the stronger current?" (see Appendix A for example).

Transfer Instruction. Interleaved between the two assessments was a 10-min video lecture covering the topics of resistors and resistance (https://www.youtube.com/watch?v=J4Vq-xHqUo8&ab_channel=BozemanScience). Though these concepts are relevant to circuit construction, they were not explicitly taught during the first instruction phase. The purpose of this phase, as well as the subsequent assessment, was to examine how instructional order (i.e., instruct-first vs. explore-first) prepares students for future learning of similar concepts (Schwartz & Martin, 2004).

Transfer Assessment. The second assessment consisted of 13 multiple choice items adapted from Roll and colleagues (2014), intended to assess transfer of acquired knowledge to new, but similar, topics. These items assessed knowledge of circuit resistors and resistance.

Procedure

Participants worked at a computer station in a session by themselves. After participants provided informed consent, the researcher explained that the purpose of the study was to see how people learn new information, and that they would be watching learning videos and answering questions about what they learn. Participants began the experiment by either completing the simulation activity (explore-first) or watching the 8-min instructional video (instruct-first), completing survey 1, then subsequently completing the other activity. Participants were then provided with answers to the activity and given time to review. After the activity review, participants completed survey 2. The first assessment was then administered, with additional instructions on transfer items to follow. An additional assessment, this time with items targeting transfer concepts, was then completed. After completing the study, participants were debriefed. The session lasted approximately 1-hr and 15-min. All study procedures were approved by the university Institutional Review Board.

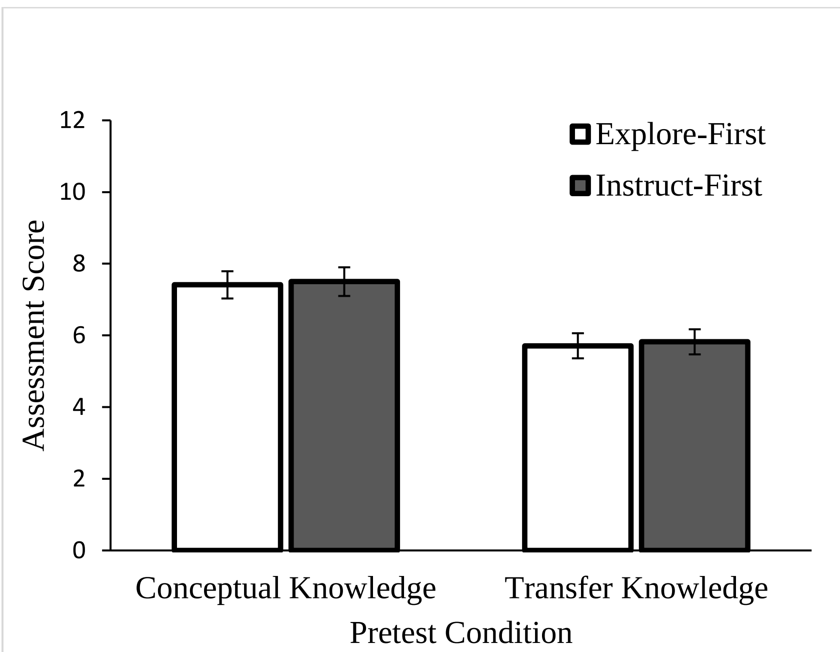
Results

Learning Outcomes

As a preliminary analysis, we examined whether participants in the two conditions were equal in terms of prior knowledge. Participants in the explore-first condition (M=2.03, SE=.13, 95% CI [1.76,2.29]) and instruct-first condition (M=1.87, SE=.14, 95% CI [1.59,2.16]) did not significantly differ in prior knowledge, F<1.

Performance on the learning assessment was examined using a 2 (instructional order: explore-first, instruct-first) × 2 (knowledge type: conceptual, transfer) mixed-factorial analysis of variance (ANOVA), with order as a between-subjects factor, and knowledge type as a within-subjects factor. As shown in Figure 1, the results revealed a significant main effect of order, in the opposite direction than hypothesized, $F(1,64)=4.39$, $p=.040$, $\eta_p^2=.063$. Participants in the instruct-first condition (M=8.58, SE=.41, 95% CI [7.76, 9.40]) scored higher than participants in the explore-first condition (*M*=7.40, *SE*=.56, 95% CI [6.63, 8.17]). There was a significant main effect of knowledge type, $F(1,64)=30.43$, $p<.001$, $\eta_p^2= .321$, with higher accuracy on items assessing conceptual knowledge (*M*=7.99, *SE*=.28, 95% CI [7.43, 8.55]) than transfer knowledge (*M*=6.15, *SE*=.29, 95% CI [5.58, 6.73]). There was no significant order × knowledge type interaction, $F<1$: explore-first conceptual knowledge (*M*=7.41, *SE*=.38, 95% CI [6.66,8.16]), instruct-first conceptual knowledge (*M*=7.50, *SE*=.40, 95% CI [6.67,8.26]), explore-first transfer knowledge (*M*=5.71, *SE*=.35, 95% CI [5.02,6.39]), instruct-first transfer knowledge (*M*=5.82, *SE*=.37, 95% CI [5.01,6.55]).

Figure 1: Assessment Scores as a Function of Order of Instruction



Note: Error bars represent standard error of the mean

Survey Items

To assess cognitive load, a 2 (instructional order: explore-first, instruct-first) × 2 (survey administration time: survey 1, survey 2) mixed-factorial ANOVA was conducted, with instructional order as a between-subjects factor, and the timing of the two surveys (i.e., after simulation activity/instruction, after activity review) as a within-subjects factor. Results revealed a significant main effect of order, $F(1,64)=5.15$, $p=.027$, $\eta_p^2=.071$, with participants in the explore-first ($M=6.29$, $SE=.24$, 95% CI [5.80, 6.77]) condition reporting significantly higher cognitive load than participants in the instruct-first condition ($M=5.48$, $SE=.26$, 95% CI [4.97, 5.99]). There was no significant main effect of time, $F(1,64)=3.74$, $p=.058$, and no significant order × time interaction, $F<1$.

Similar mixed-factorial ANOVAs were conducted on the remaining survey items (Table 2). For perceived knowledge gaps, no main effect of order was found, $F(1,64)=2.94$, $p=.091$. Because of our stated a priori hypothesis, we proceeded with simple effects analysis. Planned comparisons revealed that, on survey 1, participants in the explore-first condition ($M= 3.65$, $SE=.14$, 95% CI [3.38, 3.92]) reported higher perceived knowledge gaps than participants in the instruct-first condition ($M=3.23$, $SE=$, 95% CI [2.94, 3.52]), $F(1,64)=$, $p<.040$, $\eta_p^2=064$. Participants in the explore-first condition also reported higher perceived knowledge gaps on survey 1 than survey 2, $F(1,64)=18.02$, $p<.001$, $\eta_p^2=.222$. The results revealed a main effect of survey administration time, $F(1,64)=18.77$, $p<.001$, $\eta_p^2= .231$, with participants reporting higher knowledge gaps after survey 1 ($M=3.44$, $SE=.10$, 95% CI [3.24, 3.64]) compared to survey 2 ($M=3.12$, $SE=.09$, 95% CI [2.93, 3.31]). There was no significant order × time interaction, $F(1,64)=2.21$, $p=.142$.

Assessing interest and enjoyment, there was no significant main effect of order, $F<1$, survey time, $F(1,64)=3.41$, $p=.07$, or interaction, $F<1$. When assessing fluency of performance, there was no significant main effect of order, $F<1$, survey administration time $F(1,64)=1.88$, $p=.176$, nor was there a significant interaction, $F<1$. Assessing absorption by the activity, there was no significant main effect of order or survey administration time, nor was there a significant interaction, *F*s<1. Examining curiosity, results revealed a main effect of order, $F(1,64)=4.15$, $p=.046$, $\eta_p^2=.021$, with participants in the explore-first condition ($M=3.58$, $SE=.12$, 95% CI []) reporting higher curiosity than participants in the instruct-first condition ($M=3.24$, $SE=.12$, 95% CI []). There was no main effect of survey time, $F(1,64)=3.25$, $p=.076$, or interaction, $F(1,64)=3.65$, $p=.060$.

Table 2: Descriptive Statistics for Survey Measures

	Survey 1				Survey 2			
	Explore-First		Instruct-First		Explore-First		Instruct-First	
	M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
Cognitive Load	6.49	0.26	5.58	0.28	6.09	0.27	5.39	0.28
Perceived Knowledge Gaps	3.65	0.14	3.23	0.15	3.22	0.13	3.02	0.14
Interest/Enjoyment	3.81	0.16	3.82	0.17	3.71	0.15	3.67	0.16
Fluency of Performance	3.49	0.14	3.52	0.15	3.39	0.13	3.44	0.14
Absorption by Activity	3.83	0.13	3.69	0.14	3.87	0.13	3.67	0.14
Curiosity	3.68	0.12	3.24	0.12	3.24	0.12	3.24	0.13

Student Behaviors during Simulation Activity

Screen recordings were coded using the method outlined by Roll (2018). Four student behaviors during the simulation activity were quantified for analysis: construct (i.e., adding resistors, connecting wires, splitting junctions), test (i.e., using the ammeter and voltmeter to conduct measurements), pause (i.e., not engaging with the simulation for longer than 15 seconds), and reset (i.e., removing all components from the testbed and starting from scratch). We addressed whether these behaviors were associated with learning. Twenty percent of the video recordings were scored by a second observer (r=.76). Preliminary analyses examined correlations between assessment scores and each of the four behaviors. As shown in Table 3, more use of the simulation measurement tools (i.e., ammeter and voltmeter) was associated with higher scores on both conceptual items, $r(64)=0.36$, $p=.003$, and transfer items, $r(64)=0.44$, $p<.001$. No other behaviors were associated with assessment scores (see Table 3).

