Inquiry-based learning and retrospective action: Problematizing student work in a computer-supported learning environment

Nikoletta A. Xenofontos[1], Tasos Hovardas[1], Zacharias C. Zacharia[1], Ton de Jong[2]

[1]Department of Educational Sciences, University of Cyprus, Nicosia, Cyprus

[2]Department of Instructional Technology, Faculty of Behavioral, Management and Social Sciences, University of Twente, Enschede, The Netherlands

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Abstract
We examined student performance in a computer-supported learning environment after students undertook, among others, a graphing task within an inquiry context. Students were assigned in two conditions: (a) Students were given one variable, and they had to select the second one to construct their graph; (b) students were given four variables, and they had to select two to construct their graph. Both conditions problematized student work by triggering retrospective action, where students returned to previous stages of the learning activity sequence. Retrospective action correlated positively to knowledge gains in Condition 2, where students were more likely to revisit earlier stages of their inquiry. Time-on-task, when students passed through learning tasks for the first time, correlated negatively with retrospective action (second pass), which indicated that there was a minimum amount of time needed to effectively execute tasks. Trade-offs between time-on-task (first pass) and retrospective action demarcate a novel field of research.

Keywords: Learning products; problematizing; retrospective action; scientific inquiry; software scaffolds; time-on-task

1. Introduction

A challenge for designing and assessing software scaffolds has always been to accommodate two different needs, namely, structuring student work, on the one hand, and "problematizing" student work, on the other (Reiser, 2004). Structuring is needed to assist students in managing complex, open-ended tasks by simplifying them and reducing complexity (e.g., offering a serial processing of simpler subtasks). At the same time, instruction often needs to add complexity locally and engage students in demanding learning trajectories, which would be core characteristics of a problematizing functionality. In this direction, problematizing inquiry for students would come along with prompting students to consider alternative options and direct their attention to aspects that would remain unaccounted for, otherwise (De Backer, Van Keer, & Valcke, 2016; Molenaar, Sleegers, & van Boxtel, 2014; Molenaar, van Boxtel, & Sleegers, 2011). Structuring and problematizing student work may impose different, and at times, inconsistent requirements for designing and implementing learning tasks (see Reiser, 2004, p. 296), especially in terms of handling their complexity (frequently decreased by structuring but locally increased by problematizing), initiative to be undertaken by students (usually taken away by structuring but augmented by problematizing), and continuity and directionality of tasks (often facilitated by structuring but deliberately interrupted or questioned by problematizing). Analogous issues have been highlighted in inquiry learning, in terms of how much support is to be offered to students (Arnold, Kremer, & Mayer, 2014; Koksal & Berberoglou, 2014; Minner, Jurist Levy, & Century, 2010). If there is too much support and guidance, then learners may not be adequately motivated to take over initiative and responsibility for their learning; if more degrees of freedom are provided than students can handle, then the goals of inquiry learning remain largely unattainable (e.g., Chang, Chen, Lin, & Sung, 2008).

The design and assessment of software scaffolds in enacting inquiry in science education has largely concentrated on their structuring effects rather than the ones problematizing inquiry for students (Saye & Brush, 2002; Simons & Klein, 2007; Zacharia et al., 2015). For instance, tools developed to scaffold experimental design have often incorporated a heuristic (known as the VOTAT heuristic or strategy) that directs students towards Varying One Thing (i.e., an independent variable) At a Time (Chang et al., 2008; Veermans et al., 2006; Zacharia et al., 2015). The basic idea in this heuristic is that by changing values for one variable at a time, one can track its effects on the dependent variable and, thus, design and run a fair experiment. A similar pattern, in which structuring is emphasized more than problematizing, could be found across all types of guidance (e.g., prompts, heuristics, and scaffolds) used in prior studies when enacting inquiry activities (e.g., see Zacharia et al., 2015). Needless to say, the potential for problematizing student inquiry has been somewhat under-researched in comparison to structuring (Efstathiou et al., 2018; Reiser, 2004).

In contrast to most previous research, where separate scaffolds were developed for either structuring or problematizing student work (for a comprehensive review see Zacharia et al., 2015 & De Backer et al., 2016; e.g., of separate structuring and problematizing scaffolds, see Molenaar et al., 2011, 2014), our study focused on a software scaffold for supporting students in constructing graphs during a scientific experimentation (Data Viewer, see Section 4), which offered both structuring and problematizing functions. The structuring function involved splitting the graphing task in two subsequent stages, namely, variable selection and graph construction. The problematizing function concentrated on variable selection, which was distinguished in two conditions: Students were offered either one variable only (less than needed to complete the task; first condition), and they had to insert another variable for constructing their graph later on, or they were offered four variables (more than needed to complete the task; second condition), and in this case, they had to select two out of these four variables for graph construction. In both conditions of the Data Viewer, students were required to take on initiative in retrieving or screening variables for concluding variable selection (problematizing function) and then move to graph construction. Our main purpose was to examine student performance after students had been confronted with variable selection in the first stage of the graphing task. In so doing, we tracked student navigation, measured their knowledge gains and assessed the quality of their learning products in both conditions of the Data Viewer.

2. Theoretical Background

The activity sequence implemented in this study was orchestrated on the basis of core components of an inquiry cycle, namely, of a number of interrelated phases/steps (i.e., orientation, conceptualization, investigation, conclusion, and discussion) that are essential for students to carry out a scientific inquiry. Each one of these phases was comprised by a series of learning tasks (for details see Pedaste et al., 2015). For instance, the investigation phase includes experimentation, which in turn includes the following: identification of variables; the development of an experimental design; the execution of an experiment; data collection in real or virtual laboratories, data organization and analyses/graphing; and finally, data interpretation (Hofstein, Navon, Kipnis, & Mamlok-Naaman, 2005; Kremer, Specht, Urhahne, & Mayer, 2014).

Prior research has revealed that students face difficulties in enacting inquiry, including the aforementioned tasks followed during the investigation phase (de Jong, 2006). These difficulties appear to exist even at the secondary school level, when the students are more mature (Arnold et al., 2014; De Boer et al., 2014; Furtak, 2006; Kirschner, Sweller, & Clark, 2006). In a recent literature review, Lazonder and Harmsen (2016) showed that successfully enacted inquiry-based learning was heavily dependent upon providing students with proper guidance. Similar findings were found by a preceding literature review by Alfieri, Brooks, Aldrich, and Tenenbaum (2011). The latter review showed that the provision of proper guidance during inquiry-based learning enhances students learning more than when the same curriculum materials are introduced via unguided or minimally guided inquiry-based learning. A crucial question is how this guidance can be facilitated in computer-supported and online learning environments. In such learning arrangements, the investigation phase has been most often supported by software scaffolds in inquiry learning across all grades (Authors et al., 2015a).

In scientific inquiry, it is obvious that students in preceding tasks produce learning artefacts needed for other tasks that follow. Namely, an experimental design needs to be aligned to the hypotheses that were previously formulated. Further, the execution of an experiment must follow the trials prescribed in the experimental design, while data organization and analyses are based on data collection. Going through an inquiry cycle, students must carry along the learning products they constructed in previous tasks in order to be able to respond to new tasks. In terms of instruction, the learning activity sequence equates to a sequence of learning products manufactured all along an inquiry cycle, where learning products coming out of previous activities are used as necessary input for learning activities to be undertaken later on. In terms of software design, learning products need to be stored so that students can retrieve them and work with them to undertake an upcoming learning activity. Learning products offer valuable insight for monitoring student actions and performance (Hovardas, 2016), and this might have a series of implications for computer-supported learning environments. The construction of learning products in these learning environments again raises the design requirements for structuring and problematizing student work. In the ideal situation, the configuration of the learning environment would both facilitate the tractability of tasks to allow learners maintain directionality and follow the learning activity sequence (structuring function; see Reiser, 2004, p. 274, 283), as well as interrupt the continuity of learning tasks at certain points to allow learners reflect on their work during previous activities (problematizing function; see Reiser, 2004, p. 289, 299).

As mentioned above, designing effective scaffolding software is rather challenging due to the need to incorporate both structuring and problematizing functions. Structuring is aiming at supporting students perform a task by guiding them throughout the task (Quintana et al., 2004; Reiser, 2004). Three broad strategies for designing software scaffolds to structure student work have been proposed by Reiser (2004, p. 283, 284): (a) Decompose tasks to reduce their complexity, and allow students handle sub-tasks serially; (b) focus student effort on productive aspects of learning tasks by narrowing student options and reducing degrees of freedom given to them; and (c) assist students monitor their work and progress and have an overview of their performance. With regard to the investigation phase of inquiry, structuring could be provided when designing an experiment and deciding which variable to vary, measure and control (e.g., through partitioning experimental design in variable classification and outlining experimental trials), when collecting, organizing and analysing data (e.g., through pre-selecting data), and when properly representing the results of the data analysis (e.g., through offering applications for data representation such as diagrams and graphs).

Problematizing learning for students, on the other hand, centres on exposing students into situations that they have to resolve on their own. The three general strategies proposed by Reiser (2004, p. 289, 290) for designing software scaffolds to problematize student inquiry involve: (a) “elicit articulation”, where students are encouraged to present and exemplify their reasoning; (b) “elicit decisions”, where students are confronted with decision-making procedures; and (c) “surface gaps and disagreements”, where students need to engage in resolving disagreements among peers in collaborative learning arrangements. With regard to problematizing the investigation phase of inquiry for students, students may be encouraged to take initiative and proceed on their own to variable selection, experimental design, data collection and representation. In all these cases, students are confronted with the complexity of learning activities and task difficulty increases in the short-term. However, this should be aimed and designed to direct or keep students on productive learning pathways. Learning is expected to occur when the students consider and treat these complex situations as problems to be solved, through exploring potential solutions and reflecting on work already undertaken. Although these desirable outcomes of problematizing student work should not be taken for granted (Reiser, 2004, p. 299), they are indispensable at certain points of learning activity sequences for letting students take over responsibility and regulation for their own learning. The complication for pedagogical design in computer-supported environments increases further if we take into account that structuring and problematizing student inquiry often entail different or even inconsistent design requirements (see Reiser, 2004, p. 296; see also Moulder et al., 2016, p. 505, 507). This includes task complexity, which is counteracted by structuring but capitalized on by problematizing arrangements, student initiative and agency, which is removed by structuring but fostered by problematizing settings, and continuity and directionality in undertaking learning tasks, which is sustained by structuring but intentionally questioned by problematizing functions.

