Research Article doi: 10.12973/eu-jer.10.2.989

# European Journal of Educational Research

**Volume 10, Issue 2, 989 - 1007.**

ISSN: 2165-8714
http://www.eu-jer.com/

# Enhancing Scientific Discovery Learning by Just-in-Time Prompts in a Simulation-Assisted Inquiry Environment

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*Received: December 28, 2020 ▪ Revised: February 19, 2021 ▪ Accepted: April 10, 2021*

**Abstract:** We investigated the effects of just-in-time guidance at various stages of inquiry learning by novice learners. Thirteen participants, randomly assigned to an intervention (n = 8) or control (n = 5) group, were observed as they learned about DC electric circuits using a web-based simulation. Just-in-time instructional prompts to observe, predict, explain, systematically test, collect evidence, and generate rules were strongly associated with diagnosing and correcting misconceptions, and constructing correct scientific concepts. Students' repeated use of predictions, systematic testing, and evidence-coordinated reasoning often led to formulating new principles, generalizing from observed patterns, verifying comprehension, and experiencing "Aha!" moments. Just-in-time prompts helped learners manage embedded cognitive challenges in inquiry tasks, achieve a comprehensive understanding of the model represented in the simulation, and show significantly higher knowledge gain. Just-in-time prompts also promoted rejection of incorrect models of inquiry and construction of robust scientific mental models. The results suggest ways of customizing guidance to promote scientific learning within simulation environments.

**Keywords:** *Guidance, inquiry learning, prompts, simulation.*

**To cite this article:** Hajian, S., Jain, M., Liu, L. A., Obaid, T., Fukuda, M., Winne, P. H., & Nesbit, J. C. (2021). Enhancing scientific discovery learning by just-in-time prompts in a simulation-assisted inquiry environment. *European Journal of Educational Research, 10*(1), 989-1007. https://doi.org/10.12973/eu-jer.10.2.989

## Introduction

Scientists seek to understand our complex natural world through systematic inquiry. They identify a problem and search for solutions through methodical observation, informed prediction, and analysis of outcomes. This process often features recurrent questioning, idea-testing, decision-making, explaining and justifying on the way to constructing causal theories.

Doing science is not just for scientists. Inquiry learning in which students investigate, explain, and predict phenomena is intended to promote the same cognitive engagement (Balim, 2009; Jonassen, 2000; Kearsley & Shneiderman, 1998).

According to Ausubel (1968), the most important factor affecting learners' development of conceptual knowledge is their pre-existing system of knowledge and beliefs. Robust misconceptions can interfere with acquiring scientific concepts such as Newton's laws, Ohm's law, and laws of thermodynamics (Neidorf et al., 2020; Prastyaningrum & Pratama, 2019). For example, the false idea of energy as a substance seems to arise from ideas about creating and destroying energy prompted by frequent exposure to common phrases referring to 'filled up' with energy, 'used up' energy, lost energy, or exhaustion of batteries (Zhang et al., 2019). Such misconceptions can challenge concepts of energy as a conserved quantity that can only change from one form to another (Chi, 2008; Tatar & Oktay, 2007).

Misconceptions have been repeatedly observed for physics concepts (Alwan, 2011; Cardak, 2009; Chi, 2005; Turgut et al., 2011). For example, by analogy with water flowing through a pipe, electricity is often thought to be a flow of electrons supplied by a source, such as a battery or a generator. In reality, electrons are not created by a battery but moved in the circuit (Turgut et al., 2011).

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Students use coherent but flawed mental models to explain new observations (Chi, 2008). Thus, identifying existing assumptions, especially if they are misconceptions, is essential for learning as it allows learners to recognize, refute, and restructure those assumptions (Srisawasdi & Panjaburee, 2015). Access to students' initial knowledge has value to a tutor in shaping the type of guidance required by the learner for analyzing naïve mental models and transforming them into accurate scientific frameworks (Anderson & Krathwohl, 2001). Many inquiry learning models, such as the 3P model (Peterson & Jungck, 1988), the 5E inquiry learning model (Bybee, 2006), the 5-phase model of inquiry (White & Frederiksen, 1998), and the inquiry model of Pedaste et al. (2015), embed guidance at various stages of learning. However, most of these models do not identify what types of instructional guidance are most required by learners and when they need to be delivered for effective discovery learning within simulations.

## Literature Review

*Inquiry Learning as a Multistage Process*

Inquiry learning challenges learners to investigate natural phenomena through asking questions, collecting evidence, constructing explanations, comparing alternative explanations, and justifying decisions.

Most models cast scientific inquiry as a multifaceted activity involving many different conditions and phases. "[F]rom a pedagogical perspective, the complex scientific process is divided into smaller, logically connected units that guide students and draw attention to important features of scientific thinking. These individual units are called inquiry phases, and their set of connections forms an inquiry cycle" (Pedaste et al., 2015, p. 48). For example, the 3 Ps model of Peterson and Jungck (1988) describes three phases: problem-posing, problem-solving, and persuasion. According to this model, students need to explore a topic to frame a solvable problem, apply a relevant strategy to solve that problem, and develop explanations that are persuasive.

The 5E Instructional Model of Inquiry (Bybee & Landes, 1990) consists of five cognitive stages: engaging, exploring, explaining, elaborating, and evaluating. Inquiry learning organized by this model has positive impacts including increasing learners' engagement and deepening understanding of scientific concepts, such as heat and heat transfer (Bybee, 2006; Duran & Duran, 2004; Piyayodilokchai et al., 2013; Putra et al., 2018). With the intent of enhancing its effectiveness, the 5E model was modified by inserting conscious pauses in learning cycles (Duran et al., 2011) to formatively assess students' progress through early phases in the cycle and incorporate an evaluative dimension into their inquiry process. Similarly, adding the presentation of analogies helped learners overcome misconceptions (Orgill & Thomas, 2007). Analogies can be highly beneficial in transferring prior knowledge to the newly learned concepts and can be considered effective tools for understanding complex scientific notions (Hajian, 2018, 2019).

Although the effectiveness of all these models has been evaluated by many instructional designers and researchers, the evaluations have mostly focused on student posttest performance and not the learning process. This before-and-after approach to evaluation often gives less attention to learners' performance during the inquiry process (Lazonder & Harmsen, 2016) and the way mental frameworks and misconceptions are revised (Chi, 2008). This is an important oversight as one of the primary goals of inquiry learning is to immerse students in inquiry activities and help them develop authentic scientific discovery skills (Gormally et al., 2009; Pedaste et al., 2015). From this perspective, research consistently shows students need structure in the form of scaffolding to guide learning (Alfieri et al., 2011; Crawford, 2000; van der Valk & de Jong, 2009). Lazonder and Harmsen's (2016) meta-analysis showed support was important in promoting learning activities ($d$ = 0.66, 95% CI [0.44, 0.88]) and enhancing learning outcomes ($d$ = 0.50, 95% CI [0.37, 0.62]).