Table 3: Simple Correlations between Scores and Simulation Activity Behaviors

			Conceptual Items	Transfer Items
	M	*SD*	*Pearson's r (p-value)*	
Construct	49.37	21.10	-0.12 *(.341)*	-0.74 *(.556)*
Measurements	23.67	19.05	0.36** *(.003)*	0.44** *(<.001)*
Pause	7.95	1.12	-0.68 *(.585)*	0.10 *(.424)*
Reset	2.21	1.91	-0.13 *(.317)*	-0.13 *(.293)*

Between-subjects ANOVAs were used to further examine the relation between instructional order and the four coded behaviors (see Table 4). When examining measurement tool use, results revealed a significant difference between conditions, $F(1,64)=4.02$, $p=.049$. Participants in the instruct-first condition used the measurement tools with higher frequency ($M=28.52$, $SE=3.34$, 95% CI [21.83, 35.19]) than participants in the explore-first condition ($M=19.31$, $SE=3.14$, 95% CI [13.03, 25.60]). No other ANOVAs were significant (Fs=0.02-1.54, ps=.219-.984). Based on these preliminary findings, we next tested whether the difference in performance on conceptual items depended on the use of measurement tools. A between-subjects ANCOVA was used to examine the effect of instructional order on assessment performance of conceptual items while controlling for the effects of measurement tool use. Results revealed no significant main effect of order when controlling for measurement tools, $F(1,64)=2.20$, $p=.143$. There was a significant main effect of measurement tool use, $F(1,64)=6.96$, $p=.011$, $\eta_p^2=.099$, suggesting that the use of measurement tools is a potential mediator of the effect of condition on assessment outcomes.

Table 4: Descriptive Statistics for Simulation Activity Behaviors by Condition

	Explore-First		Instruct-First	
	M	*SE*	*M*	*SE*
Construct	49.31	3.94	49.42	3.91
Measurements	19.31	2.54	28.52	3.94
Pause	1.77	0.17	1.81	0.22
Reset	2.48	0.35	1.90	0.30

Discussion

Participants in the instruct-first condition scored significantly higher on assessment items, averaging across both conceptual and transfer items. Furthermore, we found evidence that the relation between instructional order and assessment accuracy was mediated by the use of measurement tools during the simulation. The latter finding is consistent with prior literature demonstrating that learners conduct more formal testing during simulation learning when provided with some direct guidance/instruction (Roll et al., 2018).

Our findings are not consistent with much of the literature demonstrating the benefits of exploratory learning (cf. Loibl et al., 2017). However, our findings are consistent with literature suggesting that instruct-first approaches may be preferred when intrinsic load is too demanding (Ashman et al., 2020; Fyfe et al., 2014). Our results also revealed a significant difference in self-reported cognitive load, with students in the explore-first condition reporting higher cognitive load than participants in the instruct-first condition. This finding suggests that element interactivity may have been too high for students in the explore-first condition to identify important problem features. This explanation is especially likely given the sample of participants, as the majority were early college students majoring in psychology or neuroscience (69.3%). Most of our sample reported never having encountered similar materials before or reported that they had not been taught these materials recently. Thus, the majority of our sample can be considered novices, and did not have adequate prior knowledge to fall back on while independently exploring.

Other survey items suggested that student perceptions were similar across conditions, with the exception of curiosity and perceived knowledge gaps. Participants in the explore-first condition reported higher curiosity overall than participants in the instruct-first condition. Planned comparisons also revealed that on the first survey, participants in the explore-first condition reported higher perceived knowledge gaps than participants in the instruct-first condition. Participants in the explore-first condition also reported higher perceived knowledge gaps on the first survey than the second survey. These findings suggest that exploration did heighten their 'need to know' and raise their metacognitive awareness, but other mechanisms may not have been in place (e.g., discerning problem features) to successfully prepare them for subsequent learning.

Limitations

One limitation of this study was the single self-reported item used to assess cognitive load. Though the results suggested that participants in the explore-first group experienced higher cognitive load than participants in the instruct-first group, we did not assess the type of cognitive load experienced. Furthermore, this limitation makes it difficult to determine whether the cognitive load experienced was a hinderance to learning through exploration.

A second limitation was the sparse mention of the measurements tools made by the activity worksheet, relative to the instructions. Because participants in the instruct-first condition were exposed to those instructions prior to completing the simulation activity, they may have been more likely to use the measurements tools compared to participants in the explore-first condition. Given that use of tools was correlated with learning outcomes, it is possible that providing instruction on the tools explains the differences between conditions beyond the impact of instructional order more generally.

Another limitation to consider is the low reliability between assessment items: conceptual knowledge, 14 items, α=.42; transfer knowledge, 13 items, α =.11. Thes scores indicate that items were not closely related to one other, suggesting they may not be assessing similar constructs.

Conclusion

The results of Experiment 1 suggest that, for simulation-based learning, direct instruction methods may benefit students more than exploration. These findings were driven by student strategy use, with students in the instruct-first condition engaging in more formal testing through the simulation's tools. However, cognitive load was also relatively high in the explore-first condition, which is known to impede the benefits of exploration (e.g., Ashman et al., 2020; Fyfe et al., 2014). It is possible that adding guidance, or reducing intrinsic load, will promote the mechanisms necessary for exploration to benefit learning. Experiment 2 was designed to replicate and expand upon the findings of Experiment 1, measuring the different types of cognitive load reported by participants, and manipulating the load elicited by the exploration activity.

CHAPTER III: EXPERIMENT 2

Experiment 1 suggested that, when given minimal guidance, completing a simulation activity prior to instruction results in higher cognitive load than receiving instructions prior to completing the simulation activity. Furthermore, receiving instructions prior to completing an activity worksheet led to higher scores than an explore-first condition. Following these findings, the goal of Experiment 2 was to investigate how to best reduce cognitive load of the same activity worksheet. Experiment 2 examined how reducing the intrinsic demand of activities affects learning outcomes, and whether increased guidance would improve exploratory learning, with the goal of better understanding STEM learning processes.

As in Experiment 1, the primary measured outcomes were participants' learning on items assessing their conceptual understanding of the material and transfer items. Experiment 2 assessed the same secondary variables as Experiment 1 (i.e., cognitive load, perceived knowledge gaps, interest and enjoyment, curiosity, and perceived flow). Experiment 2 also assessed different types of cognitive load (i.e., germane, extraneous, and intrinsic) to understand how these types of cognitive load affected learning outcomes.

Method

Participants

A G*Power analysis for ANOVA ($\alpha = 0.05$, power = .95, df =3, groups=4) showed that a sample size of 195 would be sufficient to achieve $\eta_p^2 = .100$ ($f = 0.33$;

medium effect=0.25, large=0.40). Participants (*N*=195, M_{age}=19.34, *SD*=3.44, 67% female) for Experiment 2 were undergraduate students in the psychology participant pool. Sixteen additional participants were excluded from analyses for not following the study protocol. Two versions of the activity worksheet were used, varying between conditions. The phases throughout the experiment, as well as their order, were identical to Experiment 2. Participants were randomly assigned to one of four conditions: explore-first with a worksheet designed to reduced intrinsic load (explore-first ILR, *n*= 50), instruct-first with a worksheet designed to reduce intrinsic load (instruct-first ILR, *n*=45), explore-first with a worksheet that included worked examples designed to reduce extraneous load (explore-first ELR, *n*=49) or instruct-first with a worksheet that included worked examples to reduce extraneous load (instruct-first ELR, *n*=51).

Activity. The worksheet varied between conditions, with some participants receiving partially completed worked examples (ELR, see Appendix B) and the others receiving a worksheet with the same problems as Experiment 1, but with those problems broken down into smaller comparisons (ILR, see Appendix C). To further reduce intrinsic load for participants in the ILR condition, the final two items had their cover stories removed. Additionally, both versions of the worksheet made explicit mention of the measurement tools that are available in the simulation interface. Both worksheets included the same problems, which tasked students to learn about circuit construction by examining brightness and current in a PhET physics simulation (https://phet.colorado.edu/sims/html/circuit-construction-kit-dc/latest/circuit-construction-kit-dc_en.html).

Survey. Survey items were identical to Experiment 1, with the addition of 13 items to measure different types of cognitive load (Klepsch et al., 2017; Leppink et al., 2013). Three items measured intrinsic load (e.g., while working on the learning activity, I needed to keep many things in mind simultaneously), 6 items measured extraneous load (e.g., it was difficult to figure out the important information), and 4 measured germane load (e.g., each part of the learning activity added to my understanding of the key concepts).

Procedure

The study procedures were identical to Experiment 1, except that participants were randomly assigned to two different activity conditions as well as instructional orders.