This last aspect of continuity and directionality is another issue that has not received proper attention by previous research. Although student processing of tasks in inquiry-based learning does not always have to evolve in a linear fashion (e.g., Pedaste et al., 2015; see also a relevant critique in Bevins & Price, 2016), most perspectives have pre-supposed such a linear onwards processing of learning tasks (see, for instance, Grossmann & Wilde, 2019; Schiefer, Golle, Tibus, & Oschatz, 2019). Structuring may imply a segmentation of learning tasks in separate steps to allow learners process them serially, thus dividing overall workload in subsequent actions. Given this partitioning and serial undertaking of learning activities, structuring mostly complies with a linear conceptualization of inquiry-based learning, namely, with a linear succession and processing of activities in a learning activity sequence. Problematizing student work, on the other hand, signals a deviation from this linear workflow because it always requires some reflective work from students. When problematized, students are alerted so that they remain mindful of how their decisions connect to the subject domain. Therefore, problematizing student work will be effective as long as it interrupts any unproductive undertaking of learning activities. For example, students may need to move backwards, revisit former steps in their inquiry, rework their learning products, if needed, and complete tasks left undone or incomplete in their first passage through learning activities. This navigation backwards in a sequence of learning activities and within an inquiry cycle (i.e., retrospective action), which is enacted in order to take any additional necessary action before moving forward, has not been comprehensively addressed by previous studies.

3. Purpose of the study

For the purposes of this paper we have focused on the investigation phase of the inquiry cycle, since it is at the heart of each inquiry enactment and has proven to be quite challenging for students (Efstathiou et al., 2018). Without the investigation phase students will not be able to move from the conceptualization phase to the conclusion phase, which will in turn handicap all of their inquiry endeavours aiming at answering their research questions or testing their hypotheses. Despite the great significance of the investigation phase, enacting it poses a series of difficulties and problems for students (Arnold et al., 2014), such as taking a research question or a hypothesis and designing a proper experiment for investigating it or identifying the proper variables needed for an experiment (i.e., the dependent variable, the independent variable and the control variables) and understanding which variable to vary and which to measure (de Jong, 2006). It turns out that variable identification and selection is crucial for several actions in the investigation phase.

We have developed a computer-supported learning environment with a virtual laboratory on electric circuits and tools for supporting students while designing their experiments and constructing their graphs. All these applications were integrated in the investigation phase. Students designed and executed an experiment and, at some point, they were required to construct a graph, with the data they had collected earlier while working in the virtual lab. The focus of our research was a Data Viewer with a graphing tool used by students for variable selection and graph construction. The Data Viewer included an interface where students were first asked to select two variables and then use these variables to create a two-dimensional scatterplot. We used two different configurations of the Data Viewer, which shared the same structuring function but differed in their problematizing function. Structuring involved partitioning the graphing task in two steps, variable selection, and graph construction. The problematizing function concentrated on variable selection, where the two configurations of the Data Viewer differed in the number of variables that were offered to students. In the first configuration (Condition 1), students were given only the dependent variable (less than they needed to select for graph construction) and they had to manually insert the independent variable to plot data required by the learning material. In the second configuration (Condition 2), students were offered all of the variables involved after running the experiment at task (more than they needed to select for graph construction), a dependent and another three independent ones (four variables, overall). Students had to select two variables to construct their graph. Both conditions had the same graphing interface.

Our aim was to study student performance in the two conditions after students were confronted with the problematizing function in variable selection. Because students were responsible to decide which two variables to plot, the completion of this task would necessitate some reflection on previous stages of their inquiry. Therefore, we expected that this problematizing function could also cause some additional action by students, for instance, confirmatory action, especially if students would wish to secure variable selection before moving on to graph construction, or corrective action to fill gaps. The two conditions we used had different requirements for concluding variable selection. In the first condition, students could wish to validate their option for the second variable required to proceed to graph construction. This could be enacted by moving back to previous steps in the computer-supported learning environment. However, the second condition of the Data Viewer offered a list with enough variables (four variables) for students to construct their graph. Therefore, they could have concluded the task without resorting to any additional confirmatory action or navigation back to earlier stages of their inquiry if they did not have good reason to do so, for instance, if they were confident enough for variable selection.

For identifying any differences between the two conditions in the way the students worked, we examined how the students navigated in the computer-supported learning environment. Specifically, we investigated the time-on-task (i.e., time spent working with a virtual laboratory and a tool for designing experiments in the learning activity sequence, the first time around) as well as the navigation paths that the students followed and time spent during retrospective action (i.e., after students were confronted with the graphing task and when they returned to previous stages of their inquiry). In addition, we examined whether the two conditions differed in terms of student knowledge as well as in the properties of the learning products constructed by students. Finally, we computed correlations among these parameters to account for any complementarity between time-on-task (first pass) and retrospective action (second pass) or for any potential influence of time-on-task and retrospective action on knowledge gains and the quality of learning products delivered by students.

3.1 Research questions

Given the aforementioned objectives, we aimed at investigating the following research questions:

(1) Did the two conditions differ in terms of student knowledge gains and the quality/properties of their learning products?
(2) Did the two conditions differ in terms of time-on-task (first pass through the learning activity sequence) and time spent during retrospective action (second pass, when students returned to previous steps of their inquiry)?
(3) Were there any significant correlations in the two conditions between parameters examined?

4. Methods

4.1 Participants

The study involved 51 10th graders (16-17 years old; 36 boys and 15 girls) from two classes at two public senior high schools (Lyceums) in Larnaca, Cyprus. These classes were recruited based on the voluntary response of their teachers to take part in the study. Student participation was also voluntary and they were involved in the research after they and their parents had granted their informed consent. Students were offered the option to withdraw from the study at any stage if they needed to do so. Students in the first class (25 students) followed the treatment of Condition 1. Students in the second class (26 students) followed the treatment of Condition 2. All students had advanced computer skills and were of similar academic ability. Prior knowledge and skills did not differ between the two classes (see Section 4.4 for the tests used). No gender differences were found in student knowledge and skills, before or after the educational intervention.

4.2 Learning environment and conditions

The study was undertaken within the frame of the Go-Lab project (https://www.golabz.eu/). Our learning environment focused on electrical circuits connected in series and in parallel. We used the Go-Lab authoring tool (de Jong et al., 2014) to create an Inquiry Learning Space, which includes all phases of a typical inquiry process (see Pedaste et al., 2015b). Students in both conditions formulated hypotheses in the Hypothesis Scratchpad (https://www.golabz.eu/app/hypothesis-scratchpad) and they prepared their experimental designs by means of the Experiment Design Tool (Figure 1; https://www.golabz.eu/app/experiment-design-tool). This tool allowed students to classify variables in dependent, independent and controlled ones and then schedule experimental trials based on that classification. After having concluded their experimental design, students constructed electrical circuits in the Electrical Circuit Lab (Figure 2; http://www.golabz.eu/lab/electrical-circuit-lab). In this virtual lab, students were offered various components with which to construct electrical circuits according to their experiment designs. Students recorded their observations (e.g., values for various variables in electrical circuits) using the Observation Tool (https://www.golabz.eu/app/observation-tool). Observations in the lab were based on a series of questions that acted as prompts (see Appendix, prompts embedded in the learning environment; A. Prompts in the Observation Tool). This was done for each experimental trial. The next step in student inquiry was graph construction. Students constructed their graphs in the Data Viewer (https://www.golabz.eu/app/data-viewer), and they interpreted their graphs in the Input Box (https://www.golabz.eu/app/input-box) using a series of questions for guidance (see Appendix, prompts embedded in the learning environment; B. Prompts in the Input Box for graph interpretation). The entire learning activity sequence is depicted in Figure 3a.

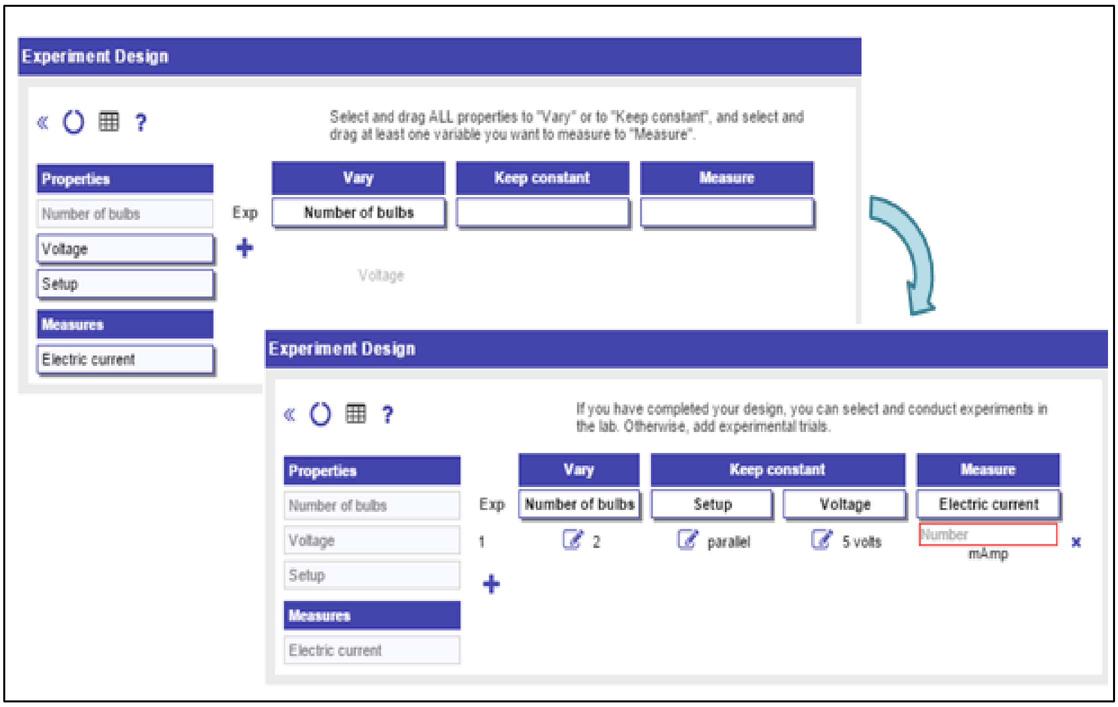

Figure 1. The Experiment Design Tool (https://www.golabz.eu/app/experiment-design-tool).