Almost all inquiry models, including the ones discussed above, were reference environments other than learning via simulations. Because simulation-assisted inquiry learning is becoming increasingly popular (Morley et al., 2019), it is worthwhile to ask whether well-established inquiry models need to be modified to better serve students' needs within simulations. In particular, explanation-oriented questions and prompts adapted just-in-time as students engage in inquiry with simulations may offer value (Veermans et al., 2005) as these interventions invite learners to organize their knowledge and become actively involved in their own discovery process (Lazonder & Harmsen, 2016). Accordingly, we propose an adapted framework for incorporating prompts within a simulation environment (Figure 1) called *Inquiry Learning in Action (ILA).* Inspired by previous inquiry models and their constituent phases, we investigated several types of prompts as scaffolds for learning in simulation-assisted inquiry. Our research examined the effects of just-in-time discovery prompts on (a) student inquiry learning processes and (b) knowledge gain. We prepared two experimental conditions with the same learning tasks and strategy instruction except the intervention condition received additional just-in-time strategic prompts throughout the inquiry phases. Because just-in-time prompting of inquiry strategies helps learners activate prior knowledge and detect misconceptions, we hypothesized giving instruction in discovery strategies would be less effective than giving the instruction plus just-in-time prompting of the same strategies at an opportune time (Table 1).

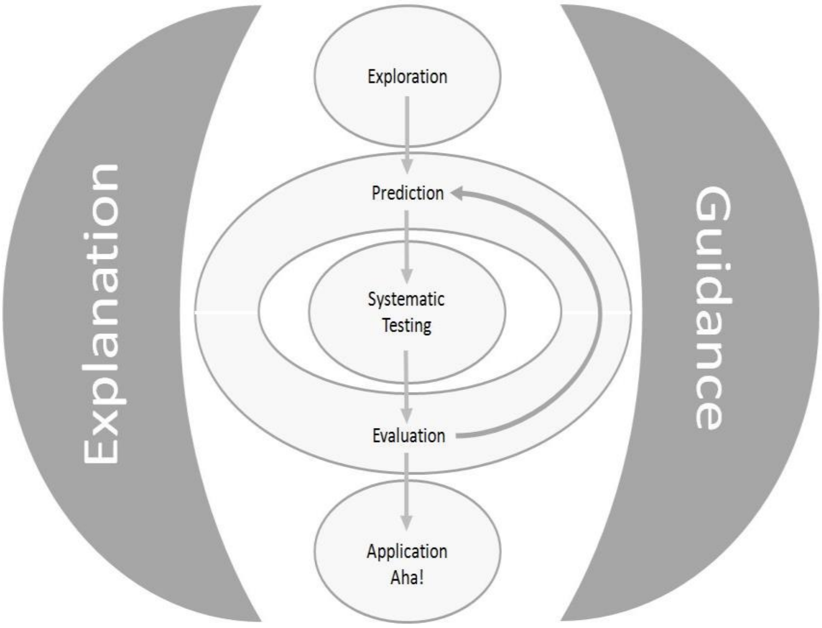


*Figure 1. Inquiry learning in action (ILA): From exploration to aha!*

*Note.* The figure illustrates the necessity of tutor guidance in inducing effective explanation at all stages of learning.

## Methodology

### *Participants*

27 undergraduates attending a western Canadian university volunteered to participate for monetary reimbursement. From this sample, 17 were randomly assigned to a treatment condition with just-in-time prompts during inquiry learning tasks, and 10 were assigned to a control condition with no given prompts.

To provide opportunity for genuine inquiry, we applied exclusion criteria to remove participants with relatively high prior domain knowledge or strong skills in discovery strategies. Thus, we removed seven participants who scored greater than 50% on a pretest about DC electric circuits and three other participants who demonstrated advanced discovery skills such as control-of-variables strategy or systematic testing. Three other participants were excluded due to lack of compliance with experimental protocols of thinking aloud, exceeding the stated time limit, or inattention to instructions at the beginning of the experiment. One participant was excluded due to technical problems in the video recording. Data available from remaining participants ($N$ =13) were analyzed, eight in the intervention group and five in the control group.

### *Procedure*

First, all participants watched an instructional strategy video explaining fundamental strategies of scientific experimentation shown in Table 1. The instruction was provided to diminish pre-existing differences in participants' knowledge of discovery strategies. The participants then completed a pretest of knowledge about DC circuits.

*Table 1. Discovery strategies presented in an instructional video at the start of the session*

| | Discovery Strategies | Conditions | Examples of learner's questions to ask oneself |
|---|---|---|---|
| 1. | Setting Goals | Before performing an action | What variables can you manipulate directly? |
| 2. | Making Prediction | Before performing any action | Predict what will happen and make multiple predictions. |
| 3. | Recording Information | Before performing an experimental action | Write what you want to test in a table. |
| 4. | Generating Experiments | After performing each action | Did you run multiple trials for each action? What action would fix the observed anomalous event? |
| 5. | Control-of-Variables Strategy | Before performing an experimentation action | Which variables stay the same during the experiment? Which variables should be held constant in order to see the relationship between the dependent and independent variables? |
| 6. | Formulating rules for actions and outcomes | After observing and recording the outcome of an action | Can you formulate a rule for the cause and effect relationship? |
| 7. | Evaluating Rules | After formulating a rule | Have you tested your rule in different conditions? Does your rule contradict in any of the conditions? |
| 8. | Finding Patterns | After recording multiple rules | Did you compare the numerical results between the trials of multiple conditions? |
| 9. | Explaining and justifying the patterns | After connecting the gathered rules | Have you explained the rules and provided evidence? |
| 10. | Self-evaluating performance and understanding | After performing a set of actions or after finishing a task | How effective was your data collection in helping you to see patterns? Which strategy helped you correct your misunderstanding? |

Following the pretest, participants were given a supplementary text explaining the fundamental physics concepts (e.g., current, resistance, voltage, and voltage drop) and learning goals (constructing a functioning circuit, discovering relationships among the three variables of current, resistance, and voltage for circuits with various components and testing misconceptions) for the session. Each inquiry session lasted 60 minutes. At the end of the 60-minute inquiry session, participants completed the posttest on DC circuits. They were instructed to verbalize their thoughts (think-aloud protocol) as they engaged with the learning tasks and were encouraged to ask questions about procedures for the session. Next, participants were introduced to the simulation and its features. For example, they were told how to navigate the simulation, how to use the measuring devices, and how to construct simple series circuits. Pilot testing had indicated this same information likely would be needed during task-related investigations so we provided just-in-time *enabling* prompts to help participants carry out basic operation of the simulation. As these prompts did not concern discovery learning strategies or scientific models of electric circuits, they were provided as necessary for participants in both the intervention and comparison groups.

Participants in the intervention group received just-in-time prompts (Table 2) guiding learners to use discovery strategies at appropriate times. For example, prediction prompts were generally given at the outset of a learning task, e.g., "Can you predict how the current changes throughout the circuit?" Testing prompts were usually given after predicted statements or claims, e.g., "How can you test your prediction about the current values at the individual resistor locations?" And, rule generation prompts were mostly given after participants stated a causal or correlational relationship involving two or more variables, e.g., "Can you formulate a rule based on the cause and effect relationship between the total voltage and the individual voltages of components A, B, and C?" Explanation prompts were given at all phases of inquiry, particularly after activities such as describing observations, stating rules, detecting errors, applying, and making inferences. Questions such as "What's your explanation for the current observation?", "Do you think this rule is applicable in other conditions as well?" and "How do you explain the failure of the relationship in case A and not B?" were repeatedly asked by tutors.

