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ARTICLE

Designing novel activities before instruction: Use of contrasting cases and a rich dataset

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Abstract

Background: In exploratory learning, students first explore a new topic with an activity and then receive instruction. This inversion of the traditional tell-then-practice order typically benefits conceptual knowledge and transfer, but not always.

Aims: The current work examines the impact of including contrasting cases in an exploration activity, which can enhance student perception of novel problem features.

Samples: Undergraduate physics students (Experiment 1, $N = 129$; Experiment 2, $N = 92$) participated as part of their regular classroom instruction.

Methods: Students completed an activity either before or after instruction (explore-first or instruct-first conditions). In Experiment 1, the activity included contrasting cases; in Experiment 2, the activity instead included a rich dataset. Students completed a post-test assessing procedural knowledge, conceptual knowledge and transfer.

Results: In Experiment 1, students in the explore-first condition demonstrated similar procedural knowledge, higher conceptual knowledge and higher transfer than students in the instruct-first condition. In Experiment 2, there were no significant differences in learning outcomes between explore-first and instruct-first conditions. In both experiments, students in the explore-first and instruct-first conditions reported similar cognitive load and interest and enjoyment after the activity.

Conclusions: Contrasting cases may be important when designing exploratory learning activities, helping to improve both conceptual understanding and transfer to new topics.

KEYWORDS

exploratory learning, productive failure, STEM education, transfer, undergraduate education

INTRODUCTION

Active learning strategies enable instructors to better engage students and provide opportunities for deeper learning (Borda et al., 2020; Freeman et al., 2014; Streveler & Menekse, 2017; Theobald et al., 2020). One promising active learning technique is *exploratory learning*, which reverses the more traditional instruct-then-practice order. Exploratory learning methods include a novel activity given prior to instruction on the topic (DeCaro & Rittle-Johnson, 2012). This general term includes research using this two-phase method, including research on productive failure (e.g., Kapur, 2008), inventing to prepare for future learning (e.g., Schwartz et al., 2009) and problem solving prior to instruction (PS-I) methods (Loibl & Rummel, 2014). Across these literatures, research has demonstrated that exploratory learning can benefit conceptual knowledge and transfer to new concepts when compared to traditional tell-then-practice methods (e.g., Darabi et al., 2018; Loibl et al., 2017). The benefits of exploring are generally selective to conceptual understanding; students' learning of problem-solving procedures tends to remain similar between exploratory learning and traditional instruct-first conditions (e.g., Loibl et al., 2017).

However, exploration activities do not always improve learning (e.g., Chase & Klahr, 2017; Fyfe et al., 2014; Loehr et al., 2014, Study 1). In their literature review, Loibl et al. (2017) noticed that existing studies differed in their instructional designs, and relatedly, their results. Conceptual knowledge gains were present when the activity was based on *contrasting cases* – examples that vary systematically across problem features. However, when the activity did not include contrasting cases, benefits were only consistently observed when the instructions built upon student solutions (Loibl & Rummel, 2014). However, Loibl et al. (2017) noted that no studies had varied the type of activity used during exploration while keeping other factors constant.

Recently, Loibl et al. (2020) performed one such experiment, manipulating instructional order (*explore-first* and *instruct-first*) and activity type (*with or without contrasting cases*). Their findings did not align with the conclusions of Loibl et al. (2017). Loibl et al. (2020) found an overall procedural knowledge gain in the instruct-first conditions and equal conceptual knowledge between instructional orders with both activity types. Loibl et al. (2020) acknowledged several limitations of their study, and it is clear that more work is needed to understand the impact of various activity designs in exploratory learning.

The current work extends the investigation of activity type in exploratory learning in a large, undergraduate physics classroom. In two studies, we compared student performance following one of two different activities and the same instruction in instruct-first and explore-first orders. Learning outcomes included procedural knowledge, conceptual knowledge and transfer. Additional measures included awareness of knowledge gaps, interest and cognitive load. Notably, these are the first studies to test the effects of exploratory learning on a transfer assessment in an undergraduate physics course.

Exploration activities

Activities used in exploratory learning studies typically include information in one of two layouts: contrasting cases or rich datasets (Loibl et al., 2017). These layouts differ in the number of data points as well as the clarity of underlying the problems' features. In contrasting cases, there are a minimal number of data points, and each pair of data points differs by a single problem feature (Roll et al., 2012; Schwartz et al., 2009). Rich datasets include many data points that effectively hide the underlying problem features (Kapur, 2008, 2010, 2014; Kapur & Bielaczyc, 2012; Loibl et al., 2017).