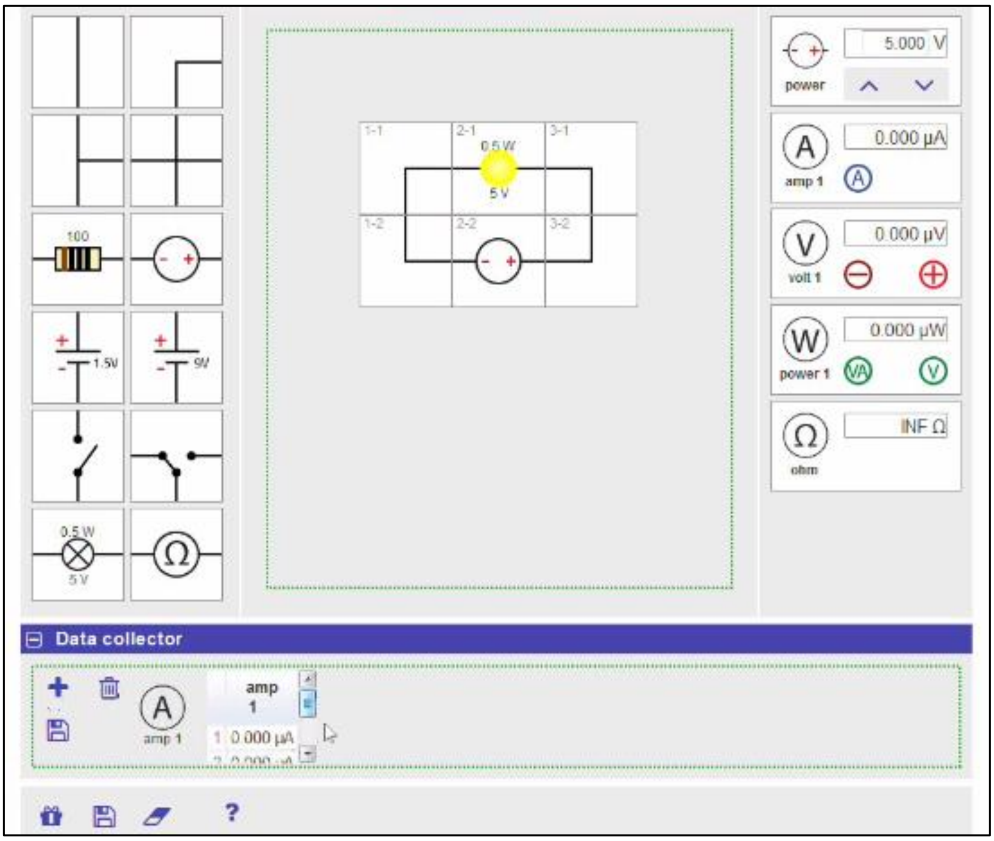

Figure 2. The Electrical Circuit Lab (http://www.golabz.eu/lab/electrical-circuit-lab).

Up to the point of graph construction, the learning activity sequence was identical for all students. The difference between the two conditions concerned primarily the configuration of the Data Viewer, specifically, the provision of variables in this tool. The Data Viewer structured the graphing task by letting students first select the variables to plot from a list of variables offered (see Figure 4a, b, “data set”). Students could then drag and drop these variables in the two-dimensional space in the right part of the tool to construct the graph (see Figure 4a, b, “data graph”). The structuring function of the Data Viewer (task decomposition in variable selection and graph construction) was the same for both conditions. The problematizing function concentrated on variable selection: The students should decide which variables to select for constructing the graph. This problematizing function differed between conditions (Table 1). In Condition 1, the Data Viewer contained the dependent variable only (i.e., the intensity of the electric current passing through a circuit; see Figure 4a and Table 1; less variables offered than needed to construct the graph). In this case, the Data Viewer was programmed to retrieve the data set for the dependent variable directly from the Electric Circuit Lab. The independent variable (i.e., number of bulbs in the electrical circuit) had to be entered by the students themselves manually in the Data Viewer before proceeding with the construction of a graph. To do so, students used the edit button on the bottom-right side of the data set (see Figure 4a, b). For plotting the graph, students just had to drag both variables (i.e., the dependent in the data set and the independent one they had created themselves) from the data set holder of the Data Viewer to the graph space of the Data Viewer on the right. In Condition 2, all variables, dependent and independent, were automatically transferred to the data set holder of the Data Viewer (see Figure 4b and Table 1; more variables offered that needed to construct the graph). These variables were the "number of bulbs", "setup", "voltage", and "electric current". In this case, the Data Viewer was programmed to retrieve the data sets for all variables from the Experiment Design Tool. The students had to choose which two variables to drag from the data set holder of the Data Viewer to the graph space of the tool on the right, in order to construct their graph.

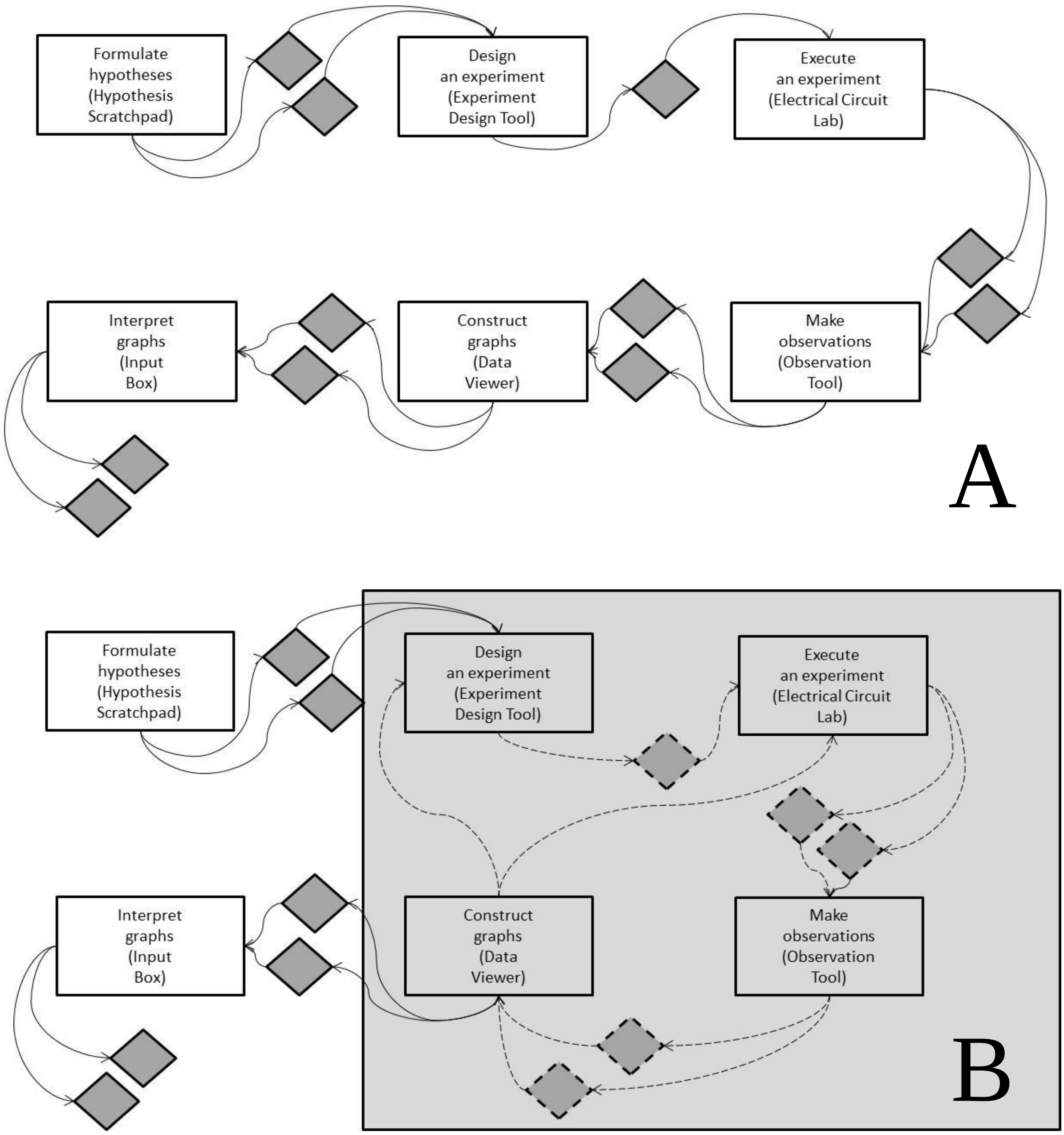

Figure 3. The learning activity sequence, on which the study focuses. Learning activities are depicted in rectangles and learning products in rhombuses. In each activity, students construct learning products, which are needed as input in upcoming activities. This is depicted by lines linking learning activities (rectangles) through learning products (rhombuses). The number of rhombuses varies to denote that the number of learning products derived from each learning activity could also vary. The first pass of students through activities is depicted in 3a with continuous lines and

rhombuses, while retrospective action is depicted in 3b by dashed lines and rhombuses. The part of the learning activity sequence where retrospective action was observed is included in 3b within a bigger, grey rectangle. Retrospective action was triggered when students encountered the variable selection task in the Data Viewer, and they returned to the Experiment Design Tool or the Electrical Circuit Lab to construct new learning products and fill any gaps (dashed rhombuses).