*Table 2. List of discovery strategy prompts given as intervention*

| Category of Intervention prompts | Conditions | Examples |
|---|---|---|
| 1. Explanation (universal follow-up prompt) | After stating a prediction | What is your explanation for this relationship? |
| | Testing | How do you explain the reliability of your data? Do you think you have collected enough data points? |
| | Generating rule/pattern | How is this explanation connected to what you previously knew? Why does A work but not B? |
| | Data/evidence Collection | What examples can you provide to explain your results in more detail? |
| | Application | Can you provide some examples to support your conclusion? |
| 2. Observation | When mindful attention to similarities and differences were | How would you differentiate between A and B? |
| 3. Prediction | Before introducing a new principle/concept/relation or after collecting more information. | Can you predict what happens next? Can you predict the outcome if we change A with B and then with C? |
| 4. Testing | After stating a prediction or an observation. | What would happen if you replaced component A with B? In how many ways can you test your ideas? In what other ways can you fix the problem? |
| 5. Evidence Collection | After manipulating independent variables. | How do you know if your collected evidence is sufficient? Do you think you need to test more data points? |
| 6. Rule Generation | After testing and recording the outcome of an action or after stating a rule based on multiple trials of testing | Do you think the pattern/relationship you found always holds? How do you provide evidence for your generalization? |
| 7. Recording | Before and during the data collection process | Do not forget to record your data. Have you recorded your observations? |
| 8. Application | After testing and recording the outcome of an action or after stating a rule based on multiple trials of testing | Do you think the relationship you just found (e.g., voltage sum) can be generalized to other situations as well? |

*Table 3: Examples of enabling prompts employed in the experiment*

| | |
|---|---|
| 1. Information regarding functionality of simulation components | Interchange the voltmeter handles to switch the reading measure display from positive to negative or vice versa |
| | To measure the current, use the ammeter on the right side of the simulation screen |
| | Wire and battery resistivity can be adjusted by dragging the scroll of the wire resistance and battery resistance respectively |
| | The wires can be extended or shortened by clicking on the circles at the end and adjusting the length |
| 2. Information regarding fundamental concepts | When the circuit is closed, the current is able to flow |
| | Batteries or power supplies are often used to produce a voltage source in an electric circuit |

*Materials*

A pretest and posttest were administered to all participants. The pretest served as a screening tool to exclude participants with high prior knowledge of DC circuits and as a measure of knowledge about the topic in the upcoming inquiry session. Although the two tests were not identical, each consisted of 5 parallel items evaluating a distinct component of Ohm's Law: (a) conservation of energy (b) potential charge across resistance (c) current sum (d) voltage sum and (e) proportionality of brightness and resistance. Items were designed based on previous research to test misconceptions about fundamental concepts and principles of DC electric circuits (e.g., Chang et al., 1998; Küçüközer & Kocakülah, 2007) and Ohm's Law. Gain scores were calculated as a difference between pretest and posttest score ($\Delta S$).

At first, we provided participants with a supplementary handout about foundational terms needed to build knowledge. We selected the *DC Circuit Construction Kit* from the PhET website (https://phet.colorado.edu/en/simulation/circuit-construction-kit-dc) (Figure 2). Participants were tasked to construct series circuits using simulated wires, bulbs, resistors, and batteries as means for investigating relationships among voltage (V), resistance (R), and current (I). Details of the learning tasks and their goals are presented in the next section.

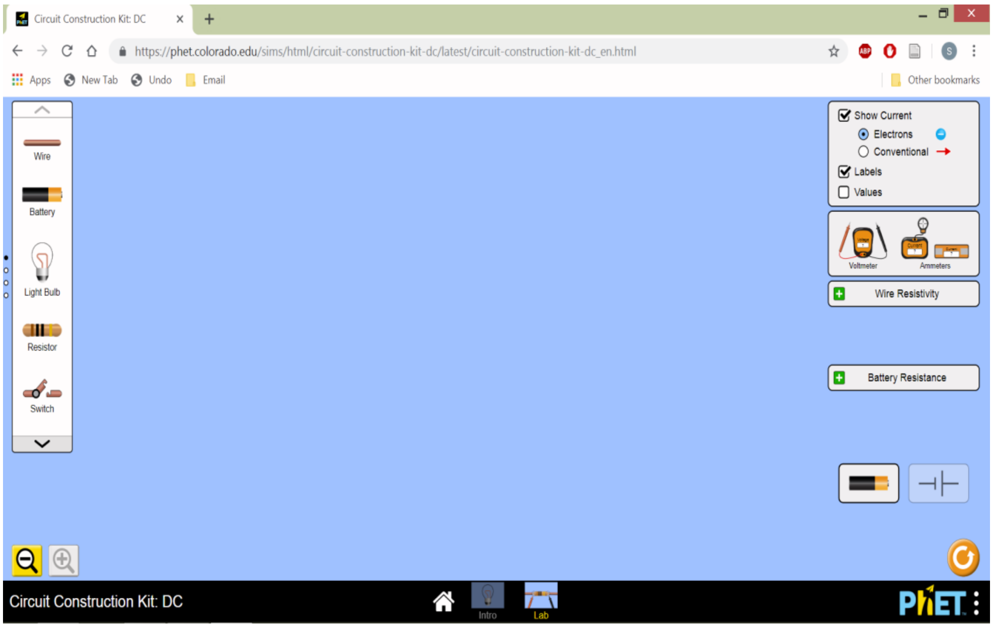


*Figure 2. Screenshot of PhET Circuit Construction Kit Simulation*

*Learning Tasks*

We designed three progressive tasks (Table 4). The first task asked participants to explore the simulation, make a series circuit and investigate binary relationships between voltage, current and resistance. The second task asked participants to make predictions. The third task asked participants to investigate the predictions generated in task 2.

*Table 4: Learning tasks with corresponding phases*

| | **Learning Tasks** |
|---|---|
| Task 1 | 1. Explore the components available in the simulation.<br>2. Make a series circuit using components.<br>3. Use measuring tools to find relationships between<br>a. voltage & current<br>b. resistance & current<br>c. voltage & resistance |
| Task 2 | Put the simulation aside and use a piece of paper.<br>1. Draw a series circuit with all the components you want.<br>2. Assign values for all the components in your circuit.<br>3. Predict the current and voltage (called voltage drop) for all the components.<br>4. Predict the brightness of the bulb(s). |
| Task 3 | Use the simulation to investigate what you predicted in Task 2 |

*Intervention*

Throughout the inquiry, all participants (regardless of their group), received just-in-time enabling prompts, which provided information about the correct operation of simulation components such as measuring devices and fundamental electrical concepts needed to construct a simple circuit (Table 3). Just-in-time intervention prompts were only provided to participants in the treatment group in the third subtask of task 1, where they were mainly prompted to observe binary relationships and explain their reasoning; in the third and fourth subtask of task 2, where they were prompted to make predictions and give their explanations; and in task 3 where they were prompted to test, collect and record evidence, generate rules, give explanations of the observed events, and apply observations in new situations (Table 2). Verification feedback such as "Yes, it's correct" or "No, it's incorrect" was also provided if participants' requested confirmation of their explanations or actions.