For example, Schwartz et al. (2011) studied the effectiveness of exploring contrasting cases to teach eighth-grade students about density. They presented six cases that varied systematically by features analogous to mass, volume and density. These problem features were clear and discoverable. In this activity, students were asked to invent a strategy for calculating 'crowdedness', a well-known concept that is similar to density.

In contrast, Kapur (2014) used a rich dataset (i.e., two long lists of data) when introducing standard deviation to ninth graders in an activity before instruction. Students were asked to generate a method for determining which dataset was more ‘consistent’, a well-known concept similar to the novel concept of standard deviation. In this case, problem features were not obvious.

Learning mechanisms

It is likely that both contrasting cases and rich dataset activity types invoke some of the same learning mechanisms but also different ones, or to a different degree. For instance, regardless of activity type, learners must *draw from their existing knowledge* as they attempt to solve a novel problem (Capon & Kuhn, 2004; Kapur, 2011, 2012, 2014; Schwartz & Bransford, 1998). Then, as students discover that their prior knowledge is not enough to solve the problem at hand, they become *aware of the gaps in their knowledge* (e.g., Glogger-Frey, Kappich, et al., 2015; Loibl et al., 2017; Loibl & Rummel, 2014). Students' metacognitive awareness of their knowledge gaps likely motivates them to attend subsequent instruction (Wise & O'Neill, 2009).

Importantly, students will likely experience prior knowledge activation, knowledge gap awareness and increased attention to instruction regardless of activity type. In addition, these processes do not depend on whether students are successful at problem-solving, because the problem-solving phase is followed by instruction. Unsuccessful problem solving during exploration has been called *productive failure* because, following instruction, students have demonstrated learning gains compared to a more traditional instruct-then-practice order (e.g., Kapur, 2008, 2016).

However, contrasting cases and rich datasets may differ in whether they promote an opportunity for students to *discern underlying problem features* during the activity (Loibl et al., 2017; Schwartz et al., 2011). During the exploration of a new problem, students can begin to determine what information is useful and what is not (DeCaro & Rittle-Johnson, 2012). This process enables students to identify important problem features during the activity and consider the meaning and significance of these features. Students may even derive relational structures of individual variables in a complex formula that will be later introduced in instruction (Alfieri et al., 2013; Chin et al., 2016). In prior studies, students who attended to the deep structure of the activity had greater learning outcomes (Glogger-Frey et al., 2015; Holmes et al., 2014; Schwartz et al., 2011). Because of their design, contrasting cases might make it easier for students to discern problem features than rich datasets (Alfieri et al., 2013; Roelle & Berthold, 2015; Schwartz & Bransford, 1998).

Learning outcomes

Exploratory learning benefits are most often observed in students' *conceptual knowledge*, which is abstract and relational (Jonassen, 2009; Rittle-Johnson et al., 2001). Conceptual knowledge consists of the principles in a domain as well as the connections between associated concepts. In contrast, *procedural knowledge* is a series of sequential actions that can be used to solve problems (Jonassen, 2009; Rittle-Johnson et al., 2001). Assessments of procedural knowledge have participants complete the same procedures that were taught during instruction, whereas conceptual assessments query relational principles. Exploratory learning has been shown to generally result in equal procedural knowledge and higher conceptual knowledge when compared to an instruction-first order (Loibl et al., 2017).

In addition, exploratory learning can benefit *transfer*, learners' ability to adapt existing knowledge to a new situation or different type of problem (Barnett & Ceci, 2002). Transfer assessments target knowledge generalization, depth and flexibility, which are higher-level goals than specific knowledge acquisition (Kalyuga & Singh, 2016). One method of assessing generalized domain understanding and transfer is a dynamic future learning assessment (Schwartz & Martin, 2004). *Future learning assessments* include a learning resource on a new topic (e.g., a worked example with explanations) within the assessment, and students are then asked questions on the new content. Schwartz et al. (2009) argue that there are benefits of methods such as exploratory learning that can only be observed with future learning assessments, and some research on exploratory learning support this point (Schwartz et al., 2009; Schwartz & Bransford, 1998; Schwartz & Martin, 2004; Sears, 2006). However, future learning assessments are rarely implemented. No prior exploratory learning studies have assessed future learning with a rich dataset activity or with an undergraduate student sample.

Current research

The current experiments examined the impact of exploratory learning in an undergraduate physics course. In Experiment 1, we assessed the benefits of exploration with contrasting cases. In the *explore-first* condition, students were given the exploration activity followed by instructions. In the *instruct-first* condition, students received instruction and then worked on the same activity. Thus, students completed the same learning materials in both conditions, and the only difference was whether the activity came before or after instruction. All students then completed a post-test that included procedural, conceptual and future learning assessments. We measured interest/enjoyment and cognitive load after the activity. The same basic experimental design and assessments were used in Experiment 2, which utilized a rich dataset instead of contrasting cases in the activity.