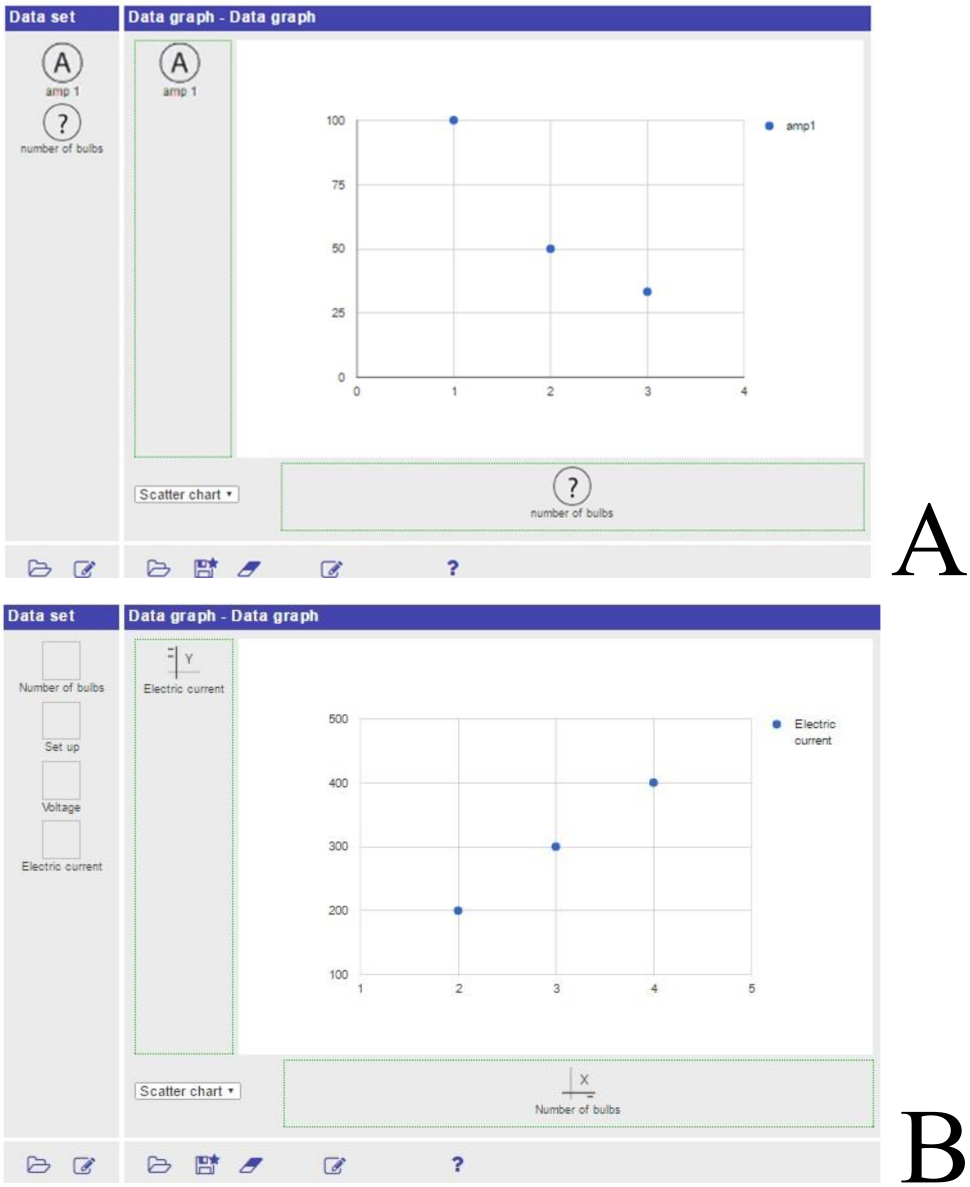

Figure 4. The (a) first and (b) second configuration of the Data Viewer (https://www.golabz.eu/app/data-viewer). In (a), the Data Viewer was linked to the Electrical Circuit Lab and only one variable was included in the data set (on the left part of the tool). In (b), the Data Viewer was linked to the Experiment Design Tool and four variables were included in the data set.

It should be noted that if the students had failed to collect the necessary data for a variable during their first inquiry pass from the Experiment Design Tool and the Electrical Circuit Lab, then they could not plot this variable in the Data Viewer. The instructions in the inquiry learning space guided students to collect at least three values for the dependent variable and plan and execute at least three experimental trials (record intensity of the electric current passing through the electrical circuit, which was the dependent variable, for one, two and three bulbs; number of bulbs in the electrical circuit was the independent variable), when they worked in the Experiment Design Tool and the Electrical Circuit Lab. When one variable was dragged and dropped in the data graph part of the Data Viewer, which contained one or two values only, it could not be plotted, and then the Data Viewer gave to the student a warning in the form of a short text explaining why the graph could not be constructed. When students did not have enough data to plot their variables or if they wanted to be sure about which variables to plot, they could return to previous stages of the learning activity sequence to have an overview of their prior actions or to reconsider and rework their learning products and fill any gaps. This retrospective action is presented in Figure 3b with dashed lines and rhombuses (learning products). We should highlight, however, that no prompt was given to students for retrospective action either by the Data Viewer, the learning environment or by the teacher.

Table 1. Structuring and problematizing functions of the two conditions of the Data Viewer

	First condition	Second condition
Structuring function (decompose task)	Partitioning the graphing task in variable selection and graph construction	Partitioning the graphing task in variable selection and graph construction
Problematizing function (elicit decision)	Less variables offered to students for variable selection than needed to construct the graph (one instead of two); students had to insert the second variable to construct the graph	More variables offered to students for variable selection that needed to construct the graph (four instead of two); students had to choose two variables to construct the graph

Note: In structuring and problematizing functions, the typology of Reiser (2004) is used in parentheses.

4.3 Procedure

Implementations were carried out by the same science teacher. Before the implementation, the teacher took part in a face-to-face preparatory meeting to become familiarized with the learning environment and elaborate on the role of the teacher in each lesson. Teacher guidance was kept to a minimum, so that we could track student performance during the learning activity sequence with only the support offered by the learning environment itself.

Each implementation involved four class meetings of 40 minutes each, which spanned over 3 days (Day 1 = meeting 1; Day 2 = meetings 2 and 3; Day 3 = meeting 4). The first and last meetings covered pre- and posttests (see Section 4.4). The second and third meeting occurred in the computer lab of each school so that each student was able to work in a computer. The teacher briefly introduced the learning environment and then let students go individually through the learning activities. There was no student interaction within or between these two 40-min sessions and the teacher was instructed to not allow any interaction between students but resolve any issues with each student separately.

4.4 Data sources and data analyses

We collected data from different data sources that provided considerable depth and complemented each other in order to shape a holistic picture of student performance. Because this study was exploratory in nature, we opted for examining possible patterns and relationships by including in our data analyses as more potentially related variables as possible.

We used two tests to assess student knowledge and graph interpretation skill. The knowledge test was based on a revision of Bloom's (1956) taxonomy of educational objectives by Anderson and Krathwohl (2001) and it was further elaborated by de Jong (2014) and Zervas (2013) (Appendix, the knowledge test). It was pilot tested for validity (an expert panel deemed it to be appropriate) and reliability (a sample of 30 10th graders was used, who were not involved in this study; Cronbach's alpha = 0.82), after which adjustments were made in wording and two items were deleted. We used a rubric to score open-ended items in the knowledge test. The inter-rater agreement between two independent coders (first two authors) for 20% of data was acceptable (Cohen's Kappa = 0.93). For assessing graph interpretation skill, we used items from the graph interpretation factor in the TIPSII instrument (Burns, Okey, & Wise, 1985). Both tests were scored blind to the condition of the learning environment to which each student had been assigned.

Learning products constructed by students during the learning activity sequence were stored in the learning environment, and they were retrieved and analysed. We used a coding procedure for assessing the quality/properties of learning products that should be profiled and logged (Appendix, variables examined for learning activities to assess the quality properties of learning products). Additionally, we recorded student actions while undertaking learning activities using computer screen capture software (i.e., River Past Screen Recorder Pro). In this case, we focused on student navigation after students encountered the variable selection task in the Data Viewer, which induced retrospective action, namely a return to an earlier stage of the learning activity sequence (see Figure 3, dashed lines). Students returned to the Electrical Circuit Lab or to the Experiment Design Tool to validate their routes and reconsider and rework their learning products, if needed (see Appendix variables examined for learning activities undertaken during retrospective action,, e.g., after students had reached the Data Viewer and when they returned to previous steps of their inquiry). We also calculated total time students spent in retrospective action. For both coding processes (learning products and screen captured data), a coding scheme was developed and used by the first author to code data. To measure inter-rater reliability, the second author used the same coding scheme to code 10% of data referring to learning products and another 10% referring to data on student navigation. Cohen's Kappa was higher than 0.87 across all data categories. All divergences were settled through discussion between coders.