*Data Collection*

We used Open Broadcaster Software (OBS) to make audio and video recordings of participants' behaviours coordinated with screen recordings of their engagement with the simulation.

*Design and Analysis*

We adopted a qualitative descriptive (QD) protocol for coding participants' behavioural and verbal data. This entailed generating codes for analyzing learners' utterances and behaviours. This approach to analysis allowed including new codes during data analysis to adapt to observations made from the data.

We used NVivo software for coding participants' verbalizations and interactions with the simulation to examine how prompts affected inquiry practices. Statistical analysis was conducted using JMP (SAS Institute, 2019).

Coding categories and examples are presented in Table 2. One researcher coded the discovery behaviours of all participants. Another researcher coded 80% of those participants. Percentage agreement was 87.5%. Cohen's kappa was $\kappa$ = 0.71. These values represent strong concurrence of coding between the two coders.

## Results

Pretest scores showed extensive misconceptions and low prior knowledge about electric circuits among all 13 participants ($M$ = 0.20, $SD$ = 0.16). As shown in Table 5, the intervention group made greater gain ($M$ = 0.59, $SD$ = 0.15) than the control group ($M$ = 0.16, $SD$ = 0.32). Shapiro-Wilk tests found no significant departure from normality for the gain scores of the intervention group ($W$ = 0.93, $p$ = .516) and the control group ($W$ = 0.82, $p$ = .110). An independent samples $t$-test found a statistically detectable difference between the two groups, $t(11)$ = 3.32; $p$ = .007; $d$ = 1.72.

*Table 5: Means (standard deviations), t-ratio, probability, and Cohen's d of pretest, posttest, and gain scores*

| | **Intervention (I) (n = 8)** | **Control (C) (n = 5)** | **t** | **p** | **Cohen's d** |
|---|---|---|---|---|---|
| Pretest | 0.24 (0.19) | 0.16 (0.05) | | | 0.58 |
| Posttest | 0.83 (0.09) | 0.32 (0.27) | | | 2.53 |
| Gain | 0.59 (0.15) | 0.16 (0.32) | 3.32 | .007* | 1.72 |

We compared the groups on 11 types of coded utterances and behaviours: observing relationships, making prediction, systematic testing, unsystematic testing, collecting evidence, recording observation, generating rules, explaining and reasoning, expressing aha moments, seeking clarification, and indicating confusion. For each comparison, we used a Mann-Whitney $U$ test to detect differences between the groups and the rank-biserial correlation ($r_{\text{rb}}$) to present the corresponding effect size. The nonparametric test was used because the samples were not normally distributed in most cases. As shown in Figures 3 to 13, the intervention group scored statistically detectably higher compared to the control group on: observing relations, prediction, systematic testing, collecting evidence, recording observations, rule generation, and explanation. This response to tutor prompts enhanced learning and led to experience of aha moments in some instances in the intervention group. No difference was statistically detected in the frequency of unsystematic testing and seeking clarification during the discovery process. The intervention group was found less likely to indicate confusion.

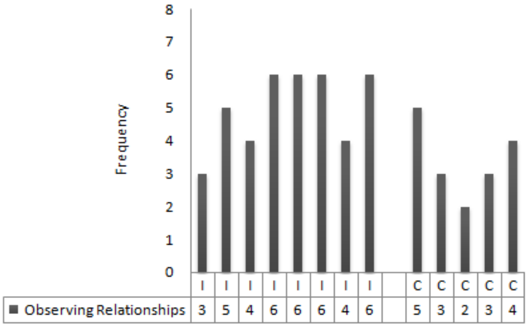


*Figure 3. Observing Relationships*

*Note*. Intervention: $M = 5.00$, $SD = 1.20$. Control: $M = 3.40$, $SD = 1.14$. $U = 6.50$, $p = .042$, $r_{rb} = 0.68$.

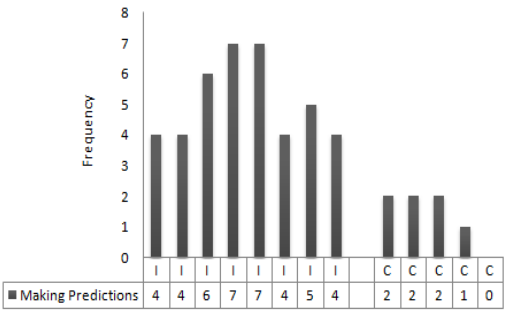


*Figure 4. Making Predictions*

*Note.* Intervention: $M = 5.13$, $SD = 1.36$. Control: $M = 1.40$, $SD = 0.89$. $U = 0.00$, $p = .003$, $r_{rb} = 1.00$.

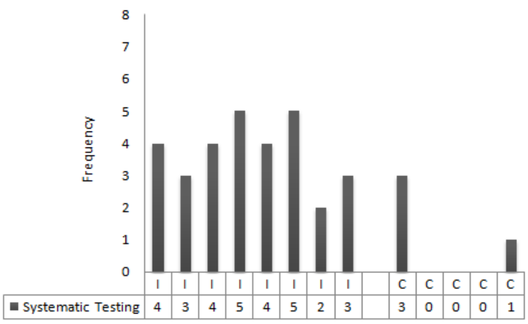


*Figure 5. Systematic Testing*

*Note.* Intervention: $M = 3.75$, $SD = 1.04$. Control: $M = 0.80$, $SD = 1.30$. $U = 2.00$, $p = .007$, $r_{rb} = 0.90$.

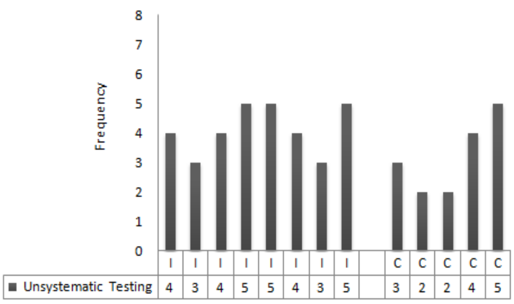


*Figure 6. Unsystematic Testing*

*Note.* Intervention: $M = 4.13$, $SD = 0.83$. Control: $M = 3.20$, $SD = 1.30$. $U = 11.00$, $p = .172$, $r_{rb} = 0.45$.

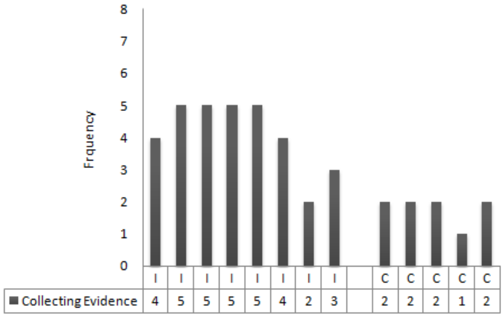


*Figure 7. Collecting Evidence*

*Note.* Intervention: $M$ = 4.13, $SD$ = 1.13. Control: $M$ = 1.8, $SD$ = 0.45. $U$ = 2.00, $p$ = .006, $r_{rb}$ = 0.90.