Results

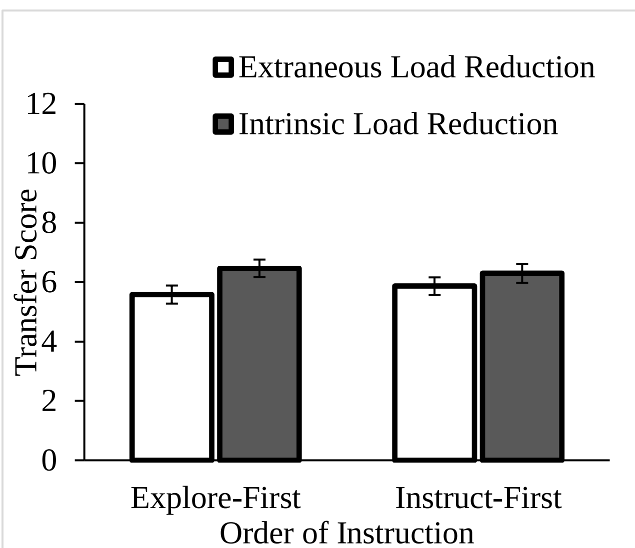
Learning Outcomes

Preliminary results showed no significant main effects of prior knowledge for instructional order, $F(1, 194)=1.10$, $p=.295$, or load reduction, $F<1$, nor an interaction effect, $F(1,194)=2.69$, $p=.103$, suggesting that participants in the explore-first ILR ($M=2.10$, $SE=.13$, 95% CI [1.84, 2.37]), instruct-first ILR ($M=2.18$, $SE=.14$, 95% CI [1.9, 2.46]), explore-first ELR ($M=2.29$, $SE=.13$, 95% CI [2.02, 2.55]), and instruct-first ELR ($M=1.92$, $SE=.13$, 95% CI [1.66, 2.18]) conditions began with, on average, the same level of content knowledge.

Performance on the conceptual assessment items was examined using a 2 (instructional order: explore-first, instruct-first) × 2 (load reduction: intrinsic load, extraneous load) between-subjects factorial ANOVA. Results showed no significant differences between participants in the explore-first conditions (M=7.22, SE=.22, 95% CI [6.79, 7.66]), and instruct-first conditions (M=7.45, SE=.22, CI [7.01, 7.89]), F<1. Results also suggest no significant differences between participants in the ILR conditions (M=7.22, SE=.23, 95% CI [6.77, 7.66]) and ELR conditions (M=7.46, SE=.22, 95% CI [7.02, 7.90]). The interaction was not significant, $F(1,172)=1.55$, $p=.215$.

Performance on the transfer items was examined using the same ANOVA. Results showed no significant differences between participants in the explore-first conditions (M=6.02, SE=.21, 95% CI [5.60, 6.44]) and instruct-first conditions (M=6.08, SE=.22, 95% CI [5.65, 6.51]), F<1. Results revealed a main effect of load reduction, $F(1,172)=4.65$, $p=.032$, $\eta_p^2=.024$ (Figure 2). Participants in the ILR conditions (M=6.38, SE=.22, 95% CI [5.95, 6.81]) scored higher on transfer items than participants in the ELR conditions (M=5.72, SE=.21, 95% CI [5.31, 6.14]). There was no significant interaction, F<1.

Figure 2: Transfer Assessment Scores as a Function of Order of Instruction and Load Reduction



Note: Error bars represent standard error of the mean

Cognitive Load Items

Due to a technical error, a portion of participants (n=19) did not complete the survey portion of Experiment 2. To assess overall cognitive load, a 2 (instructional order: explore-first, instruct-first) × 2 (load reduction: intrinsic load, extraneous load) × 2 (survey administration time: survey 1, survey 2) mixed-factorial ANOVA was conducted, with instructional order and load reduction as between-subjects factors, and the timing of the two surveys as a within-subjects factor. Results revealed no main effect of order, F<1. Results show a significant main effect of load reduction, F(1,172)=4.21, p=.042, η_p^2=.024. Participants in the ELR conditions reported higher cognitive load (M=5.64, SE=.16, 95% CI [5.32, 5.96]) than participants in the ILR conditions (M=5.16, SE=.17, 95% CI [4.84, 5.49]). The main effect of survey administration time was not significant, F(1,172)=1.00, p=.318. The interactions were also not significant, Fs<1 (see Table 5).

Specific types of cognitive load were examined using similar mixed-factorial ANOVAs (Table 5). Analyzing germane load, results reveal a main effect of instructional order, F(1,172)=4.07, p=.045, η_p^2= .023. Participants in the instruct-first conditions (M=3.84, SE=.06, 95% CI [3.72, 3.95]) reported higher germane load than participants in the explore-first conditions (M=3.67, SE=.06, 95% CI [3.56, 3.79]). A significant main effect of survey administration time was found, F(1,172)=5.12, p=.025, η_p^2=.029. Participants reported higher germane load after receiving instruction (M=3.79, SE=.04, 95% CI [3.71, 3.89]) than after completing the activity (M=3.72, SE=.05, 95% CI [3.62, 3.81]).

These main effects were qualified by a significant instructional order × load reduction × survey administration time interaction effect, $F(1,172)=6.22$, $p=.014$, $\eta_p^2=.035$. Comparing instructional order conditions, a simple effect was found between participants in the ILR condition, $F(1,170)=4.64$, $p=.033$, $\eta_p^2=.020$. Participants in the instruct-first-ILR condition ($M=3.96$, $SE=.90$, 95% CI [3.81, 4.16]) reported significantly higher germane load after receiving instruction than participants in the explore-first-ILR condition ($M=3.72$, $SE=.08$, 95% CI [3.56, 3.88]). No other significant simple effects were found between instructional order conditions: explore-first and instruct-first ILR after activity, $F(1,172)=1.14$, $p=.287$, explore-first and instruct-first ELR after activity, $F(1,172)=1.30$, $p=.065$, explore-first and instruct-first ELR after instruction, $F<1$. Comparing load reduction conditions, a simple effect was found between participants in the instruct-first condition, $F(1,172)=4.63$, $p=.893$, $\eta_p^2=.027$. After instruction, participants in the instruct-first-ILR condition ($M=3.96$, $SE=.90$, 95% CI [3.81, 4.16]) reported significantly higher germane load than participants in the instruct-first ELR condition ($M=3.74$, $SE=.08$, 95% CI [3.58, 3.90]). No other significant simple effects were found between load reduction conditions, Fs<1.

Table 5: Descriptive Statistics for Cognitive Load Measures

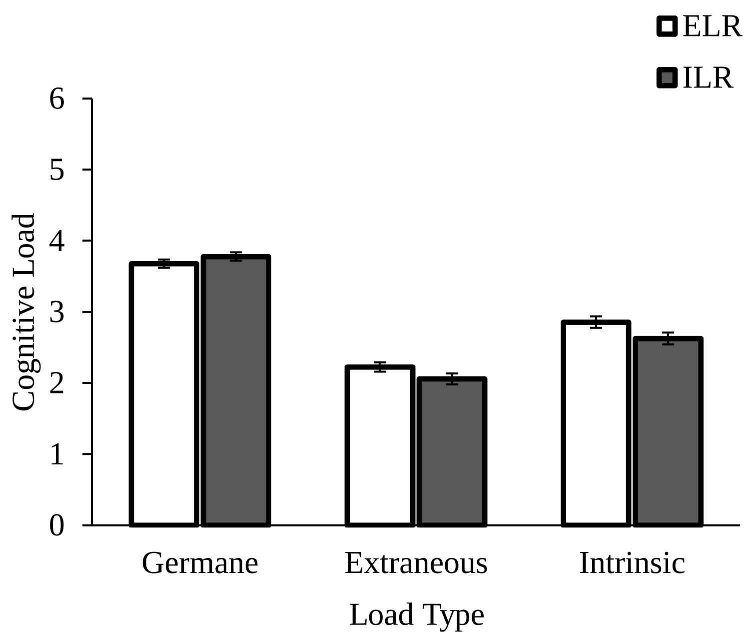
Intrinsic Load Reduction	After Activity				After Instruction			
	Explore-First		Instruct-First		Explore-First		Instruct-First	
	M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
Paas (2003) Mental Effort	5.44	0.21	4.95	0.25	5.31	0.23	4.95	0.27
Germane Load	3.67	0.09	3.81	0.11	3.72	0.09	3.98	0.09
Extraneous Load	2.14	0.09	2.22	0.11	2.14	0.09	1.87	0.09
Intrinsic Load	2.53	0.12	2.74	0.12	2.77	0.12	2.50	0.13

Extraneous Load Reduction								
Paas (2003) Mental Effort	5.51	0.23	5.55	0.21	4.95	0.27	5.75	0.24
Germane Load	3.57	0.08	3.81	0.09	3.73	0.07	3.74	0.08
Extraneous Load	2.22	0.11	0.00	0.00	2.25	0.10	0.00	0.00
Intrinsic Load	2.77	0.12	2.90	0.11	2.86	0.13	2.89	0.12

Examining extraneous load, no main effects were found for instructional order, $F(1,172)=1.06$, $p=.306$, load reduction, $F(1,172)=2.47$, $p=.118$, or survey administration time, $F(1,172)=3.44$, $p=.065$. Results revealed a significant instructional order × survey administration time interaction, $F(1,172)=5.16$, $p=.024$, $\eta_p^2=.029$. Planned comparisons revealed that, after instruction, participants in the explore-first conditions ($M=2.20$, $SE=.07$, 95% CI [2.06, 2.33]) reported significantly higher extraneous load than participants in the instruct-first conditions ($M=2.00$, $SE=.07$, 95% CI [1.87, 2.14]), $F(1,172)=4.11$, $p=.044$, $\eta_p^2=.024$. No other significant interaction effects were observed: instructional order × load reduction, $F<1$, load reduction × survey administration time, $F(1,172)=1.03$, $p=.313$, instructional order × load reduction × survey administration time, $F<1$.