Time-on-task was measured as time devoted by students to working with the Experiment Design Tool and the Electrical Circuit Lab. We used a fine-grained approach and observed screen captured data to distinguish on-task from off-task actions (e.g., time spent on a website other than the one hosting the Inquiry Learning Space used in the implementation) (see for instance Cohen, Manion, & Morrison, 2007). Time spent on the latter was subtracted from time-on-task.

We used Wilcoxon tests to investigate knowledge or skill gains in each condition and chi-square and Mann-Whitney tests to compare student navigation and performance between the two conditions of the learning environment. The Spearman's rho correlation coefficient was also calculated for parameters of student performance within each condition. In all tests, we employed the Bonferroni correction (i.e., level of significance divided by number of pairwise tests).

5. Results

5.1 Similarities and differences between conditions in knowledge gains and quality/properties of learning products

Students presented significant knowledge gains in both Condition 1 (pretest average = 0.35, posttest average = 0.52; Wilcoxon Signed Ranks Test Z = -3.76, $p < 0.001$) and Condition 2 (pretest average = 0.33, post-test average = 0.42; Wilcoxon Signed Ranks Test Z = -2.39, $p < 0.05$). These findings imply that both conditions promoted student knowledge. However, student skills in interpreting graphs did not improve significantly. This latter result indicates that the effects of our design may have pertained to variable selection and its contribution to student overall knowledge and did not move beyond that point to interpreting graphs.

Moreover, in both of the pretests and posttests, no significant difference was identified between conditions concerning either their knowledge gains or skill acquisition. No statistically significant difference was also found between conditions in the quality/properties of learning products (Appendix, variables examined for learning activities to assess the quality properties of learning products). Overall, these findings indicate that the learning outcomes of the two conditions did not differ.

5.2 Similarities and differences between conditions in the first pass through the learning activity sequence and during retrospective action (second pass)

There were significant differences between conditions in student navigation after they were confronted with the variable selection task in the Data Viewer (Table 2). All of these differences revealed that students in Condition 2 were much more likely to return to previous stages of their inquiry and engage in more retrospective action than students in Condition 1. Specifically, almost all students in Condition 2 returned to the Experiment Design Tool, and they spent more extra time there than students in Condition 1 (more than 5 times as much). Students in Condition 2 who returned to the Electrical Circuit Lab were almost doubled in number compared to Condition 1 (Table 2). In addition, total time spent during retrospective action was higher in Condition 2 (almost twice as much as for students in Condition 1). It was further found that the improvement in student knowledge for Condition 2 (calculated as difference between the pretest and the posttest) was positively correlated to extra time spent on the Experiment Design Tool (Spearman's rho = 0.40; $p < 0.05$) and extra time spent in the Electrical Circuit Lab (Spearman's rho = 0.43; $p < 0.05$). These results indicate that retrospective action was positively linked to knowledge improvement in Condition 2. No such effects were found for Condition 1.

For both conditions, extra time spent on the Experiment Design Tool increased when students constructed new learning products in this tool (e.g., new experimental trials; Mann-Whitney Z = -3.99; $p < 0.001$, for students in Condition 1, and Mann-Whitney Z = -3.96; $p < 0.001$, for students in Condition 2). In an analogous manner, extra time spent in the Electrical Circuit Lab again increased for students who created new learning products in the lab (e.g., new electrical circuits; Mann-Whitney Z = -

4.44; $p < 0.001$, for students in Condition 1, and Mann-Whitney Z = -4.38; $p < 0.001$, for students in Condition 2). These findings reflect that retrospective action was spent constructively by students in either condition because it was devoted to producing new learning products.

5.3 Correlations between parameters in each condition

Tables 3 and 4 present Spearman's rho correlation coefficients calculated for parameters of time-on-task and retrospective action in both conditions. Overall, we need to highlight that time spent on either the Experiment Design Tool or the Electrical Circuit Lab during the first pass through the learning activity sequence (EDTTime and LABTime, respectively) was negatively correlated to extra time spent on working with the Experiment Design Tool or the Electrical Circuit Lab during retrospective action (ExtraTimeEDT and ExtraTimeLAB, respectively). In Condition 1, the more time students had spent in the Electrical Circuit Lab the first time around, the less time they spent in the lab during retrospective action (Table 3; Spearman's rho = -0.45; $p < 0.05$). Further, in Condition 2, the more time students had spent in the Experiment Design Tool the first time around, the less time they spent in the same tool during retrospective action (Table 4; Spearman's rho = -0.58; $p < 0.01$). Overall, correlational analyses revealed that time-on-task (first pass) and retrospective action were of a complementary nature because the second decreased when the first increased and vice versa.

Table 2. Differences between conditions in time-on-task (first pass through the learning activity sequence) and retrospective action (extra time spent after students had reached the Data Viewer and when they returned to previous steps of their inquiry)

	Students in Condition 1 (Data Viewer linked to the Electrical Circuit Lab; n = 25)	Students in Condition 2 (Data Viewer linked to the Experiment Design Tool; n = 26)	Statistic
Time-on-task working with the Experiment Design Tool in seconds (EDTTime)	278.72 (*SD* = 144.13)	203.00 (*SD* = 122.69)	Mann-Whitney Z = -1.91^{ns}
Percentage of students who returned to the Experiment Design Tool (ReturnEDT)	44.0	92.3	Chi Square = 15.05***; Phi = 0.52***
Average extra time spent on the Experiment Design Tool in seconds (ExtraTimeEDT)	25.52 (*SD* = 43.23)	142.96 (*SD* = 118.50)	Mann-Whitney Z = -4.53***
Time-on-task working with the Electrical Circuit Lab in seconds (LABTime)	475.88 (*SD* = 286.71)	347.15 (*SD* = 137.06)	Mann-Whitney Z = -1.14^{ns}
Percentage of students who returned to the Electrical Circuit Lab (ReturnLAB)	36.0	65.4	Chi Square = 4.47*; Phi = 0.29*
Average extra time spent on the Electrical Circuit Lab in seconds (ExtraTimeLAB)	107.56 (*SD* = 216.87)	121.58 (*SD* = 130.02)	Mann-Whitney Z = -1.68^{ns}
Average total time spent during retrospective action (TotalTimeReturn)	142.28 (*SD* = 268.31)	278.50 (*SD* = 251.82)	Mann-Whitney Z = -3.06**

Note: Likelihood ratio chi-square values are displayed; ns = non-significant; * $p < 0.05$; ** $p < 0.01$.

Table 3. Correlations among parameters of time-on-task (first pass through the learning activity sequence) and retrospective action (extra time spent after students had reached the Data Viewer and when they returned to previous steps of their inquiry) in Condition 1 (Data Viewer linked to the Electrical Circuit Lab).

	Time-on-task working with the Electrical Circuit Lab (LABTime)	Extra time spent on the Experiment Design Tool (ExtraTimeEDT)	Extra time spent on the Electrical Circuit Lab (ExtraTimeLAB)
Time-on-task working with the Experiment Design Tool (EDTTime)	0.42^{*}	-0.33^{ns}	-0.20^{ns}
Time-on-task working with the Electrical Circuit Lab (LABTime)		-0.47^{*}	-0.45^{*}
Extra time spent on the Experiment Design Tool (ExtraTimeEDT)			0.52^{**}

Note: n = 25; Spearman's rho correlation coefficients are displayed; ns = non-significant; * $p < 0.05$; ** $p < 0.01$.

Table 4. Correlations among parameters of time-on-task (first pass through the learning activity sequence) and retrospective action (extra time spent after students had reached the Data Viewer and when they returned to previous steps of their inquiry) in Condition 2 (Data Viewer linked to the Experiment Design Tool).

	Time-on-task working with the Electrical Circuit Lab (LABTime)	Extra time spent on the Experiment Design Tool (ExtraTimeEDT)	Extra time spent on the Electrical Circuit Lab (ExtraTimeLAB)
Time-on-task working with the Experiment Design Tool (EDTTime)	0.09^{ns}	-0.58^{**}	-0.14^{ns}
Time-on-task working with the Electrical Circuit Lab (LABTime)		-0.17^{ns}	-0.29^{ns}
Extra time spent on the Experiment Design Tool (ExtraTimeEDT)			0.76^{***}

Note: n = 26; Spearman's rho correlation coefficients are displayed; ns = non-significant; * $p < 0.05$; ** $p < 0.01$.

6. Discussion

For the purposes of this study we developed two different conditions of a software scaffold for supporting students in constructing graphs (Data Viewer). The structuring function of the Data Viewer was the same (partitioning of the task in variable selection and graph construction) but the problematizing function in variable selection differed between conditions: The first condition offered to students less variables than needed to plot data (the dependent variable only), whereas the second condition offered more variables than needed to construct the graph (all four variables encountered during experimentation). Our findings showed that both conditions problematized student work. This was revealed by retrospective action, when students returned to previous stages of their inquiry and spent extra time to work in the Experiment Design Tool and/or the virtual laboratory to construct new learning products and fill any gaps they had left in their first pass through learning activities.

Although there was no difference between the two conditions of the Data Viewer in terms of learning outcomes (i.e., student knowledge; quality/properties of learning products), there was a significant difference in extra time spent during retrospective action. Condition 2 triggered more retrospective action than Condition 1. There can be several explanations for this difference, for instance the fact that students were more probable to have more gaps (e.g., incomplete data set) and incomplete actions (e.g., fewer experimentation trials than needed) concerning the four variables offered to them in Condition 2, as compared to the one variable offered in Condition 1. Because the Data Viewer did not allow students to plot their graph if they had an incomplete set of values in their variables they could not move forward to graph construction unless they filled these gaps. In addition, students in Condition 2 had to overview all values for their variables and address any gaps, if needed, in the Experiment Design Tool, which was placed in the learning activity sequence before the virtual lab (see Figure 3a, b). This return has often necessitated the reuse of the Electrical Circuit Lab later on. Instead, a number of students in Condition 1 returned directly in the virtual lab to validate values for the independent variable, which they needed to conclude variable selection, and they skipped the Experiment Design Tool. This means that securing values for variables in the experimentation or producing new learning products to address gaps took more extra time in retrospective action for students in Condition 2 and this concentrated on earlier stages of their inquiry.