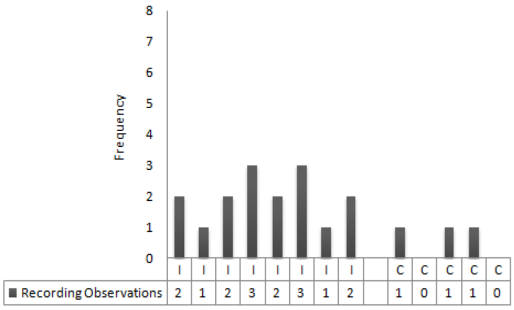


*Figure 8. Recording Observations*

*Note.* Intervention: $M$ = 2.00, $SD$ = 0.76. Control: $M$ = 0.60, $SD$ = 0.55. $U$ = 3.00, $p$ = .009, $r_{rb}$ = 0.85.

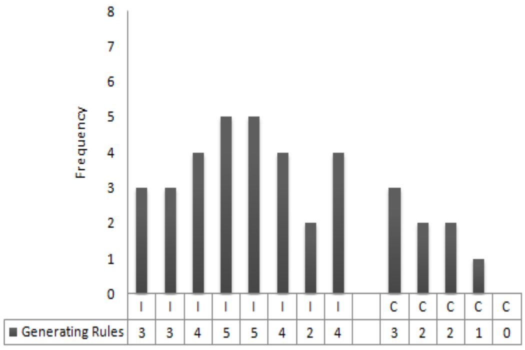


*Figure 9. Generating Rules*

*Note.* Intervention: $M$ = 3.75, $SD$ = 1.04. Control: $M$ = 1.6, $SD$ = 1.14. $U$ = 3.00, $p$ = .011, $r_{rb}$ = 0.85.

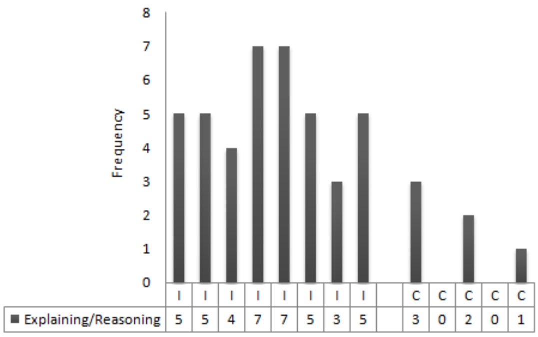


*Figure 10. Explaining/Reasoning*

*Note.* Intervention: $M$ = 5.13, $SD$ = 1.36. Control: $M$ = 1.2, $SD$ = 1.30. $U$ = 5.00, $p$ = .004, $r_{rb}$ = 0.98.

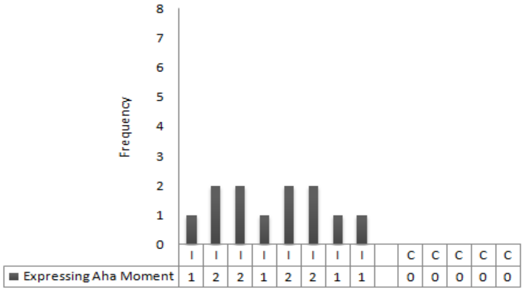


*Figure 11. Expressing Aha Moments*

*Note.* Intervention: $M$ = 1.5, $SD$ = 0.53. Control: $M$ = 0.00, SD = 0.00. $U$ = 0.00, $p$ = .002, $r_{rb}$ = 1.00.

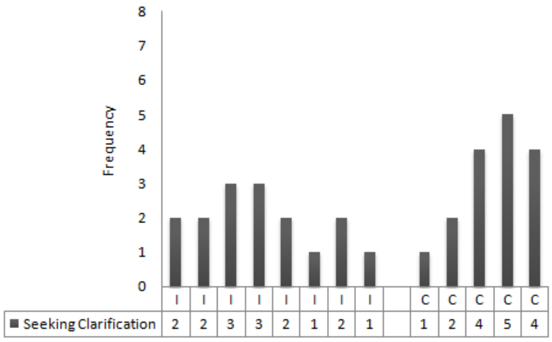


*Figure 12. Seeking Clarification*

*Note.* Intervention: $M$ = 2.00, $SD$ = 0.76. Control: $M$ = 3.20, $SD$ = 1.64. $U$ = 11.00, $p$ = .172, $r_{rb}$ = - 0.45.

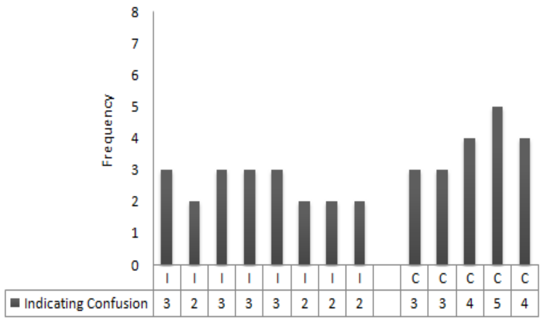


*Figure 13. Indicating Confusion*

*Note.* Intervention: $M$ = 2.5, $SD$ = 0.53. Control: $M$ = 3.8, $SD$ = 0.84. $U$ = 4.00, $p$ = .012, $r_{rb}$ = - 0.80.

*Table 6: Correlations among the Dependent variables of (1-11) and Knowledge Gain (12)*

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Observing Relations | - | | | | | | | | | | | |
| 2 | Prediction | .56* | - | | | | | | | | | | |
| 3 | Systematic Testing | .75* | .76** | - | | | | | | | | | |
| 4 | Unsystematic Testing | .61* | .35 | .53 | - | | | | | | | | |
| 5 | Collecting Evidence | .56* | .81** | .83** | .40 | - | | | | | | | |
| 6 | Recording Data | .60* | .73** | .85** | .50 | .68* | - | | | | | | |
| 7 | Generating Rules | .70** | .87** | .83** | .35 | .86** | .79** | - | | | | | |
| 8 | Explaining/Reasoning | .74** | .85** | .90** | .51 | .86** | .81** | .89** | - | | | | |
| 9 | Expressing Aha | .58* | .77** | .76** | .33 | .86** | .65* | .71** | .76** | - | | | |
| 10 | Seeking Clarification | -.58* | -.56 | -.56* | .02 | -.33 | -.33 | -.55 | -.49 | -.42 | - | | |
| 11 | Indicating Confusion | -.60* | -.54 | -.59* | .00 | -.49 | -.38 | -.55 | -.58* | -.64* | .87** | - | |
| 12 | Knowledge Gain | .53 | .69** | .77** | .14 | .59* | .50 | .66* | .75** | .58* | -.74** | -.71** | - |

*Note. N = 13; * p < .05; ** p < .01*

We also found correlations among the variables within the intervention group (Table 6). If participants in this group responded to tutor prompts, the prompted behaviours tended to correlate.