We predicted that students in the explore-first condition with contrasting cases (Experiment 1) would demonstrate equal procedural knowledge, greater conceptual knowledge and greater transfer than students in the instruct-first condition, similar to other exploratory learning studies using contrasting cases. For Experiment 2 (rich datasets), we predicted one of two outcomes. One possibility was that we would obtain results similar to Experiment 1, consistent with prior studies using rich datasets (e.g., Kapur, 2012, 2014). However, students may have difficulty discovering important problem features when exploring rich datasets. If the process of discovering relevant problem features is necessary for exploratory learning, then it is possible that no difference between explore-first and instruct-first conditions would be found when the activity is based on rich datasets.

Importantly, many prior studies – including those using either contrasting cases or rich datasets – vary other factors in addition to the order of activity and instruction (see Hsu et al., 2015; Loibl et al., 2017; Schwartz et al., 2011). In addition, none of the prior studies has used the same topic or materials as the current study, and the majority were done with younger students. Thus, it would not be entirely unexpected if we did not replicate the benefits of exploration in these experiments when using a controlled experimental design with a new topic and sample.

As discussed previously, Loibl et al. (2020) directly compared the use of contrasting cases versus rich datasets as exploration activities and found results that contradict the typical pattern of findings. Post-test performance was very low in all conditions, indicating that the learning materials may have been quite difficult for this age group, leading to a high cognitive load. Prior research has shown that more difficult materials (i.e., an activity with high element interactivity) can reduce the benefits of exploring before instruction, such that an instruct-first condition results in higher learning (e.g., Ashman et al., 2020; see also Chen et al., 2015). The current studies included measures of cognitive load and interest/enjoyment to gauge both difficulty and engagement of our materials for our sample. We expected that these materials could be attempted by students without being overly difficult because the instructor collaborated on the material design and was familiar with students' prior knowledge. Based on the potential for exploration to be more challenging but engaging (Kapur, 2016), we predicted that students in an explore-first condition would perceive equal or higher cognitive load and equal or higher interest and enjoyment of the activity compared to students in an instruct-first condition, in both experiments. This prediction aligns with the concept of productive failure (e.g., Kapur, 2008, 2016). Students in the explore-first conditions were expected to be able to attempt the activities, but not necessarily gain high accuracy (Kapur, 2016). Yet, this experience of exploring was expected to translate to a higher conceptual understanding.

By examining different activity designs and resulting learning outcomes in undergraduate physics, these studies allow us to further investigate the importance of contrasting cases in exploratory learning. Because contrasting cases are designed to help students discover problem features, a differential benefit of exploring in Experiment 1 but not in Experiment 2 would indicate that emphasizing deep problem features during exploration may be important to achieve the learning benefits observed in the literature. If instead we found higher learning scores when exploring in both experiments (using contrasting cases and rich datasets), the findings would indicate that the learning mechanisms similar to both (prior knowledge activation and knowledge gap awareness) may be enough to generate the learning benefits of exploration. Alternatively, this finding could suggest that, despite not being intentionally designed to highlight problem features, rich datasets still enable students to sufficiently explore these features. Either outcome would further our understanding of whether contrasting cases are important when designing exploration activities.

EXPERIMENT 1

Experiment 1 tested learning outcomes following a contrasting cases activity and instruction in an undergraduate physics classroom in two instructional orders: explore-first and instruct-first.

Methods

Participants

Participants (N = 129) were all students who attended a first-semester undergraduate physics course for engineers and physics majors on the date of the study and completed all learning materials.

Materials

All materials are provided in Figures 1 and 2 and the Supplemental Online Materials.

Instruction

The course instructor lectured with a slideshow presentation. He began by relating the current topic (gravitational field) to the preceding topic (gravitational force). The instructor then outlined the basic formulas, and how another previous course topic (vector addition) could be used to do the calculations. Students were familiar with vector addition at this point in the course, having used it in several different contexts including gravitational force. Therefore, the emphasis of this lesson was on the gravitational field concept and magnitude formula. Lastly, the instructor walked through an example problem by hand on his laptop which was projected on the same screen as the slideshow (see Figure 1).