The different navigation patterns between conditions may have had further implications. In fact, in the case of Condition 2, it was found that the time spent during retrospective action (i.e., time after the first round of inquiry), and not time-on-task (i.e., time during the first round of inquiry), was positively correlated to knowledge improvement. This was not confirmed for Condition 1, which indicates that retrospective action may correlate with knowledge improvement only after it overrides some duration threshold and that duration may not have been reached for Condition 1. In addition, the navigation pattern of students in Condition 2 may have allowed them to acquire a broader overview over a larger part of the learning activity sequence as compared to students in Condition 1, which may have also contributed to the effect of retrospective action on the knowledge improvement of students in Condition 2 only. Future research needs to shed more light and details about these effects of retrospective action and the conditions under which they can be traceable. There have been clear indications in the literature of the domain that time devoted to a task may not present a linear effect on student performance but an inverted U-shape, with performance being poor when too little (e.g., not sufficient) or too much time (e.g., not beneficial for performance, after a certain point) is spent (Goldhammer et al., 2014; Greiff, Niepel, Scherer, & Martin, 2018).

Another interesting finding of the study was that, for both conditions, the more time students had spent in the Electrical Circuit Lab and the Experiment Design Tool during their first pass through the learning activity sequence, the less time they spent in the lab or the Experiment Design Tool, respectively, during retrospective action (in their second pass). This finding points to the complementary nature of time-on-task (first pass) and retrospective action. It also points to the added value of retrospective action. Our results are in line with previous studies, which have revealed that time devoted to tasks is linked to student judgments concerning time allocation (e.g., Metcalfe & Finn, 2008; Thiede, Anderson, & Therriault, 2003). Moreover, the time dimension has been underlined by previous research as a crucial factor for determining metacognition in technology-enhanced learning in science education (Yıldız-Feyzioğlu, Akpınar, & Tatar, 2015). Metacognition has been associated with self-regulation of learning (Fiorella, Vogel-Walcutt, & Fiore, 2012). However, our study showed that retrospective action was linked to knowledge improvement only and did not have a wider effect on graphing skills. This may imply a local or context dependent character of the effects of retrospective action, which may compromise its metacognitive impact. Future research should delve deeper in these aspects and employ additional research instruments to examine heterogeneous metacognitive effects caused by alternative designs and retrospective action in student inquiry. Investigating differences between novices and more knowledgeable learners would be also insightful in this regard (Hofstein & Lunetta, 2003; Kalyuga & Sweller, 2004; Reisslein, Atkinson, Seeling, & Reisslein, 2006; Reisslein, Sullivan, & Reisslein, 2007; Seufert & Brünken, 2006).

More research is also needed to differentiate effects between time-on-task during an initial processing of tasks along a learning activity sequence as opposed to additional time allocated to learning tasks during retrospective action. A possible complementary functioning of time-on-task (first pass) and retrospective action (second pass), as the one indicated by our correlation analyses, may imply that there is a minimum time interval needed to effectively execute tasks with virtual labs and software scaffolds during scientific inquiry. When less time than this time interval was spent during the learning activity sequence (first pass), then the remainder needed to be devoted to working with labs and tools during retrospective action, in order to complete basic requirements for designing or executing an experiment. These findings re-iterate the importance of linking learning to time when accomplishing learning tasks, which has been frequently underlined (e.g., Karweit & Slavin, 1982; Slavin, 2014). However, not all time-on-task or retrospective action may be beneficial for students. Although computer-supported learning environments may optimize high-quality time spent on learning tasks, there have been numerous indications that a negative influence of technology on student attention cannot be ruled out, for instance, when students are confronted with multiple tasks (e.g., Bowman, Waite, & Levine, 2015). Future research needs to examine in more detail these effects of time-on-task allocation during serial processing of learning activities versus extra time allocation during retrospective action.

7. Limitations of the study

A major limitation of the present study has been the limited number of participants, which does not allow for generalizing our results. Because our emphasis was on data richness, we used a rather confined sample size (51 students). Future research needs to engage a greater number of students and examine the effects of time-on-task and retrospective action in computer-supported learning environments across various grades and levels of education.

8. Implications for instruction and design of computer-supported learning environments

In terms of implications for science education and inquiry learning, our study demarcates a novel field of research, namely, the one opened up by trade-offs between time-on-task and extra time spend during retrospective action, which is only realizable within computer-supported, inquiry-based learning environments. Problematizing student work by adequately configuring the architecture of these environments might initiate retrospective action, which could prove beneficial for student performance if planned appropriately. Previous research has approached inquiry more or less in a continuous and unidirectional manner, taking a one-way, serial succession of learning activities as a basic design for students to follow (see, for instance, Minner et al., 2010). Although retrospective action has been indicated as a possible pathway (e.g., Pedaste et al. 2015), it has remained an unexplored alternative for students, educators and software developers. Our results imply that retrospective action may be used constructively and it may contribute substantially to achieving learning trajectories, especially when adequate time had not been devoted to working on certain tasks during the initial processing of learning activities. Revisiting inquiry tasks could be a possibility in computer-supported inquiry-based learning environments, which may add significantly in improving student knowledge, and, most importantly, when applied through a proper architectural/scaffold design, as in Condition 2. Hence, retrospective action introduces new horizons for designing inquiry learning, insofar, as it might offer novel options for developing learning sequences, for instance, a desirable, purposeful revisit of inquiry tasks.

The results of our study do also provide valuable insight for configuring feedback in computer-supported, inquiry-based learning environments. Two aspects should be underlined in this regard. First, choosing the proper timing for providing instructional guidance may be crucial for learning (Pol, Harskamp, & Suhre, 2008). Agents scheduled for computer-supported, inquiry-based learning environments need to be related to various instances of learner actions, navigation patterns, and performance in order to be able to introduce or remove any type of guidance (e.g., agents should be able to differentiate between time-on-task during the first pass through the learning activity sequence and extra time spend during retrospective action). These notifications could also be used for managing how to handle the delicate balance between structuring and problematizing student work. For instance, monitoring time-on-task and extra time spent during retrospective action would allow educators to know when time allocated to virtual labs or computer applications and scaffold tools is or is not sufficient for productive learning routes. Such a development might assist in addressing the gap of diagnosing student actions and performance in order to offer constructive and timely feedback and build learner-tailored environments (see, for instance, Kalyuga, 2007). Apart from quantitative indicators, qualitative indicators of student actions could also be monitored. For example, a qualitative indicator could be whether or not students have returned to a lab or tool. Overall, the potential of providing feedback to learners needs to be investigated and linked to formative assessment enacted on the basis of student interaction with virtual labs and scaffold tools and on the basis of the opportunities that are available for monitoring student progression along a learning activity sequence. Such a direction for future research would be quite valuable for educators to use in designing their instruction, as long as technology allows them to save precious learning time by supporting or taking over part of their instructional and procedural tasks.

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References

Alfieri, L., Brooks, P. J., Aldrich, N. J., & Tenenbaum, H. R. (2011). Does discovery-based instruction enhance learning? Journal of Educational Psychology, 103, 1-18. DOI:10.1037/A0021017

Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. New York: Addison Wesley Longman.

Arnold, J. C., Kremer, K., & Mayer, J. (2014). Understanding students' experiments - What kind of support do they need in inquiry tasks? *International Journal of Science Education, 36*, 2719-2749. DOI: 10.1080/09500693.2014.930209.

Bevins, S., & Price, G. (2016). Reconceptualising inquiry in science education. *International Journal of Science Education*, *38*, 17-29, DOI: 10.1080/09500693.2015.1124300.

Bloom, B. S. (1956). *Taxonomy of educational objectives. Handbook I: The cognitive domain*. New York: David McKay.

Bowman, L. L., Waite, B. M., & Levine, L. E. (2015). Multitasking and attention. In L. D. Rosen, N. A. Cheever, & L. M. Carrier (Eds.), *The Wiley handbook of psychology, technology, and society* (pp. 388-403). Chichester, UK: John Wiley & Sons, Ltd. DOI:10.1002/9781118771952.ch22.

Burns, J., Okey, J., & Wise, K. (1985). Development of an integrated process skill test: TIPS II. *Journal of Research in Science Teaching*, 22, 169-177. DOI: 10.1002/tea.3660220208.

Chang, K.-E., Chen, Y.-L., Lin, H.-Y., & Sung, Y.-T. (2008). Effects of learning support in simulation-based physics learning. *Computers and Education*, *51*, 1486-1498. DOI: 10.1016/j.compedu.2008.01.007.

Cohen, L., Manion, L., & Morrison, K. (2007). *Research methods in education* (6th ed.). London/New York: Routledge.

De Backer, L., Van Keer, H., & Valcke, M. (2016). Eliciting reciprocal peer-tutoring groups' metacognitive regulation through structuring and problematizing= scaffolds. *The Journal of Experimental Education*, 84, 804–828. DOI: 10.1080/00220973.2015.1134419.