As indicated by analysis of students' learning behaviours (Figures 3 – 13, Table 6), some strategies such as making prediction, collecting evidence, testing, recording and comparing multiple outcomes, and explaining and making inferences seem to be responsible for correct manipulation and utilization of fundamental concepts and variables. We next explore strategies participants used during their inquiry session and elaborate on factors that may have led to the emergence of such learning behaviours and strategies.

## Discussion

We provided just-in-time prompts for discovery strategies to a group of randomly assigned participants engaged in inquiry learning with a simulation of DC circuits. The experimental group showed increased levels of seven prompted behaviours or verbalizations (Figure 3, 4, 5, 7, 8, 9, 10), less confusion (Figure 13), increased frequency of aha expressions (Figure 11), and greater gain in domain knowledge (Table 5).

### *Inquiry as a System*

Learning by inquiring requires coordinating multiple processes to construct a systematic model of a scientific phenomenon (Clement, 1989; Metcalf et al., 2018). Like other phase models of inquiry, our ILA model (Figure 1) reflects this characteristic. What distinguishes ILA is learners' use of *evidence-coordinated explanation* (ECE) in every phase. Just-in-time prompts supplied to participants in the intervention group brought ECE to the fore of their inquiry learning processes.

### *Conditions and Timing of Tutor Prompts*

The Inquiry Learning in Action model (ILA) suggests conditions and timings for prompts. These recommended conditions, which are based on observations and analyses of student behaviours during their inquiry process, repair missing, unproductive, or inaccurate inquiry behaviours, such as making predictions without supporting evidence or generating relational statements based on insufficient data. For example, when a participant claimed, "I think the bulbs in the circuit function differently from the resistors in the circuit," an explanation prompt such as "Why do you think bulbs and resistors play different roles in a circuit?" guided students to reason about the functions of resistors and light bulbs. This prompt was then followed by prompts about testing and evaluating effects of placing identical light bulbs in the circuit and measuring their resistance as well as adding or subtracting more resistors and observing the resulting brightness of the bulb.

We employed particular instructional prompts to address specific learner engagements under specific circumstances. For instance, when participants stated a prediction, manipulated the state of the system, and confirmed understanding based on observed outcomes, a series of prompts were provided to deepen participants' understanding and support their reasoning, e.g., "Can you provide any other evidence to confirm the results?", "Does A = B and B = C always lead to A = C?" and "What are the consequences of your assumption?" (Tables 1, Table 2). Appropriate sequencing of prompts also assisted learners to transition to more advanced stages of inquiry when they indicated observation error, uncertainty, confusion, or long pauses of inactivity. For example, sometimes learners employed the control of variables strategy and recorded data collected in the simulation but could not identify recognizable patterns in the data. At this moment, the tutor prompted the learners to look for similar patterns and general rules. This prompt was usually operationalized as "What happens to voltage when another variable such as resistance goes up or down?" or "What happens when the resistance is very high and everything else stays constant?" to which the learner responded, "The current goes down. So, it's an inverse relationship."

### *Evidence-Coordinated Explanation*

The ILA model emphasizes eliciting explanation to support scientific reasoning throughout all phases of inquiry. Explanation prompts guided learners to develop and justify explanations based on their existing knowledge, acquired knowledge, and accumulated evidence during the experiment. Analysis of learners' behaviours during the experiment indicated the explanations they generated encouraged simplification, clarification, verification, and regeneration of knowledge (Chi et al., 1994; Nokes et al., 2011; Rittle-Johnson & Loehr, 2017; VanLehn et al., 1992).

We refer to this recurrent strategy in each phase of our inquiry action model as *the universal tool* of inquiry. According to the ILA model, each phase is initially guided by a set of specific and general questions that prompted learners to extend and refine their domain knowledge and strategy skills by inquiring. Specific explanation prompts elicited specific information and generic explanation prompts elicited general explanations about the coherence and sensibility of knowledge in relation to the overall purpose of learning. For example, when a student predicted "The movement of electrons would slow down if the resistance increased," the tutor prompted the student to explain the reason behind the established inverse relationship between the movement of electrons and the value of resistance. Subsequently, the learner referred to their measuring process and explained resistance as the opposite force of movement (e.g., "When the resistance is 83 Ω, the current is 0.67A and when the resistance is 40 Ω, the current is 1.40A"). Explanation prompts encouraged learners to provide more precision by mapping observations and numerical evidence into an explanatory framework. These prompts also allowed learners to examine whether a prediction about a specific principle or pattern aligned to observed patterns of data (Sandoval & Reiser, 2004; Williams & Lombrozo, 2010) in the simulation. We noticed that specific explanation prompts drew learners' attention to more conceptual issues and eventually led to greater clarity and relevance (Bisra et al., 2018).

Our results indicated a statistically detectable difference between the intervention and control group for generating explanations (Figure 10). The explanation prompts were designed to guide learners to evaluate assumptions, assess coherence, link fragmented pieces of knowledge, justify logic in explanations, validate the collected evidence, and verify the predicted principles. They also helped learners resolve unexpected contradictory cases by addressing exceptions, anomalies, and extreme cases. For example, when the tutor asked "Can you explain what happens to the current when a new resistor is added in a series circuit?" the participant explained, "I'm thinking the current passing through the components in a series circuit would be different across each resistor." The tutor's following prompt to explain this incorrect reasoning invited the participant to pause and think about the reasoning underlying the statement and provide explanations such as "I guess the resistance is different because every time the current passes through each resistor it becomes less powerful." This learner's misconception led to further guidance by the tutor such as prompt to measure and test current at various points of the circuit (across different resistors) to check for invariance. The participant then noticed a discrepancy between their explanations and these observations, leading to statements such as "Oh, right…because resistance only works as a whole. So only the total circuit resistance changes with current, right?" This partial reasoning, which was initiated by the learner, was elaborated by the tutor to ensure sufficient explanation was provided and complete understanding had been attained by the learner. Therefore, the tutor stated: "Yes. So, when you increase the resistance the current goes down in the whole system but the current is the same at each resistor" to which the participant replied, "Interesting! Cool!"

The tutor prompted learners to explain every phenomenon that was unusual to them. For example, when participants encountered a condition where the battery was in flame in the simulation, they often justified their observation (i.e., fire in the circuit) as "There's no brightness because the current goes too fast." At this stage, the tutor requested the participants to approach the problem by explaining their observation in more detail, e.g., "What did you notice about the circuit and the resistance of the objects in the circuit?" to which they responded "Oh, the light bulbs are actually unlit, and the resistance is zero." Shortly after, the tutor asked about ways the anomaly could be corrected, e.g., "How could the fire in the battery be stopped?" This request for a solution prompted the learners to generate explanations such as "By increasing the resistance the fire can be stopped ... but only by a little bit because once you increase it too much you get lower brightness," "You could also add a separate resistor." Additional explanation was also provided, "The resistance is necessary to have a working circuit" and "There are multiple ways you can increase the battery resistance." Due to repeated explanation prompts, the participants were able to explain an unexpected outcome of the inflamed battery and understand the importance of resistance in a series circuit. The prompts also guided learners to consider multiple solutions such as increasing the resistance of the bulb, adding another resistor in the circuit, and increasing the wire or the battery resistance.