Contrasting cases activity

The contrasting cases activity is illustrated in Figure 2. The complete set of 10 scenarios (points $P_A - P_J$) were designed to differ along critical problem features (distance, mass, relative position and number of objects). To make the different problem features discoverable, the 10 points were grouped into three diagrams. The first diagram had only one particle, m_1, with points either directly below it or directly to the right. Points P_A and P_B differed only by distance from the particle, and points P_C and P_D differed from P_A and P_B only by relative position. The third diagram had two particles of different masses with points along

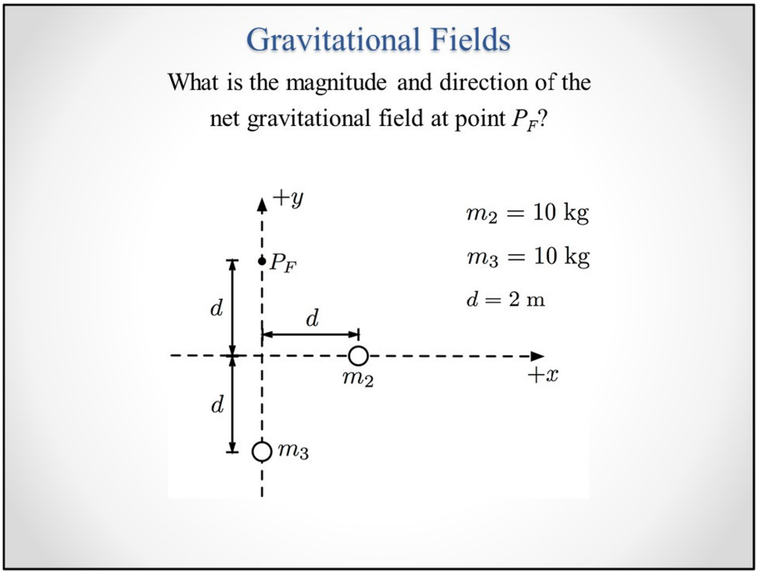


FIGURE 1 Example problem worked by the instructor during instruction in Experiments 1 and 2

a single axis. This diagram made the relative value of mass to distance ($g = m/d^2$) discoverable. The second diagram had multiple points and masses that were not on a single axis, which introduced the vector addition component of multiple masses. Only P_F and P_G were points for which the gravitational field was at an angle, and P_F was given as an example. Students could therefore deduce the vector addition nature of the gravitational field, although again this was not necessary due to the instruction that followed.

The activity instructions for the explore-first and instruct-first conditions were as parallel as possible (Figure 2). In the explore-first condition, students were instructed to 'invent a mathematical formula…' We used invention instructions in keeping with prior studies using contrasting cases (e.g., Schwartz et al., 2011). Chin et al. (2016) found that invention instructions led to higher learning outcomes, and more global synthesis across cases, than explicit instructions to compare contrasting cases.

Contrasting cases activity review

The activity review consisted of showing the correct answers on a slide and asking students if they had any questions.

Survey

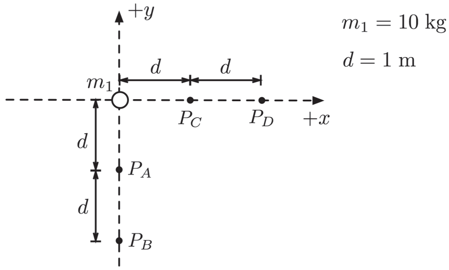
The survey was designed to assess interest/enjoyment and cognitive load following the activity. The interest and enjoyment scale was adapted from Ryan (1982; Cronbach's α = .82; see Weaver et al., 2018). Students responded to four items on a Likert scale from 1 (*strongly disagree*) to 7 (*strongly agree*), such as 'Today's activity has been interesting'. Cognitive load was measured with the single-item Mental Effort Rating Scale (Paas, 1992). The question read, 'In completing the learning activity today I invested:', and the response was on a Likert scale ranging from 1 (*very, very low mental effort*) to 9 (*very, very high mental effort*).

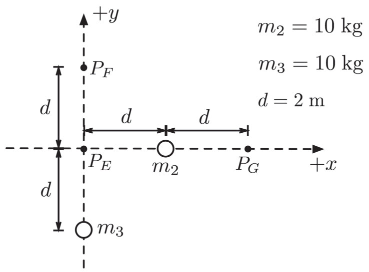
Assessments

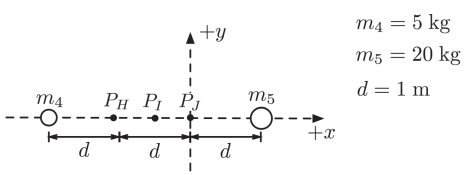
The *procedural knowledge* scale (7 items, α = .71) consisted of multiple-choice questions requiring students to use formulas from recent instruction for different scenarios. The *conceptual knowledge* scale (10 items; α = .76) consisted of True/False questions that queried relational and verbal understanding, including several common misconceptions. The *future learning assessment* consisted of a learning resource followed

Gravitational Field Activity

The figures below on the left show a series of particles, labeled m_1 through m_5, and points in space, labeled P_A through P_J. Values for masses and distances are given in each figure.