De Boer, G. E., Quellmalz, E. S., Davenport, J. L., Timms, M. J., Herrmann-Abell, C. F., Buckley, B. C., Jordan, K. A., Huang, C.-W., & Flanagan, J. C. (2014). Comparing three online testing modalities: Using static, active, and interactive online testing modalities to access middle school students' understanding of fundamental ideas and use of inquiry skills related to ecosystems. *Journal of Research in Science Teaching*, *51*, 523-554. DOI: 10.1002/tea.21145.

de Jong, T. (2006). Computer simulations – Technological advances in inquiry learning. *Science*, 312, 532–533. DOI: 10.1126/science.1127750..

de Jong, T., (Ed.). (2014). *Preliminary inquiry classroom scenarios and guidelines. D1.3. Go-Lab Project* (Global Online Science Labs for Inquiry Learning at School).

de Jong, T., Sotiriou, S., & Gillet, D. (2014). Innovations in STEM education: the Go-Lab federation of online labs. *Smart Learning Environments*, *1*, 1-16. https://doi.org/10.1186/s40561-014-0003-6.

Efstathiou, C., Hovardas, T., Xenofontos, N., Zacharia, Z., de Jong, T., Anjewierden, A., & van Riesen S. A. N. (2018). Providing guidance in virtual lab experimentation: The case of an experiment design tool. Educational Technology Research & Development, 66, 767–791. https://doi.org/10.1007/s11423-018-9576-z

Fiorella, L., Vogel-Walcutt, J. J., & Fiore, S. (2012). Differential impact of two types of metacognitive prompting provided during simulation-based training. *Computers in Human Behavior*, *28*, 696-702. DOI:10.1016/j.chb.2011.11.017.

Furtak, E. M. (2006). The problem with answers: An exploration of guided scientific inquiry teaching. *Science Education*, *90*, 453-467. DOI: 10.1002/sce.20130.

Goldhammer, F., Naumann, J., Stelter, A., Toth, K., R€olke, H., & Klieme, E. (2014). The time on task effect in reading and problem solving is moderated by task difficulty and skill: insights from a computer-based large-scale assessment. *Journal of Educational Psychology*, 106, 608-626. DOI: 10.1037/a0034716.

Greiff, S., Niepel, C., Scherer, R., & Martin, R. (2018). Understanding students' performance in a computer-based assessment of complex problem solving: An analysis of behavioural data from computer-generated log files. *Computers in Human Behavior*, 61, 36-46. DOI: 10.1016/j.chb.2016.02.095.

Großmann, N. & Wilde, M. (2019). Experimentation in biology lessons: Guided discovery through incremental scaffolds, *International Journal of Science Education*, *41*, 759-781. DOI: 10.1080/09500693.2019.1579392.

Hofstein, A., & Lunetta, V. N. (2003). The laboratory in science education: Foundations for the twenty-first century. *Science Education*, *88*, 28-54. DOI: 10.1002/sce.10106.

Hofstein, A., Navon, O., Kipnis, M., & Mamlok-Naaman, R. (2005). Developing students’ ability to ask more and better questions resulting from inquiry-type chemistry laboratories. *Journal of Research in Science Teaching*, *42*, 791-806. DOI: 10.1002/tea.20072.

Hovardas, T. (2016). A learning progression should address regression: Insights from developing non-linear reasoning in ecology. *Journal of Research in Science Teaching*, *53*, 1447-1470. https://doi.org/10.1002/tea.21330.

Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review, 19*, 509-539. DOI: 10.1007/s10648-007-9054-3.

Kalyuga, S., & Sweller, J. (2004). Measuring knowledge to optimize cognitive load factors during instruction. *Journal of Educational Psychology*, *96*, 558-568. DOI: 10.1037/0022-0663.96.3.558.

Karweit, N., & Slavin, R. E. (1982). Time-on-task: Issues of timing, sampling, and definition. *Journal of Educational Psychology*, *74*, 844-851. http://dx.doi.org/10.1037/0022-0663.74.6.844.

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist*, *41*, 75-86. DOI: 10.1207/s15326985ep4102_1.

Koksal, E. A., & Berberoglou, G. (2014). The effect of guided inquiry instruction on 6th grade Turkish students' achievement, science process skills, and attitudes toward science. *International Journal of Science Education*, *36,* 66-78. DOI: 10.1080/09500693.2012.721942.

Kremer, K., Specht, C., Urhahne, D., & Mayer, J. (2014). The relationship in biology between the nature of science and scientific inquiry. *Journal of Biological Education*, *48*, 1-8. DOI: 10.1080/00219266.2013.788541.

Lazonder, A. W., & Harmsen, R. (2016). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research*, *86*(3), 681-718. DOI:10.3102/0034654315627366

Metcalfe, J., & Finn, B. (2008). Evidence that judgments of learning are causally related to study choice. *Psychonomic Bulletin & Review*, *15*, 174-179. DOI: 10.3758/PBR.15.1.174.

Minner, D. D., Jurist Levy, A., & Century, J. (2010). Inquiry-based science instruction – What is it and does it matter? Results from a research synthesis years 1984-2002. *Journal of Research in Science Teaching*, *47*, 474-496. DOI: 10.1002/tea.20347.

Molenaar, I., Sleegers, P. & van Boxtel, C. (2014). Metacognitive scaffolding during collaborative learning: A promising combination. *Metacognition and Learning*, 9, 309–332. DOI: 10.1007/s11409-014-9118-y.

Molenaar, I., van Boxtel, C. A. M., & Sleegers, P. J. C. (2011). Metacognitive scaffolding in an innovative learning arrangement. *Instructional Science* 39, 785-803. DOI: 10.1007/s11251-010-9154-1.

Mulder, Y., G., Bollen, L., de Jong, T., & Lazonder, A. W. (2016). Scaffolding learning by modelling: The effects of partially worked-out models. *Journal of Research in Science Teaching*, *53*, 502-523. https://doi.org/10.1002/tea.21260.

Pedaste, M., Mäeots, M., Siiman, L. A., de Jong, T., van Riesen, S. A. N., Kamp, E. T., Manoli, C. C., Zacharia, Z. C., & Tsourlidaki, E. (2015). Phases of inquiry-based learning: Definitions and the inquiry cycle. *Educational Research Review, 14*, 47-61. https://doi.org/10.1016/j.edurev.2015.02.003.Efstathiou, C., Hovardas, T., Xenofontos, N., Zacharia, Z., de Jong, T., Anjewierden, A., & van Riesen S. A. N. (2018). Providing guidance in virtual lab experimentation: The case of an experiment design tool. Educational Technology Research & Development, 66, 767–791. https://doi.org/10.1007/s11423-018-9576-z

Pol, H. J., Harskamp, E. G., & Suhre, C. J. M. (2008). The effect of the timing of instructional support in a computer-supported problem-solving program for students in secondary physics education. *Computers in Human Behavior*, *24*, 1156-1178. DOI: 10.1016/j.chb.2007.04.002.

Quintana, C., Reiser, B. J., Davis, E. A., Krajcik, J., Fretz, E., Duncan, R. G., Kyza, E., Edelson, D., & Soloway, E. (2004). A scaffolding design framework for software to support science inquiry. *Journal of the Learning Sciences*, 13, 337–386. DOI: 10.1207/s15327809jls1303_4.

Reiser, B. J. (2004). Scaffolding complex learning: The mechanisms of structuring and problematizing student work. *Journal of the Learning Sciences, 13*, 273-304. DOI: 10.1207/s15327809jls1303_2.

Reisslein, J., Atkinson, R. K., Seeling, P., & Reisslein, M. (2006). Encountering the expertise reversal effect with a computer-based environment on electrical circuit analysis. *Learning and Instruction*, *16*, 92-103. DOI: 10.1016/j.learninstruc.2006.02.008.

Reisslein, J., Sullivan, H., & Reisslein, M. (2007). Learner achievement and attitudes under different paces of transitioning to independent problem solving. *Journal of Engineering Education*, *96*, 45-56. DOI: 10.1002/j.2168-9830.2007.tb00914.x.

Saye, J. W. & Brush, T. (2002). Scaffolding critical reasoning about history and social issues in multimedia-supported learning environments. *Educational Technology Research and Development*, *50*, 77–96. DOI: 10.1007/BF02505026.

Schiefer, J., Golle, J., Tibus, M., & Oschatz, K. (2019). Scientific reasoning in elementary school children: Assessment of the inquiry cycle. Journal of Advanced Academics, 30, 144–177. DOI: 10.1177/1932202X18825152.

Seufert, T., & Brünken, R. (2006). Cognitive load and the format of instructional aids for coherence formation. *Applied Cognitive Psychology*, *20*, 321-331. DOI: 10.1002/acp.1248.

Simons, K. D., & Klein, J. D. (2007). The impact of scaffolding and student achievement levels in a problem-based learning environment. *Instructional Science*, *35*, 41-72. DOI: 10.1007/s11251-006-9002-5.

Slavin, R. E. (2014). *Educational psychology: Theory and practice* (11th ed.). Boston: Pearson Education.

Thiede, K. W., Anderson, M. C. M., & Therriault, D. (2003). Accuracy of metacognitive monitoring affects learning of texts. *Journal of Educational Psychology*, *95*, 66-73. DOI: 10.1037/0022-0663.95.1.66.

Veermans, K., van Joolingen, W. R., & de Jong, T. (2006). Use of heuristics to facilitate scientific discovery learning in a simulation learning environment in a physics domain. *International Journal of Science Education*, *28*(4), 341-361. DOI: 10.1080/09500690500277615.

Yıldız-Feyzioğlu, E., Akpınar, E., & Tatar, N. (2015). Monitoring students' goal setting and metacognitive knowledge in technology-enhanced learning with metacognitive prompts. *Computers in Human Behavior*, *29*, 616-625. DOI: 10.1016/j.chb.2012.11.019.