Assessing intrinsic load, no main effects were found for instructional order or survey administration time, *F*s<1. Load reduction was a significant predictor of reported intrinsic load, $F(1,172)=3.94$, $p=.049$, $\eta_p^2=.022$ (see Figure 3). Participants in the ELR conditions ($M=2.86$, $SE=.08$, 95% CI [2.70, 3.02] reported significantly higher intrinsic load than participants in the ILR conditions ($M=2.63$, $SE=.08$, 95% CI [2.46, 2.79]). Results revealed an instructional order × survey administration time interaction, $F(1,172)=14.71$, $p<.001$, $\eta_p^2=.079$. Planned comparisons revealed that participants in the explore-first conditions reported significantly higher intrinsic load after instruction (M=2.81, SE=.09, 95% CI [2.64, 2.99]) than after the activity (M=2.65, SE=.08, 95% CI [2.48, 2.82]), $F(1,172)=8.22$, $p=.005$, $\eta_p^2=.046$. The opposite was found for participants in the instruct-first conditions, who reported higher intrinsic load after the activity (M=2.82, SE=.08, 95% CI [2.66, 2.99]) than after instruction (M=2.68, SE=.09, 95% CI [2.51, 2.85]), $F(1,172)=6.53$, $p=.011$, $\eta_p^2=.037$.

Figure 3: Cognitive Load a Function of Load Reduction, collapsed across Instructional Order



Note: Error bars represent standard error of the mean

Finally, results revealed a significant instructional order × load reduction × survey administration time interaction effect, $F(1,172)=7.05$, $p=.009$, $\eta_p^2=.039$. Planned comparisons revealed that, after receiving instruction, participants in the instruct-first ELR condition (M=2.89, SE=.12, 95% CI [2.66, 3.13]), reported significantly higher intrinsic load than participants in the instruct-first ILR condition (M=2.47, SE=.13, 95% CI [2.21, 2.73]), $F(1,172)=5.82$, $p=.017$, $\eta_p^2=.033$. Planned comparisons revealed a significant simple effect for participants in the explore-first ILR condition; participants in the explore-first ILR condition reported significantly higher intrinsic load after instruction (M=2.77, SE=.12, 95% CI [2.52, 3.01]) than after the activity (M=2.53, SE=.12, 95% CI [2.29, 2.76]), $F(1,172)=9.36$, $p=.003$, $\eta_p^2=.052$. A significant simple effect was also found for participants in the instruct-first ILR condition. Participants in the instruct-first ILR condition reported significantly higher intrinsic load after the activity (M=2.74, SE=.12, 95% CI [2.50, 2.99]) than after instruction (M=2.47, SE=.13, 95% CI [2.21, 2.73]), $F(1,172)=11.03$, $p=.001$, $\eta_p^2=.060$. No other interaction effects were significant, Fs<1.

To further investigate the effect the ILR manipulation had on transfer score, a between-subjects ANCOVA was used to examine the effect of load reduction while controlling for the effects of intrinsic load reported after the activity. Results reveal no significant main effect of load reduction when controlling for intrinsic load reported after the activity, $F(1,172)=3.23$, $p=.074$. There was a significant main effect of intrinsic load reported after the activity, $F(1,172)=5.26$, $p=.023$, $\eta_p^2=.030$. These findings suggest that the reduction of intrinsic load in the ILR condition during the activity may mediate the relationship between load reduction condition and transfer score.

Survey Items

Similar mixed-factorial ANOVAs were used to examine the remaining survey items (Table 6). When assessing interest and enjoyment, there was no main effect of instructional order or load reduction, nor were there significant interaction effects, Fs<1.

For perceived knowledge gaps, there were no main effects of instructional order, $F(1,172)=1.66$, $p=.200$, or load reduction, $F(1,172)=2.96$, $p=.087$. A significant instructional order × survey administration time interaction effect was found, $F(1,172)=34.09$, $p<.001$, $\eta_p^2=.165$. Post-hoc comparisons with Bonferroni correction ($\alpha=.016$) revealed that, after the activity, participants in the explore-first conditions ($M=3.39$, $SE=.09$, 95% CI [3.21, 3.56]) reported higher perceived knowledge gaps than participants in the instruct-first conditions ($M=2.97$, $SE=.09$, 95% CI [2.79, 3.15]), $F(1,172)=9.70$, $p=.002$, $\eta_p^2=.054$. Furthermore, participants in the explore-first conditions reported significantly higher knowledge gaps after the activity ($M=3.39$, $SE=.09$, 95% CI [3.20, 3.56]) compared to after instruction ($M=3.07$, $SE=.09$, 95% CI [2.89, 3.24]), $F(1,172)=25.81$, $p<.001$, $\eta_p^2=.132$. Participants in the instruct-first conditions reported significantly higher knowledge gaps after instruction ($M=3.18$, $SE=.09$, 95% CI [3.01, 3.36]) compared to after the activity ($M=2.97$, $SE=.09$, 95% CI [2.79, 3.14]), $F(1,172)=11.40$, $p<.001$, $\eta_p^2=.063$. No other interactions were significant, *F*s <1.

Examining curiosity, no main effects of instructional order, $F(1,172)=1.50$, $p=.228$, load reduction, or survey administration time were found, *F*s<1. Results revealed a significant instructional order × survey administration time interaction effect, $F(1,172)=12.57$, $p<.001$, $\eta_p^2=.069$. Participants in the explore-first conditions ($M=3.42$, $SE=.08$, 95% CI [3.27, 3.57]) reported higher curiosity after the activity than participants in the instruct-first conditions ($M=3.18$, $SE=.08$, 95% CI [3.03, 3.33]), $F(1,172)=5.17$, $p=.024$, $\eta_p^2=.030$. No other interactions were significant, *F*s<1.

Examining fluency of performance, there was a main effect of load reduction, $F(1,172)=4.24$, $p=.041$, $\eta_p^2=.024$. Participants in the ILR conditions ($M=3.49$, $SE=.07$, 95% CI [3.35, 3.63]) reported significantly higher fluency of performance than participants in the ELR conditions ($M=3.29$, $SE=.07$, 95% CI [3.15, 3.42]). A significant instructional order × survey administration time interaction was found, $F(1,172)=13.86$, $p<.001$, $\eta_p^2=.075$. Participants in the explore-first conditions reported significantly higher fluency after the activity ($M=3.48$, $SE=.08$, 95% CI [3.32, 3.63]) than after instruction ($M=3.27$, $SE=.076$, 95% CI [3.13, 3.42]). No other interaction effects were significant, *F*s<1.

Finally, examining absorption by activity, results showed a significant main effect of survey administration time, $F(1,172)=6.86$, $p=.010$, $\eta_p^2=.039$. On average, participants reported higher absorption after the activity ($M=3.67$, $SE=.06$, 95% CI [3.56, 3.78]) than after instruction ($M=3.53$, $SE=.06$, 95% CI [3.42, 3.64]). No significant main effects of instructional order, $F(1,172)=1.68$, $p=.197$, or load reduction, $F<1$, were found. A significant instructional order × survey administration time interaction was found, $F(1,172)=19.93$, $p<.001$, $\eta_p^2=.105$. Post-hoc comparisons with Bonferroni correction ($\alpha=.025$) revealed that, after instruction, participants in the instruct-first conditions ($M=3.71$, $SE=.08$, 95% CI [3.55, 3.87]) reported significantly higher absorption by activity than participants in the explore-first conditions ($M=3.35$, $SE=.08$, 95% CI [3.19, 3.51]), $F(1,172)=10.08$, $p=.002$, $\eta_p^2=.056$. Furthermore, participants in the explore-first conditions ($M=3.72$, $SE=.08$, 95% CI [3.57, 3.88]) reported significantly higher absorption after the activity than after instruction ($M=3.35$, $SE=.08$, 95% CI [3.19, 3.51]), $F(1,172)=24.93$, $p<.001$, $\eta_p^2=.128$. These effects was further informed by a significant instructional order × load reduction × survey administration time interaction, $F(1,172)=4.36$, $p=.038$, $\eta_p^2=.025$. After instruction, participants in the instruct-first ILR condition ($M=3.74$, $SE=.12$, 95% CI [3.51, 3.98]) reported higher absorption than participants in the explore-first ILR condition ($M=3.20$, $SE=.12$, 95% CI [2.98, 3.42]), $F(1,172)=10.88$, $p=.001$, $\eta_p^2=.060$. No other interactions were significant, $F<1$.

Table 6: Descriptive Statistics for Survey Measures

	After Activity				After Instruction			
Intrinsic Load Reduction	Explore-First		Instruct-First		Explore-First		Instruct-First	
	M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
Interest/Enjoyment	3.28	0.05	3.26	0.05	3.25	0.05	3.32	0.06
Fluency of Performance	3.62	0.10	3.42	0.12	3.33	0.12	3.60	0.08
Absorption by Activity	3.70	0.10	3.55	0.12	3.20	0.13	3.74	0.11
Curiosity	3.43	0.11	3.14	0.11	3.24	0.11	3.23	0.11
Perceived Knowledge Gaps	3.31	0.12	2.90	0.14	2.93	0.12	3.13	0.13
Extraneous Load Reduction								
Interest/Enjoyment	3.29	0.04	3.29	0.06	3.24	0.06	3.28	0.06
Fluency of Performance	3.33	0.11	3.28	0.10	3.21	0.11	3.30	0.10
Absorption by Activity	3.74	0.10	3.67	0.11	3.49	0.11	3.68	0.10
Curiosity	3.41	0.96	3.17	0.11	3.31	0.11	3.30	0.10
Perceived Knowledge Gaps	3.46	0.14	3.07	0.12	3.18	0.13	3.30	0.11

Student Behaviors during Simulation Activity

Identical to experiment 1, screen recordings were coded using the method outlined by Roll (2018). Four student behaviors during the simulation activity were quantified for analysis: construct (i.e., adding resistors, connecting wires, splitting junctions), test (i.e., using the ammeter and voltmeter to conduct measurements), pause (i.e., not engaging with the simulation for longer than 15 seconds), and reset (i.e., removing all components from the testbed and starting from scratch). Twenty percent of the videos were scored by a second observer (r=.81). Preliminary analysis examined correlations between each of the four behaviors, conceptual knowledge, and transfer knowledge. As shown in Table 7, no behaviors were significantly related to performance on conceptual or transfer items. Based on the findings of Experiment 1, a between-subjects ANOVA was used to investigate whether measurement tool use varied across conditions. No significant effects were found, Fs<1.