We interpret generating explanations as a constructive activity that led to learning domain knowledge and discovery strategies by providing opportunities for learners to diagnose knowledge gaps, integrate new information, and repair faulty knowledge (Roy & Chi, 2005). These findings are consistent with Chin and Brown's (2000) depth dynamic model that argues explanation leads to a cascade of generative activities which helps learners acquire and weave missing pieces of knowledge or resolve conflicts in their understanding.

### *Exploration*

The type of exploration activities students use in inquiry environments has been shown to be related to the benefits obtained from the tools, guidance, and the model built into the simulation (Dalgarno et al., 2014; Hajian et al., 2019). Some of the most important activities that allowed students to benefit from exploration in this study were well-organized, coordinated, and mindful observation during the initial exploration phase of this experiment (Figure 3). Exploration allowed participants to become familiar with the various components and tools implemented in the simulation in relation to constructing a circuit and understanding electricity (Ohm's Law). When participants were prompted to observe specific relationships among variables, objects, and the simulation parameters, they attempted to create a relational bridge between prior knowledge and their discovery learning goals (Eberbach & Crowley, 2009; Norris, 1985). Subsequent prompts such as prompts to predict, test, and generate rules, seemed to enhance construction of that bridge and enable participants to provide explanations based on scientific evidence. Table 6 indicates the correlation of observation with other demonstrated learner behaviours in the study.

Mindful observation may well be necessary in any scientific inquiry. The observation emphasized here is not simply looking at objects or events and expressing facts such as "A bulb is generating heat when it is on" or "It seems that a DC circuit has current flowing in one direction." As Smith and Reiser (2005) argued, scientific observation "is used to generate further explanations and theories about observed phenomena" (p. 317). As such, it leads to goal-oriented exploration and results in flexible thinking and relational reasoning (Hajian et al., 2019).

*Prediction*

Prediction has profound implications for scientific inquiry learning due to opportunities it provides for learners to express their knowledge in an external form, identify their mental models about a particular concept, and make judgments. When learners were prompted to predict a solution to a problem or generate an explanation for a causal relationship, they activated their previous knowledge network (e.g., by visualizing or imagining a scenario) and associated it with the encountered new information (Lim et al., 2010). According to Skemp (1976; as cited in Lim et al., 2010), this *relational* understanding is encouraged when learners are prompted to predict (Figure 4, Table 6), whereas being prompted to solve a problem without prediction would only promote *instrumental* understanding.

The tutors' prediction prompts were also highly effective in promoting students' systematic testing, collecting evidence, generating rules, and reasoning (Table 6). The act of prediction allowed students to elicit their prior knowledge, thoughts, and intuitions about a specific concept in a particular context and subsequently inspect it in further detail. For example, when the tutor prompted students to predict what would happen to the flow of current in a circuit (with three light bulbs having different resistance values) if voltage fluctuated, students predicted that "Increase in voltage would result in increased flow since the voltage comes from the battery. More voltage means more energy and, therefore, more flow in the circuit. With the same logic less voltage means less flow in the circuit" or they predicted that "The flow would decrease in each of the bulbs with more resistance but would increase in the bulbs with lower resistance." Through successive predictions and evaluation of predicted results, understanding of electric circuits developed, cognitive involvement increased, and more advanced elaborative reasoning was produced. The act of prediction encouraged learners to seek empirical evidence and eventually distinguish between intuitive generalization and empirical evidence. Prediction prompted learners to explain their hypotheses in a scientifically rational manner and seek help if needed. Through recursive predicting, testing, and evaluating, students learned their partially correct ideas could be used to bootstrap new learning (Clement et al., 1989)

*Systematic Testing*

When prediction prompts were followed by testing with suitable experiments and explanations, learners examined their predictions through various means. For example, they measured variables in multiple ways (e.g., using tools such as voltmeter or ammeter, deletion or addition of components to the circuit, and adjusting the sliding data bar) and compared the measured results with their predicted outcomes. This systematic testing was conducted through collecting empirical evidence (Figure 7), recording observations (Figure 8), and searching for patterns and generating rules (Figure 9). Additionally, recurrent testing allowed learners to tackle confusion by challenging assumptions, collecting evidence and producing more explanations (Figure 5, Table 6) as well as fostering more engagement and processing while learning (Lodge et al., 2018). For example, when students generated a hypothesis or prediction such as "In a series circuit with multiple bulbs, the bulb with the highest resistance has the lowest brightness," they often investigated the accuracy of their prediction by testing the voltage drop of each bulb in the circuit and observing its effect on the brightness of each of those bulbs. Prompting to generate explanations was another crucial factor in evaluating the results and validating previously made assumptions as well as identifying misconceptions. This continual *inquiry testing*, *explaining*, and *confirmatory testing* strategy played a significant role in constructing new domain and strategy knowledge (Hong et al., 2014). Our observation of student behaviours in the videos indicated those who systematically tested a relationship between independent and dependent variables, such as resistance (R) and voltage drop (VD), often produced more than a single claim, spent more time comparing and contrasting outcomes, and identified relevant ideas. The participants tested multiple claims and predictions and avoided unnecessary repetitive testing of irrelevant ideas. This process of cognitive filtering allowed them to focus on ideas that were supported by evidence and discard ones that were not.

Sometimes after testing their prior knowledge or current knowledge (acquired knowledge), participants arrived at a claim or conclusion that was incorrect. Knowing that claims, inferences, or results-based-explanations could still be wrong and needed further evaluation and testing for accuracy was a valuable inquiry skill that was experienced and practiced during the learning process.

"We learn inquiry by doing it" and it is only through practicing these skills that we can transform ideas into action (Belcastro, 2017, p.172). Research shows prediction, testing, and reasoning are key aspects of scientific thinking as they lead to critical processes such as analysis, evaluation, elaboration, and making inferences. They also lead to constructing relationships and generating interesting questions (Durkin & Rittle-Johnson, 2012; Newman, 1990; Resnick, 1987). Moreover, these skills help learners formulate new scientific knowledge by modifying and refining their current understanding and integrating new knowledge to what they already know (Bransford et al., 1999; Peng & Gero, 2010).

It is worth mentioning that both the intervention and control groups performed some unsystematic testing (e.g., trial and error, random modification, and adjustment of variable values) to explore the simulation and investigate the inquiry tasks (Figure 6). However, only the intervention group managed to use failures productively and succeeded in pattern identification and rule generation. Learners who were not prompted about three follow-up inquiry practices of collecting evidence, recording evidence, and explanation often repeated testing the same concepts, ideas, or hypotheses. Very often, the no prompting group repeatedly made the same error due to using inappropriate testing strategies and confusion (Figure 13) that originated in not knowing what to measure, how to measure, and when to measure (unproductive failure).