Zacharia, Z. C., Manoli, C., Xenofontos, N., de Jong, T., Pedaste, M., van Riesen, S. A. N., Kamp, E. T., Mäeots, M., Siiman, L., & Tsourlidaki, E. (2015). Identifying potential types of guidance for supporting student inquiry when using virtual and remote labs in science: A literature review. *Educational Technology Research and Development*, *63*, 257-302. https://doi.org/10.1007/s11423-015-9370-0.

Zervas, P. (Ed.). (2013). *The Go-Lab inventory and integration of online labs – labs offered by large scientific organisations*. D2.1. Go-Lab Project (Global Online Science Labs for Inquiry Learning at School).

Appendix

Prompts embedded in the learning environment

A. Prompts in the Observation Tool:
Each time you conduct an experimental trial in the Electrical Circuit Lab, you need to record the values of variables tested and you also need to keep notes in the Observation Tool on the following aspects:
-How would you compare the brightness of the bulbs in each circuit?
- Is the brightness of the bulbs the same as the brightness of the bulb in a simple electric circuit?

B. Prompts in the Input Box for graph interpretation:
The following questions will help you to interpret your graphs.
- What is the effect on the electric current of adding bulbs in a circuit? Please try to support your reasoning by referring to your data.
- How does the brightness of the bulbs change when adding bulbs in series? What happens when adding bulbs in parallel?
- Please consider that the brightness of a bulb is an indicator of the electric current that flows through it. How does the electric current that flows through each bulb change, when adding bulbs in series, and when adding bulbs in parallel?

The knowledge test

Name: ____
School name: ____
Date: ____
Age: ____
Gender: ____

NOTE:
In order to complete this test you will need approximately 20 minutes. You must answer all items (1-6). The results of this test will not count toward your total score in the lesson. They will be used anonymously for research purposes.

1. Which components are necessary to create a simple electric circuit? Describe how these components must be connected.

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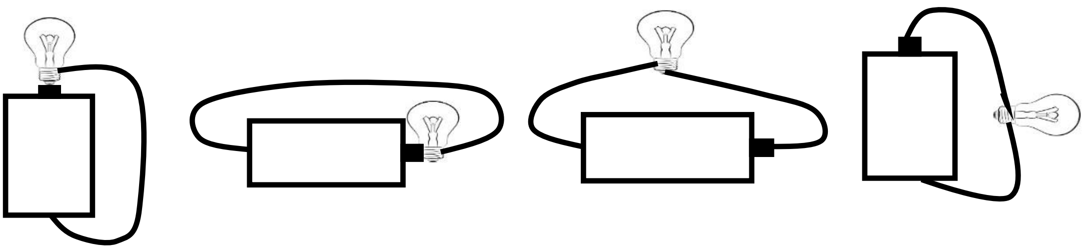
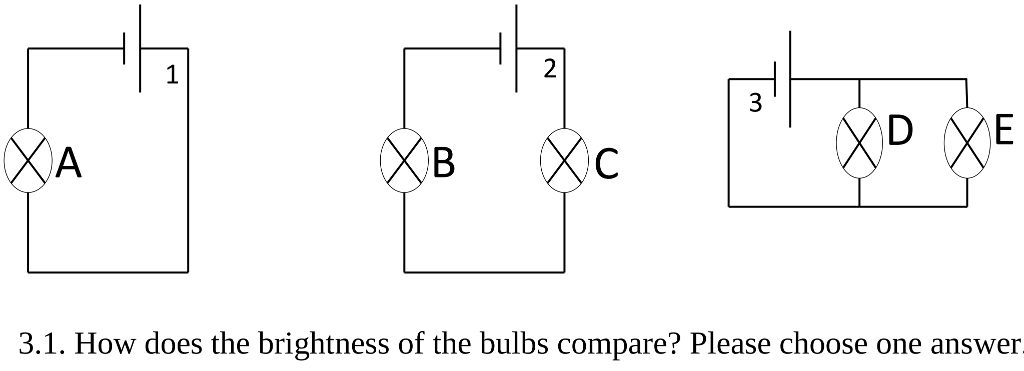
2. In which of the following will the bulb light up? Please choose one answer.



A) B) C) D)

a) A and B
b) A and C
c) C and D
d) All of them
e) None of them

3. Look at the following circuits:



3.1. How does the brightness of the bulbs compare? Please choose one answer.

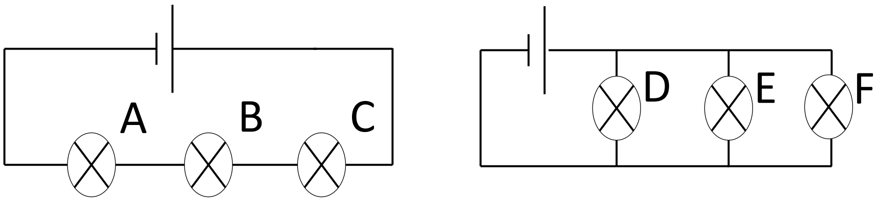
a) A > B = C = D = E
b) A < B = C < D = E
c) D = E = A > B = C
d) B = C = A < D = E

e) A > D = E < B = C

3.2 How do 1, 2, and 3 compare with regard to the electric current that flows through each circuit? Please choose one answer.

a) 1 = 3 > 2
b) 1 < 2 = 3
c) 2 = 3 < 1
d) 2 < 1 < 3
e) 1 = 2 < 3

4. What will happen if the middle bulb burns out (and it is not removed from the circuit)? Please choose one answer.



a) A and C do not light, D and F light equally
b) All the bulbs (A, C, D and F) do not light
c) A and C light equally but less than D and F, which light equally
d) All the bulbs (A, C, D and F) do light
e) D and F do not light, A and C light equally

5. What do the multiple electrical sockets, used for the operation of multiple electrical appliances, imply about the type of the connection? Please explain your reasoning.

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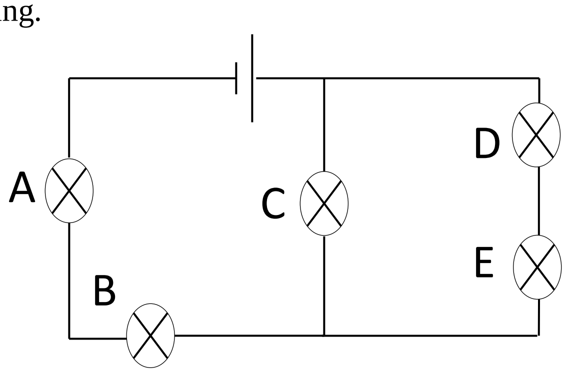
6. How does the brightness of the bulbs compare in the following circuit? Please explain your reasoning.



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Variables examined for learning activities to assess the quality/properties of learning products

Learning activity	Variable (Name of variable as it appears in the Results section); Values for variable	Measure	Range (min-max)
Formulate hypotheses	Number of hypotheses formulated (NumberHypo); Count	Scale	0-2
	Maximum score of hypotheses (ScoreHypoMax); “0” = no dependent variable included or invalid dependent variable (i.e., one that cannot be tested in the Electrical Circuit Lab); “1” = valid dependent variable but missing or invalid independent variable; “2” = valid dependent and independent variable	Ordinal	0-2
Design an experiment	Time-on-task working with the Experiment Design Tool in seconds (EDTTime); Count	Scale	28-535
	Number of pop-up windows that appeared when using EDT (EDTFeedback); Count	Scale	0-5
	VOTAT strategy (EDTVOTAT); 0/1	Binary	0-1
	Number of experimental trials planned (Trials); Count	Scale	0-5
	Values of variables recorded in at least one experimental trial (ValuesTrialsRecorded): 0/1	Binary	0-1
Execute an experiment	Time-on-task working with the Electrical Circuit Lab in seconds (LABTime); Count	Scale	125-1126
	Number of circuits created (Circuits); Count	Scale	0-6
	Data selected by operating at least one circuit (DataVCircuitRecorded): 0/1	Binary	0-1
Make observations	Number of observations recorded by the Obervation Tool (NumberObserv); Count	Scale	0-2
	Maximum score across all observations (ScoreObservMax): “0” = no dependent variable mentioned or invalid dependent variable (i.e., one that was not tested in the Electrical Circuit Lab); “1” = valid dependent variable but missing or invalid independent variable; “2” = valid dependent and independent variables	Ordinal	0-2
Construct graphs	Number of graphs created by the Data Viewer (NumberGraphs); Count	Scale	0-2
	Graphs included valid dependent and independent variables (GraphCorrectness); 0/1	Binary	0-1
	An independent variable in at least one Graph was invalid (GraphIncorrect_IND); 0/1	Binary	0-1
	A dependent variable in at least one Graph was invalid (GraphIncorrect_DEP); 0/1	Binary	0-1
Interpret graphs	Number of valid inferences (GraphInter); Count	Scale	0-6; recalculated to range between 0 and 1

Variables examined for learning activities undertaken during retrospective action (after students had reached the Data Viewer and when they returned to previous steps of their inquiry)

Learning activity	Variable (Name of variable as it appears in the Results section); Values for variable	Measure	Range (min-max)
Revisit the Experiment Design Tool	Return to the Experiment Design Tool (ReturnEDT); 0/1	Binary	0-1
	Construct new learning products with the Experiment Design Tool (ActionReturnEDT_NLP); 0/1	Binary	0-1
	Extra time spent on the Experiment Design Tool in seconds (ExtraTimeEDT); Count	Scale	0-372
Revisit the Electrical Circuit Lab	Return to the Electrical Circuit Lab (ReturnLAB); 0/1	Binary	0-1
	Construct new learning products with the Electrical Circuit Lab (ActionReturnLab_NLP); 0/1	Binary	0-1
	Extra time spent on the Electrical Circuit Lab in seconds (ExtraTimeLAB); Count	Scale	0-771
Total time spent during retrospective action	Total time spent during retrospective action after reaching the Data Viewer (TotalTimeReturn); Count	Scale	0-993