Table 7: Simple Correlations between Scores and Simulation Activity Behaviors

			Conceptual Items	Transfer Items
	M	*SD*	*Pearson's r (p-value)*	
Construct	48.73	21.16	-0.04 *(.258)*	0.08 *(.556)*
Measurements	21.13	11.57	-0.07 *(.363)*	0.07 *(.336)*
Pause	1.39	0.87	0.08 *(.246)*	0.05 *(.522)*
Reset	2.00	1.56	-0.06 *(.416)*	0.06 *(.432)*

Discussion

Experiment 2 tested whether different versions of an activity worksheet would reduce cognitive load during exploration. Experiment 2 also investigated whether load reduction would result in better learning and knowledge transfer. The results did not support our prediction regarding instructional order and learning outcomes. Despite the lack of learning benefits, the instruct-first approach appeared to be beneficial for managing cognitive load within this learning environment. Participants in the instruct-first conditions reported, on average, higher germane load than participants in the explore-first conditions. Furthermore, after receiving instruction, participants in the explore-first conditions reported, on average, higher extraneous load than participants in the instruct-first conditions.

These findings suggest that participants who explored the simulation prior to instruction were more likely to be distracted by irrelevant information than those in the instruct-first condition, and thus had fewer working memory resources to rely on for germane processing. It is possible that, despite scaffolding, this simulation's interface was too information dense for students to properly allocate resources during exploratory learning. This conclusion is supported by our findings that suggest reducing the intrinsic load improves knowledge performance, though this intervention was not sufficient for exploratory learning to be more beneficial than traditional instruction. Narrowing attention in a way that is native to the simulation environment, rather than through auxiliary resources, may be more optimal for simulation-based exploratory learning. Future research may wish to address this question further by manipulating the salience of simulation features.

There was a main effect of load reduction on knowledge transfer. Supporting our hypothesis, participants in the ILR conditions scored higher on transfer items than participants in the ELR conditions. This pattern is also consistent when examining fluency of performance, as participants in the ILR condition reported higher fluency than participants in the ELR conditions. Also consistent with our hypothesis, there was no main effect of load reduction on conceptual item performance. These findings were further informed by our analyses examining cognitive load. Looking at an overall measure of cognitive load (Paas, 2003), participants in the ILR conditions reported exerting less mental effort than participants in the ELR conditions. Participants in the ILR conditions also reported less intrinsic load than ELR participants. Additionally, we found that the benefit of the ILR worksheet on transfer score may be mediated by the amount of intrinsic load reported after the activity, suggesting the ILR worksheet reduced element interactivity, resulting in higher transfer scores.

Our results suggest that, despite differing levels of report germane and extraneous load, participants in all conditions reported similar interest and enjoyment. This finding is consistent with our hypothesis and previous exploratory learning research (Glogger-Frey et al., 2015; Kapur, 2014; Newman & DeCaro, 2019; Weaver et al., 2018), suggesting that even when simulation-based exploration is too cognitively demanding to benefit novice students, exploratory learning does not result in a lack of interest.

Though there was no main effect of perceived knowledge gaps, an instructional order × survey administration time interaction effect revealed that, consistent with our stated hypothesis, participants in the explore-first conditions reported higher knowledge gaps after the activity than participants in the instruct-first conditions. Participants in the explore-first conditions also reported higher knowledge gaps after the activity than after instructions.

Regarding curiosity, Experiment 2 found an instructional order × survey administration time interaction effect, revealing that after the activity, participants in the explore-first conditions reported higher curiosity than participants in the instruct-first conditions. This finding is consistent with our hypothesis that the explore-first condition would experience higher curiosity. Heightened curiosity (Loibl et al., 2017) and increased awareness of knowledge gaps (Glogger-Frey et al., 2015) are both critical mechanisms of successful exploratory learning, however, these findings suggest that these components are not enough for effective exploratory learning. Learners must also be able to identify critical problem features to benefit from exploration. The high cognitive demand of the simulation is likely why learners were unable to correctly discern the problem features.

As was the case in Experiment 1, participants were students with little prior knowledge of the covered concepts. An absence of relevant prior knowledge to fall back on during exploration may be another reason our data did not replicate prior research, as the activation of prior knowledge could be a stronger mechanism than curiosity or awareness of knowledge gaps. Existing research using simulations as exploratory learning activities within a chemistry classroom (DeCaro et al., 2022) found exploration to be beneficial for conceptual knowledge. This study differs from the current research in a few critical ways, one being that the study procedures took place in a live classroom of students enrolled in a chemistry course. Though this is speculation, students enrolled in a course with the intention of learning taught material may have higher average motivation and prior knowledge compared to students who are recruited for a study, wherein the knowledge they acquire may not be used in the future.

The results of Experiment 2 did not replicate Experiment 1's finding regarding participants' tool use throughout exploration. None of the four coded behaviors (i.e., construct, measure, pause, reset) were significantly related to performance on assessment items. This result may be a consequence of the redesigned worksheets, as both made more explicit mention of the measurement tools than the worksheet used in Experiment 1. In Experiment 2, the measurement tools were explained to the participants uniformly across all conditions, and participants were more likely to use those tools regardless of condition. This is a possible reason that participants in the explore-first conditions performed comparably to participants in the instruct-first conditions, rather than at the lower level shown in Experiment 1.

Limitations

Like Experiment 1, a limitation to consider is the low reliability of assessment items: taught knowledge, 14 items, α=.53; transfer knowledge, 13 items, α=.42. If items poorly relate to one another, it may be the case that they do not measure the same construct. Interpretation of these data should keep this possibility in mind.

Conclusion

Though there was no main effect of instructional order on learning, the instruct-first approach appeared to be more optimal for minimizing extraneous load and improving germane processing. On average, participants who received a worksheet designed to reduce intrinsic load performed better on transfer items than participants who received a worksheet designed to reduce extraneous load. Examining cognitive load, participants in the ILR conditions reported significantly lower overall cognitive load, as well as intrinsic cognitive load, than participants in the ELR conditions. Furthermore, our findings suggest that the level of intrinsic load reported after the activity may have mediated the effectiveness of the worksheet on transfer performance. These results suggest that reducing the element interactivity of simulation activities, by breaking them into smaller segments, prepares students to apply their knowledge when learning novel concepts.

CHAPTER IV: GENERAL DISCUSSION

Experiments 1 and 2 investigated the implementation of an interactive computer-based simulation as an exploratory learning activity. The current research also examined the roles of cognitive load, perceived knowledge gaps, perceived flow, interest and enjoyment, and curiosity. This research adapted a coding scheme (Roll et al., 2014) to study how participants' behaviors and strategies during exploration affect learning. How often students constructed circuits using new circuit components, tested circuits using measurement tools, paused all action within the simulation for 15 or more seconds, and reset the simulation testbed, were all quantified.

The results of Experiment 1 revealed a main effect of instructional order, with participants in the instruct-first condition scoring higher on conceptual items than participants in the explore-first condition. This effect was potentially mediated by tool use. Our results did not support our hypothesis based on previous exploratory learning research; however, this finding is analogous to prior simulation-based research. Findings by Roll and colleagues (2018) suggest that students who receive direct guidance are more likely to engage in formal testing than participants who receive less guidance. The worksheet featured in Experiment 1 did not make many explicit mentions of the measurement tools, whereas the video instructions made ample mention of them. It is possible that participants' attention was more likely to be directed to these tools if they had received instructions first.

There are other possible reasons Experiment 1 saw an instruct-first benefit. Though this finding is inconsistent with an abundance of exploratory learning literature suggesting that exploratory learning is more beneficial for conceptual learning (e.g., Bego et al., 2023; DeCaro & Rittle-Johnson, 2015; Kapur, 2014: Newman & DeCaro, 2019), some research suggests that exploratory learning is not ideal when element interactivity is high (Ashman et al., 2020). The element interactivity experienced by the learner does not just depend on the material, but also the knowledge of the learner (Chen, et al., 2015). Participants across both experiments reported considerably low average prior knowledge. With fewer existing schema to rely on, it may be more challenging for learners to concurrently maintain several interacting elements within working memory (Kalyuga, 2013).

In Experiment 1, participants in the explore-first condition also reported significantly higher cognitive load than participants in the instruct condition. This cognitive load was also high relative to the scale maximum (M=6.29 out of 9). Though it is impossible to determine what type of cognitive load was experienced using a single item, it is possible that much of the load reported was extraneous. For the purpose of teaching the users about electrical conduction, the PhET simulation used in these experiments features various objects (e.g., paper clips, coins, pencils, erasers) that are irrelevant to our activity. The presentation of incidental information is in violation of the *coherence principle* of multimedia learning, which argues that learning is disrupted when an abundance of irrelevant text or images are present (Mayer & Moreno, 2003). It is possible that the presence of this information may have distracted participants who were not yet instructed on which objects would be required for successfully building circuits (i.e., explore-first participants). The presence of irrelevant interface objects is also a feature that distinguishes this research from studies that have found an explore-first benefit using simulations (e.g., DeCaro et al., 2022). Future research can investigate this possibility by manipulating the number of irrelevant objects found within the simulation testbed.

In Experiment 2, participants used more heavily guiding versions of the activity worksheets. These worksheets were designed to either 1) reduce intrinsic load by breaking down problems into smaller sets or 2) reduce extraneous load by providing partially completed worked examples. Experiment 2 also addressed some limitations of Experiment 1 by introducing items measuring different types of cognitive load and revising the activity worksheets to include direct mention of the measurement tools.