*Evaluation*

Evaluation was one of the strategies in which researchers prompted learners to assess the validity of their evidence, findings, and generated rules. For example, when the tutor prompted learners to confirm causal relationships between variable such as voltage (V) & current (I), current (I) & resistance (R), and voltage (V) & resistance (R), the learners often validated those relationships by evaluating the accuracy of collected data through examination and re-testing.

Evaluation strongly contributed to learners' arriving at conclusions, making decisions, and developing big picture thinking. As Pedaste et al. (2015) argued, when learners evaluate their inferences, they can often refine their knowledge through making new conclusions, developing new perspectives, and extending ideas.

In this study, we define evaluation as self-assessment occurring at local and global levels (Hajian et al., 2019). For example, when understanding of the relation between voltage drop and current was assessed in terms of individual concepts and variables, knowledge was evaluated at a local level; and when understanding of their relationship was assessed in terms of the function of the circuit, evaluation occurred at a global level. We argue that this two-level approach to evaluation was integral to regulation of all inquiry processes conducted by the learner as it determined the next step in the discovery process and decision making. According to Rawson and Dunlosky (2007), "efficient regulation of learning can depend in part on how accurately an individual can evaluate his or her own learning" (p. 560).

In the process of discovery, learners need to assess their understanding of prior and new knowledge and identify the functionality, accuracy, and significance of this connection. One strategy that was highly beneficial for promoting evaluation was performing frequent testing and multiple comparisons. By adjusting and re-adjusting the value of variables in different conditions, learners examined the consistency of the discovered rules and their validity. Additionally, they managed to detect the problematic areas that had caused confusion (Figure 13).

In accord with descriptions of scientific discovery as the coordination between hypothesised relations and the collected evidence (Kuhn et al., 1992; Langley, 2019; Reid et al., 2003), tutors' prompts provided appropriate scaffolding in the form of hints, instructional explanations, and modeling of verbal self-regulation of discovery strategies to coach learners to perform experiments like a scientist and discover rules underlying scientific phenomena (Hitt & Smith, 2017; van Joolingen & de Jong, 1997). This scaffolding process led to thinking *in practice*, derivation of testable rules (e.g., Ohm's Law), and evaluation of the testing results.

*Application*

When learners were prompted to apply previously discovered rules in alternative and multiple conditions, they compared various outcomes of the same relationship in different settings. This ongoing systematic comparison of outcomes allowed them to understand the flexibility and generalizability of the acquired rules and see them as more than isolated facts (Rittle-Johnson & Star, 2011). For example, by applying the voltage sum rule (i.e., the algebraic sum of all the voltages around any closed loop in a circuit is equal to zero; Vbattery = ΔV1(bulb1) + ΔV2 (bulb2) + ΔV3 (bulb3)) to a DC circuit with multiple bulbs at various distinct values, the concept of voltage drop was fully understood and comments such as "Oh, the voltage drops of all the components do add to the voltage of the battery" or "So the voltage of the battery divides among the components of the circuit, that's why they all add up to zero" were provided.

The process of application included conducting additional investigations to confirm the accuracy and applicability of the previously generated rules and formulas. This process, termed elaboration by some models such as 5E, allowed learners to develop understandings of the concepts through encoding the original content in a different but related way (Hamilton, 2012).

In the application process, learners conducted experiments by testing various configurations of circuits to discover Ohm's law (e.g., by testing various sets of data; adding or subtracting various components of the simulation). As they acquired more and more understanding with each new experience, they had the opportunity to reflect and enhance their knowledge within the simulation and gain deeper understanding of the same concepts (Wrenn & Wrenn, 2009). This process of knowledge confirmation and *rediscovery* often emerged as an expression of an instant discovery or sudden comprehension, an *Aha* moment. At this moment, ideas came together and integration of knowledge occurred.

The Aha moment was observed through statements such as "Oh! It makes perfect sense! Now I get it" or "Wow! The relationship between X and Y actually holds between all these numbers and amazingly works everywhere."

Our results indicated a statistically detectable difference between the intervention and control group for expressions of *Aha* (Figure 11). We interpret Aha moments as resulting from the combination of inquiry processes such as prediction, systematic testing, collecting and recording evidence, rule generation, application, and most importantly explanation (Table 6). In the application process, learners conducted a considerable amount of investigation to ensure their formulated theories were not the result of confirmation bias or personal incorrect interpretation of the collected data (Holyoak & Morrison, 2005). They often conducted sufficient testing across an extended range of data (e.g., selecting data at minimum value, near mean value, mean value, near mean value, max value, and near max value) as well as comparing and contrasting the results of the input-output values of various functions for the final validation and functionality.

While we cannot provide a specific algorithm leading to occurrence of such Aha moments, we witnessed them when a learner was explicitly and repeatedly guided to verify and explain causal relationships among variables in a way that integrated an extended range of data. This further testing for applicability and comprehending a specific relationship apparently led to full comprehension of the underlying interrelation and a perceptible shift in thinking. We especially noticed this level of understanding became deeper and more meaningful when students confirmed the accuracy of the same relationship in unusual situations, such as zero resistance values for each bulb. According to Jones (2003), this shift in thinking occurs through representational change and progress monitoring. Sometimes learners' understanding of relationships among separate pairs of variables has been acquired while full comprehension of interrelationships comprising the system has not yet been attained. Learners experience an Aha moment when the relationship between the parts and the whole is finally completed.

## Conclusion

We investigated the efficacy of multiple discovery strategies by prompting learners at various stages of inquiry learning within a simulation environment and observing the productivity and quality of each inquiry strategy. Specific prompts to predict, systematically test, generate rules, and explain can improve student learning in simulation discovery environments. An inquiry journey that begins with exploration and ends with the experience of Aha can be charted by providing the right guidance at the right place and time.

Previous research indicates science teachers can be confused as to "what inquiry is, how to implement it, and how well it works" (Gautreau & Binns, 2012, p.169). Just-in-time prompts seem a promising tool to use in science educational programs within inquiry-driven environments.

## Limitations

The present study has several limitations that should be addressed in future research. First, the results of this study demonstrate the type of guidance that novices require in electric circuit simulations only. Second, our research design does not permit causal attribution of learning effects to specific prompted discovery strategies. Third, due to multiple Mann-Whitney U tests and a small sample size, an unknown proportion of our inferential statistical tests may be subject to inflated type I error.

## Recommendations

Similar studies need to be conducted within different virtual settings (e.g., web-based and game-based learning environments) that represent various domains of science, such as biology, chemistry, and mathematics. It is probable that virtual environments such as online video games may provide more immersive settings with better opportunities for learning from failures. Second, we used pre-post test results to measure student knowledge gain. However, formalized knowledge measured by a test may not be the most valid indicator of the effects of simulation-based learning (de Jong et al., 1999). We therefore recommend additional real-time formative assessment, such as in-process evaluations, within simulation assisted inquiry environments. Certainly, experiments with larger sample sizes and more treatment conditions are needed.

### Acknowledgement

This research was supported by a grant from the Social Sciences and Humanities Research Council of Canada (SSHRC 435-2019-0458) to John C. Nesbit and Philip H. Winne.

### Disclosure statement

No potential conflict of interest was reported by the authors.

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