Though Experiment 2 did not replicate Experiment 1's main effect of order, there was a main effect of load reduction. Consistent with our prediction, participants who received worksheets designed to reduce intrinsic load scored higher on transfer items than participants who received extraneous load reducing worksheets. Participants who received ILR worksheets also reported lower overall load, and lower intrinsic load, than participants who received ELR worksheets. The intrinsic load reported after the activity mediated the ILR worksheet's benefit on transfer score. These findings are consistent with Cognitive Load Theory's (CLT) *narrow limits of change principle*. This principle argues that, to avoid overwhelming working memory capacity, information must be structured in a way that limits the number of elements necessary at once (Suthers, 2006). All problems featured in ILR worksheet were nearly identical to those featured in

Experiment 1 but were segmented in a way that reduced the number of elements that must be maintained in working memory at once.

The finding that ELR participants scored lower on transfer items is also consistent with CLT's *randomness as genesis principle*. If learners are without adequate prior knowledge, problem-solving solutions are randomly generated and tested for effectiveness (Chen et al., 2015). CLT argues that the worked examples benefit students by removing the elements of randomness during problem-solving (Sweller, 2011). Worked examples provide step-by-step solutions without need for guesswork or relevant prior knowledge, making them especially effective for reducing erroneous solutions during learning. This procedure should provide adequate information to acquire domain-specific knowledge during the simulation activity. Because the learner did not generate this information themselves (see *generation effect*, Bertsch et al., 2007) this approach may allow for less flexibility in applying that knowledge (i.e., less knowledge transfer).

One possible reason for finding no ELR benefit for learning is a failure to reduce extraneous load, as our results showed load reduction was not predictive of reported extraneous load. Some research suggests that worked examples that require learners to integrate knowledge from several sources at once are ineffective for learning (Ward & Sweller, 1990). It is possible that tasking students to complete the problems using the complex simulation interface, while concurrently integrating the steps provided in an external worksheet may have resulted in an abundance of task-switching and consequent extraneous load.

Limitations & Future Work

As cognitive load is of central importance to the current research, one major limitation of both experiments is their reliance on self-report cognitive load measures. Such measures are both indirect and subjective, so responder biases may limit their interpretability. Future research may wish to employ more direct and objective measures (e.g., eye-tracking procedures, dual-task approaches) to measure cognitive load more effectively.

An additional limitation lies in the generalizability of these data. Both Experiments 1 and 2 recruited participants from an undergraduate psychology subject pool. Furthermore, both Experiments 1 and 2 were conducted within a laboratory setting. Future studies may expand on this research by investigating simulation-based exploratory learning in a real physics classroom.

Conclusion

Interactive computer-based simulations are affordable and accessible tools for STEM learning. Establishing guidelines to best use these tools will help instructors communicate scientific concepts to students without requiring an abundance of time or resources. Our findings highlight some steps towards discovering those guidelines: 1) when element interactivity is high, providing instructions prior to the simulation activity may result in greater conceptual understanding and transfer, and help manage working memory resources, 2) segmenting problem elements in accordance with Cognitive Load Theory's *narrow limits of change principle* may reduce intrinsic cognitive load and improve students' preparation for future learning.

The current research also has implications for physics education specifically. Simulations have become increasingly common in STEM classrooms, as they are an effective and engaging way to represent real-world scientific phenomena. Though some studies have investigated simulations as exploratory learning activities (Chin et al., 2016; DeCaro et al., 2022), no studies have tested implementing simulations as exploratory learning activities in physics. Future studies may expand on this point by using various simulations to test different physics concepts.

This research should be regarded as only a first step towards implementing simulations as exploratory learning activities within the realm of physics. There is considerably more research to be done to determine how to best implement simulations as exploratory learning activities, especially as technology allow researchers and educators to improve the accuracy, accessibility, and interoperability of computer-based simulations.

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APPENDIX A: Experiment 1: Exploration Worksheet

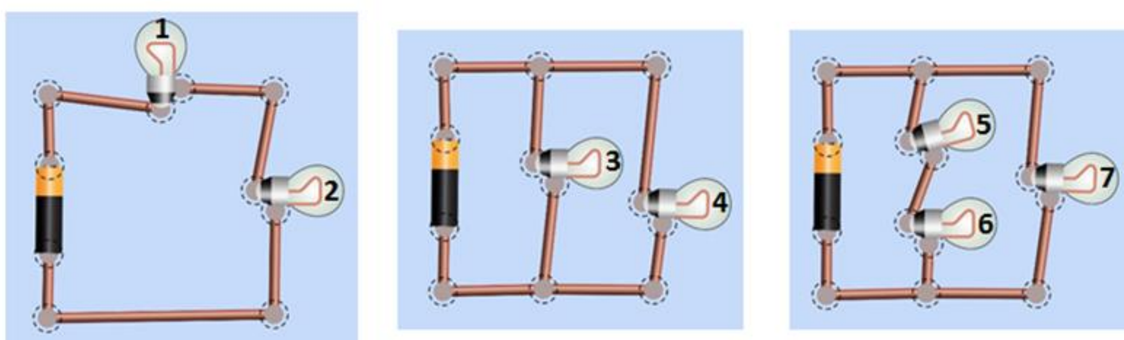
INSTRUCTIONS

Your objective is to use the simulation to explore how voltage, current, and the brightness of light bulbs depends on:

1) the number of light bulbs in the circuit,
2) the arrangement of light bulbs in the circuit

You will have 20 minutes to explore the simulation. Press the blue arrow button on the bottom right of the screen to advance to the simulation.
Use the blank spaces provided on this sheet to record your answers.

Consider the following circuits:



1. **Without using the simulation.** From the circuits above, which bulb (or bulbs) do you think will be the brightest of all 7 bulbs? Why do you think that?

   Now that you have made a prediction, use the simulation to test it. What did you find out?

2. **Current** is the flow of charge (measured in coulombs/sec = amps) in a circuit. Predict how you think current will flow in the different types of circuits above, by drawing arrows in the pictures above. Where within the circuit will current be stronger or weaker? (Label in the diagrams above).

   Now test your predictions using the simulation. What did you find out?

3. Imagine you are an engineer making a string of battery-powered holiday lights. If a bulb burns out, current cannot flow through that bulb any longer (as if the wire at the bulb has been cut). Figure out how to hook up 2 light bulbs and a battery so that, when one bulb burns out (or is disconnected), the other stays lit. Once you have finalized your design, draw the circuit below.

4. Now, you instead want to make sure the battery for your string of lights will last as long as possible. A battery will last longer if it powers a circuit with low current. How could you hook up a battery and 2 light bulbs so that the least amount of current flows through the battery? Try solving this problem without changing the voltage of the battery. Use the measurement tools in the simulation to check your design. Once you have finalized your design, draw the circuit below.

APPENDIX B: Experiment 2: Extraneous Load Reduction

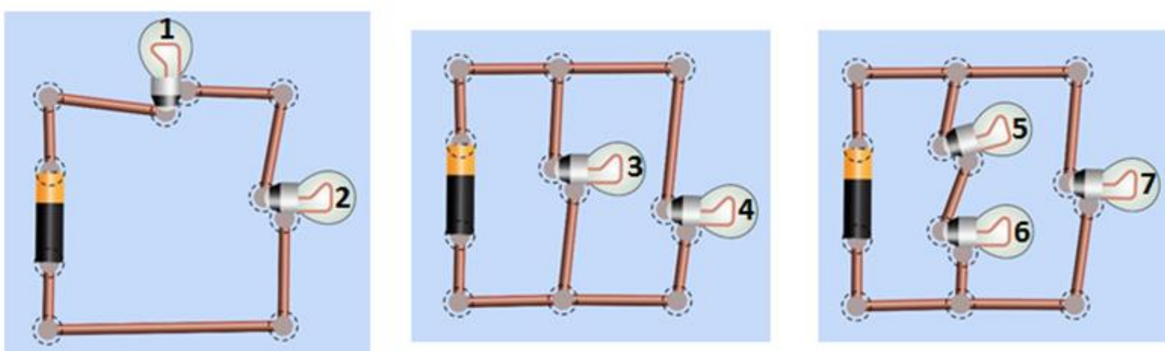
INSTRUCTIONS

Your objective is to use the simulation to explore how voltage, current, and the brightness of light bulbs depends on:

1) the number of light bulbs in the circuit,
2) the arrangement of light bulbs in the circuit

You will have 20 minutes to explore the simulation. Press the blue arrow button on the bottom right of the screen to advance to the simulation.
Use the blank spaces provided on this sheet to record your answers.

Consider the following circuits:

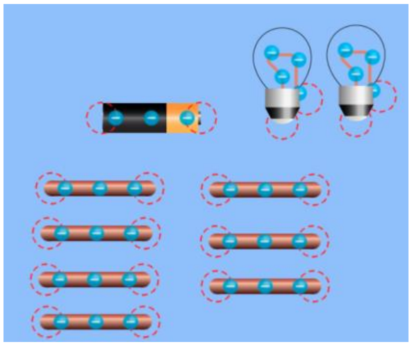


1. From the circuits above, which bulb (or bulbs) will be the brightest of all 7 bulbs?

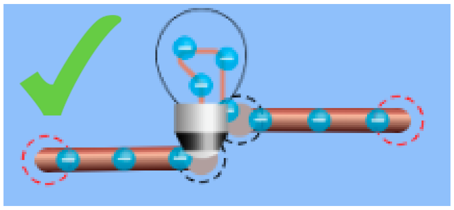
   We can use the simulation to answer this question. Let's begin by testing which bulb (or bulbs) is the brightest of bulbs 1 and 2. The following instructions will show you how to begin solving this problem. As you read the steps, try to follow them using the simulation.

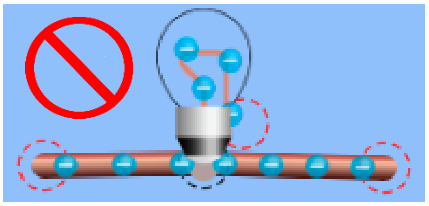
A) Let's build Circuit 1. To start, we will need to gather the necessary circuit elements. To build a circuit identical to this one, we will need 7 wire pieces, 2 light bulbs, and 1 battery.

B)

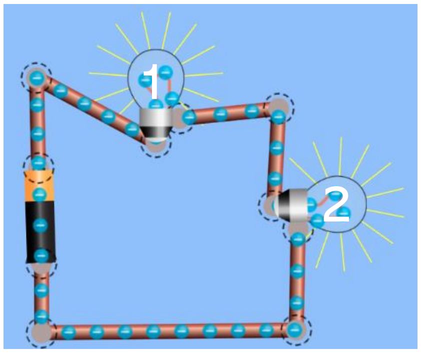


C) Next, let's assemble the circuit by connecting the light bulbs and battery to the wires. Make sure to connect wires to the light bulbs by using each junction. Connecting two wires to the same junction will cause the circuit to overheat.





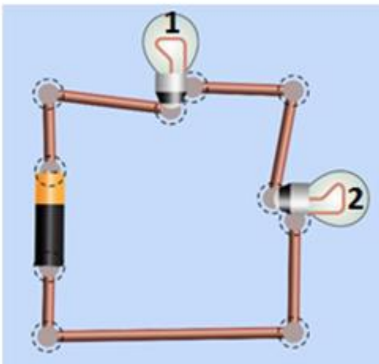
The finished circuit should look like this:

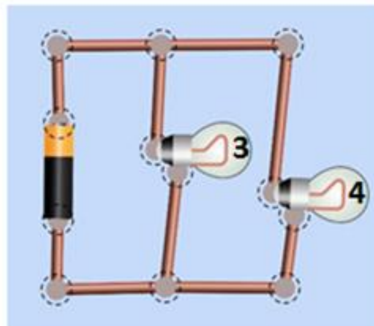


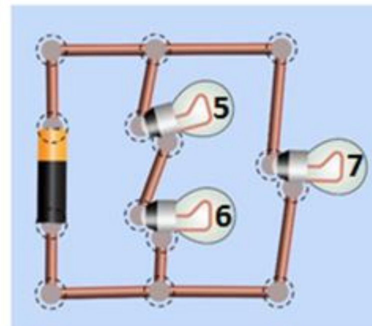
We can see that bulbs 1 and 2 are equally bright. Now that you have built one circuit, predict which bulb (or bulbs) will be the brightest of all 7 bulbs. Why do you think that?

Now that you have a made a prediction, use the simulation to test it. What did you find out?

2. **Current** is the flow of charge (measured in coulombs/sec = amps) in a circuit. Predict how you think current will flow in the different types of circuits below, by drawing arrows in the pictures below. Where within the circuit will current be stronger or weaker? (Label in the diagrams below).





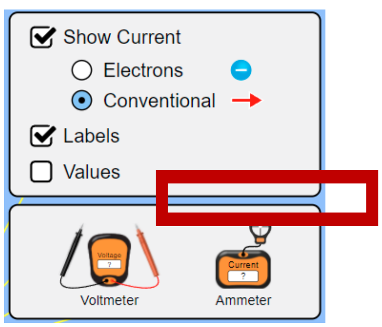


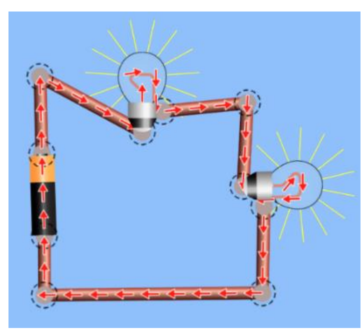
Circuit A **Circuit B** **Circuit C**

Now that you have made a prediction, use the simulation to test it by following these

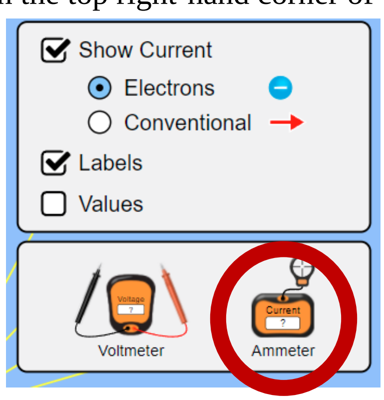
steps:

A) An easy way to view the *direction* of current is by selecting the conventional option in the top right-hand corner of the simulation interface. Now the electrons in the simulation display have been replaced by arrows, showing the current's direction.

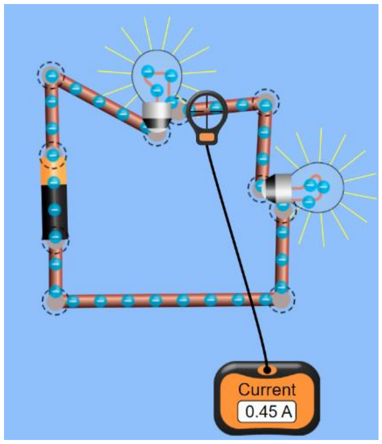




B) You can select the Ammeter tool to measure the strength of the current in the circuits. You can find this tool in the top right-hand corner of the simulation interface.



C) The strength of the current can be measured by dragging the wire end of the ammeter to various parts of the circuit. After investigating the first circuit, we see that the current is a constant 0.45 amps throughout.



Use the ammeter to test the current of the other two circuits. What did you find out?

3. Imagine you are an engineer making a string of battery-powered holiday lights. If a bulb burns out, current cannot flow through that bulb any longer (as if the wire at the bulb has been cut). Figure out how to hook up 2 light bulbs and a battery so that, when one bulb burns out (or is disconnected), the other stays lit. Once you have finalized your design, draw the circuit below.

4. Now, you instead want to make sure the battery for your string of lights will last as long as possible. A battery will last longer if it powers a circuit with low current. How could you hook up a battery and 2 light bulbs so that the least amount of current flows through the battery? Try solving this problem without changing the voltage of the battery. Use the measurement tools in the simulation to check your design. Once you have finalized your design, draw the circuit below.

APPENDIX C: Experiment 2: Intrinsic Load Reduction

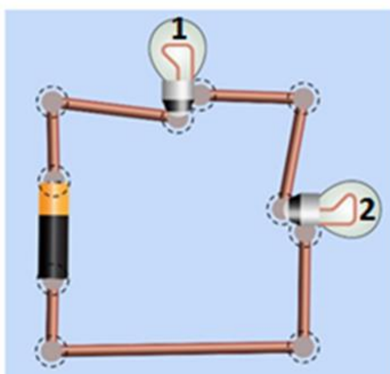
INSTRUCTIONS

Your objective is to use the simulation to explore how voltage, current, and the brightness of light bulbs depends on:

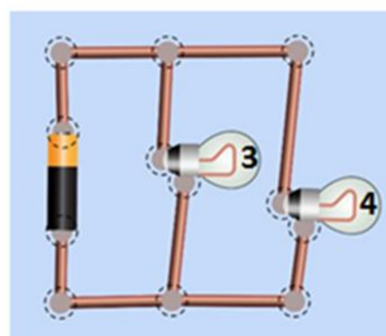
1) the number of light bulbs in the circuit,
2) the arrangement of light bulbs in the circuit

You will have 20 minutes to explore the simulation. Press the blue arrow button on the bottom right of the screen to advance to the simulation.
Use the blank spaces provided on this sheet to record your answers.

Consider the following circuits:



Circuit A

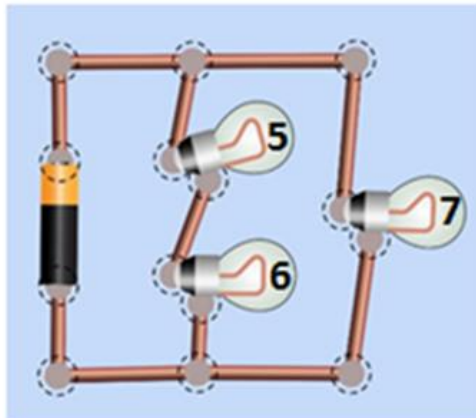


Circuit B

1. **Without using the simulation.** From the circuits above, which bulb (or bulbs) do you think will be the brightest of all 4 bulbs? Why do you think that?

   Now that you have made a prediction, use the simulation to test it. What did you find out?

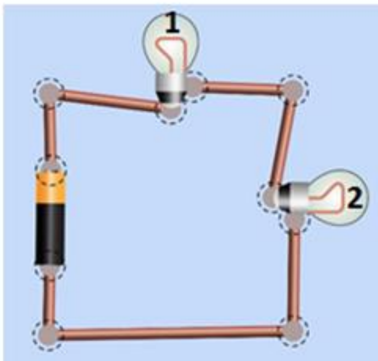
Now consider the following circuit:



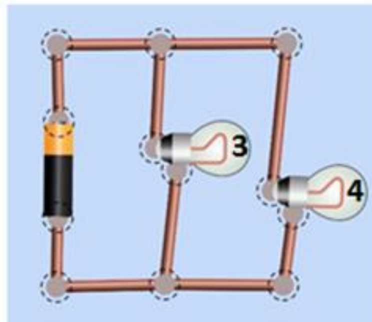
2. **Without using the simulation.** From the circuit above, which bulb (or bulbs) do you think will be the brightest of all 3 bulbs? Why do you think that?

Now that you have made a prediction, use the simulation to test it. What did you find out?

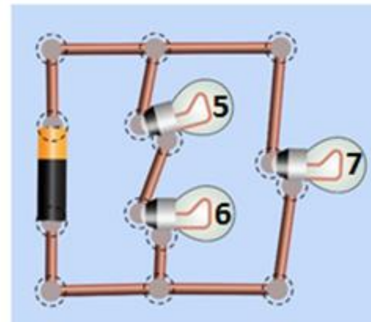
3. **Current** is the flow of charge (measured in coulombs/sec = amps) in a circuit. Predict how you think current will flow in the different types of circuits below, by drawing arrows in the pictures below. Where within the circuit will current be stronger or weaker? (Label in the diagrams below).



Circuit A

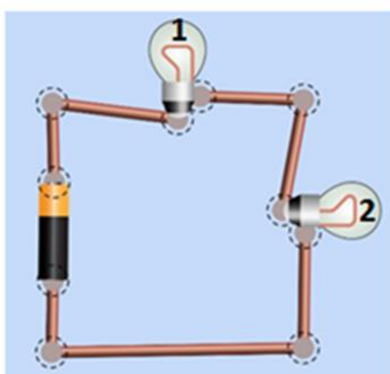


Circuit B

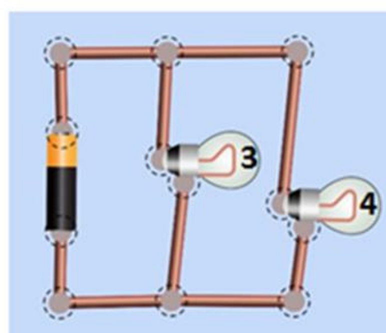


Circuit C

Now that you have made a prediction, use the simulation to test it. Use the Ammeter tool to help you. What did you find out?



Circuit A



Circuit B

4. **Without using the simulation.** Imagine you are making a string of battery-powered holiday lights. You want to design the lights so that, if a bulb burns out, current cannot flow through that bulb any longer (as if the wire at the bulb has been cut). Looking at Circuits A and B above, which of these circuits do you think is hooked up so that, if one bulb burns out (or is disconnected), the other stays lit. Explain your reasoning.

Now that you have made a prediction, use the simulation to test it. What did you find out?

5. **Without using the simulation.** Let’s say you wanted to make sure the battery for a string of lights will last as long as possible. A battery will last longer if it powers a circuit with low current. Looking at Circuits A and B above, which of these circuits do you think is hooked up so that the least amount of current flows through the battery? Assume that the two batteries have the same voltage. Explain your reasoning.

   Now that you have made a prediction, use the simulation to test it. Use the Ammeter tool in the simulation to check your prediction. What did you find out?

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EDUCATION

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Eastern Kentucky University, Richmond, KY
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Morehead State University, Morehead, KY
B.S. in Psychology, 2012 – 2016
Mentor: Lynn Haller, Ph.D., Gilbert Remillard, Ph.D.

PROFESSIONAL EXPERIENCE AND TRAINING

Inclusive STEM Teaching Project (2021)
STEM Graduate Teaching Academy (2020-2021)
Center for Drug and Alcohol Research, Lexington, KY
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Supervisors: Sharon Walsh, Ph.D., Paul Nuzzo, M.S.

TEACHING EXPERIENCE

Brain and Behavior
Instructor, University of Louisville (2022-2023)
Independent Study Research
Graduate Student Mentor, University of Louisville (2020-2022)
Sensation and Perception
Teaching Assistant, University of Louisville (2021)
Introduction to Psychology
Teaching Assistant, University of Louisville (2019-2021)
Multivariate Statistics & Research Methodology (Graduate Course)

Teaching Assistant, Eastern Kentucky University (2018)
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Introduction to Research Methods
Teaching Assistant, Eastern Kentucky University (2016)
Private tutor of **Introduction to Psychology** and **Research and Methodology** students (2014 – 2016)

MANUSCRIPTS

McClellan, D.K., Chastain, R. J., DeCaro, M.S. (under review). Embedding cognitive prompts in an online science lecture improves learning. *Journal of Computing in Higher Education*.

DeCaro, M. S., **McClellan, D. K.**, Powe, A., Franco, D., Chastain, R. J., Hieb, J. L., & Fuselier, L. (2022). Exploring an online simulation before lecture improves undergraduate chemistry learning. *Proceedings of the International Society of the Learning Sciences*.

MANUSCRIPTS IN PROGRESS

McClellan, D.K., Chastain, R.J., DeCaro, M.S., (in preparation). Exploratory learning improves knowledge transfer in undergraduate physics learning.

McClellan, D.K., Chastain, R.J., DeCaro, M.S., (in preparation). Does activity length matter? Brief exploratory learning activities improve conceptual understanding in undergraduate statistics learning.

PRESENTATIONS

* = Supervised Undergraduate Student Author

Powe, A., Franco, D., **McClellan, D. K.**, Chastain, R. J., Hieb, J. L., Fuselier, L., & DeCaro, M. S. (2022, July). Exploring a simulation on atomic structure before lecture improves undergraduate chemistry students' concept learning. Presented at the Biennial Conference on Chemical Education.

DeCaro, M. S., **McClellan, D. K.**, Powe, A., Franco, D., Chastain, R. J., Hieb, J. L., & Fuselier, L. (2022, June). Exploring an online simulation before lecture improves undergraduate chemistry learning. Paper presented at the International Conference of the Learning Sciences, Online.

McClellan, D.K., Chastain, R.J, DeCaro, M.S., (2022, May). Exploratory learning improves knowledge transfer in undergraduate physics learning. Poster presented at the *Association for Psychological Science*, Chicago, IL.

*Bhutto, N., **McClellan, D.K.,** Powe, A., DeCaro, M.S. (2022, April). Online simulations can improve students' learning. Poster presented at the *Annual Undergraduate Arts and Research Showcase*, Louisville, KY.

*Nguyen, V., **McClellan, D.K.**, Powe, A., Franco, D., DeCaro, M.S. (2022, April). Does switching the order of strategy instruction improve conceptual knowledge? Poster presented at *the Annual Undergraduate Arts and Research Showcase*, Louisville, KY.

McClellan, D.K., Chastain, R.J., DeCaro, M.S. (2021, August). Students with disorganized study habits benefit from cognitive prompts during online video lectures. Talk presented at *the APT Physics Education Research Conference*.

McClellan, D.K., Chastain, R.J., DeCaro, M.S. (2021, May). Embedding cognitive and metacognitive prompts into an online STEM lecture. Talk presented at the *Annual Meeting of the Association for Psychological Science*.

*Alquran, M., **McClellan, D.K.**, DeCaro, M.S. (2021, April). Exploratory learning using high load physics problems. Poster presented at the *Annual Undergraduate Arts and Research Showcase*.

*Islam, S., **McClellan, D.K.**, DeCaro, M.S. (2021, April). Using exploratory learning to understand physics-related problems. Poster presented at the *Annual Undergraduate Arts and Research Showcase*.

McClellan, D.K., Chastain, R.J., DeCaro, M.S. (2020, November). The effectiveness of cognitive and metacognitive prompts during an online STEM lecture. Poster presented at the *Annual Meeting of the Psychonomic Society*. Scheduled to take place in Austin, TX, but moved online.

*Clark., M.E., Bego, C.R., **McClellan, D.K.**, DeCaro, M.S. (2020, April). Exploratory learning using consistency problems: Activity type matters. Poster presented at the *Annual Undergraduate Arts and Research Showcase*, Louisville, KY.

Varakin, D.A., **McClellan, D.K.** (2019, May). Examining limits of encoding into visual long-term memory. Poster presented at the Annual Meeting of the Vision Sciences Society, St. Pete Beach, FL.

McClellan, D.K., Varakin, D.A., Renfro, A.J., Hays, J. (2018, May). The magic number 4 limits selection of object categories for encoding into visual long-term memory. Poster presented at the *Annual Meeting of the Vision Sciences Society*, St. Pete Beach, FL.

Baker, S., Moran, **M., McClellan, D.K.**, Varakin, D.A. (2018, May). Miniature models and immersion: A failed replication. Poster presented at the *Annual Meeting of the Vision Sciences Society*, St. Pete Beach, FL.

Amry, M., White, C., **McClellan, D.K.** (2018, May). With this tilt, I dub you cute: Head tilt increases cuteness in puppies and adult dogs. Poster presented at the *Annual Meeting of the Vision Sciences Society*, St. Pete Beach, FL.

Moran, M., Varakin, D.A, **McClellan, D.K** (2017, May). Going to the movies: Immersion, visual awareness, and memory. Poster presented at the *Annual Meeting of the Vision Sciences Society*, St. Pete Beach, FL.

McClellan, D.K., Varakin, D.A (2017, February). Assessing the reliability and validity of visual statistical learning tasks. Talk presented at *Brain and Cognition Seminar*, Eastern Kentucky University, Richmond, KY.

McClellan, D.K., Osbaldiston, R. (2016, November). The effects of attentional shift on visual-short term memory. Poster presentation at the *Annual Meeting of the Kentucky Academy of Science*, Louisville, KY.

Lowe, S. J., Haller, L. M., Obermayer, K. M., Justice, J. R., Yates, L., Gearhart, I. R., Duvall, A. E., **McClellan, D. K.** (2016, May). A vagina is an ugly duckling: Metaphors for sex education. Poster presentation at the *Annual Meeting of the Midwestern Psychological Association*, Chicago, IL.

McClellan, D.K., Remillard, G. (2016, April). The role of mindfulness and inhibitory control on implicit sequence learning. Talk presented at the *Annual Celebration of Student Scholarship*, Morehead State University, Morehead, KY.

References

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