Vector	Magnitude	Direction	Point
$\vec{g}_1$	$1.75G$	60° below $+x$ axis	P_F
$\vec{g}_2$	$10G$	To the left	
$\vec{g}_3$	$\frac{10}{3}G$	To the right	
$\vec{g}_4$	$2.5G$	To the left	
$\vec{g}_5$	0	N/A	
$\vec{g}_6$	$\frac{150}{4}G$	To the right	
$\vec{g}_7$	$10G$	Up	
$\vec{g}_8$	$2.96G$	4.3° below $+x$ axis	
$\vec{g}_9$	$2.5G$	Up	
$\vec{g}_{10}$	$3.54G$	45° below $+x$ axis	

Each row in the table above gives a gravitational field vector $\vec{g}$ with its magnitude and direction. Use the information given in the table to practice the calculation of gravitational field $\vec{g}$. The gravitational field $\vec{g}$ is a vector quantity that is related to the gravitational force.

a
- Use the mathematical formula you have just learned to calculate the magnitude and direction of the gravitational field $\vec{g}$ for every point in the figures above.
- In the far right column of the table, write the point P_A through P_J that corresponds to each vector. P_F has already been given, as we calculated it as part of the instruction.

b
- Determine which point P_A through P_J corresponds to each vector and write the correct point in the far right column of the table. P_F has already been given as an example.
- Invent a mathematical formula to describe the magnitude of the gravitational field $\vec{g}$, and a rule to describe the direction of $\vec{g}$, that works for every point in the figures above.

FIGURE 2 Contrasting cases activity used in Experiment 1, including instructions for the (a) instruct-first condition and (b) explore-first condition by procedural questions (9 items; α = .82) and a final transfer question (1 item). The learning resource introduced students to an electric field with a written description, equations and an example problem.

The procedures for calculating electric field properties are very similar to gravitational field calculations, and the underlying concepts are similar as well. Procedural questions required students to calculate electric field magnitude and direction. The transfer question asked students to predict the equation for electric force, which has the same relationship to electric field as gravitational force does to gravitational field.

Procedures

The experiment was conducted in one 75-min class period. Students were randomly assigned to conditions and divided between two classrooms. Students in the instruct-first condition (n = 82) completed the study in their regular classroom, which was a large lecture hall. Because no similar classrooms were available for the study, students in the explore-first condition (n = 47) completed the study in a 60-seat active learning classroom.

The experiment included six phases, as outlined in Table 1. The order of instruction and activity varied by condition. Students in the instruct-first condition received the instruction followed by the activity, and students in the explore-first condition completed the activity, then the instruction. Three instructors moved between the two classrooms for different phases of the study. The course instructor gave the instruction, a secondary instructor led the activity with the course Teaching Assistant and a third instructor gave the survey. The assessment was led by the instructor in the classroom at the end of the period. Students were debriefed about the study in a letter emailed at the end of the semester and given the opportunity to withdraw their data. All procedures were approved by the University Institutional Review Board.

Results and discussion

Learning outcomes

Performance on the procedural and conceptual assessments was examined using a 2 (*question type*: procedural and conceptual) × 2 (*order*: explore-first and instruct-first) mixed-factorial analysis of variance (ANOVA), with the order as a between-subjects factor and question type as a within-subjects factor. There was a significant main effect of question type, $F(1, 127) = 25.75$, $p < .001$, $\eta_p^2 = .17$. Procedural questions (M = 72.76%, SE = 1.67) were answered more accurately than conceptual questions (M = 61.09%, SE = 2.18). The main effect of the order was not significant, $F < 1$. However, there was a significant Order × Question Type interaction, $F(1, 127) = 7.57$, $p = .007$, $\eta_p^2 = .06$. Simple effects were examined using the 95% confidence intervals. As illustrated in Figure 3, procedural knowledge was not significantly different between students in the explore-first order (M = 70.45, SE = 2.66, 95% CI [65.19, 75.71]) and

TABLE 1 Instructional order and timing in explore-first and instruct-first conditions

Phase	Explore-first		Instruct-first	
1	Activity	20 min	Instruction	20 min
2	Survey	4 min	Activity	20 min
3	Instruction	20 min	Survey	4 min
4	Activity Review	1 min	Activity Review	1 min
5	Assessment Part 1	10 min	Assessment Part 1	10 min
6	Assessment Part 2	15 min	Assessment Part 2	15 min

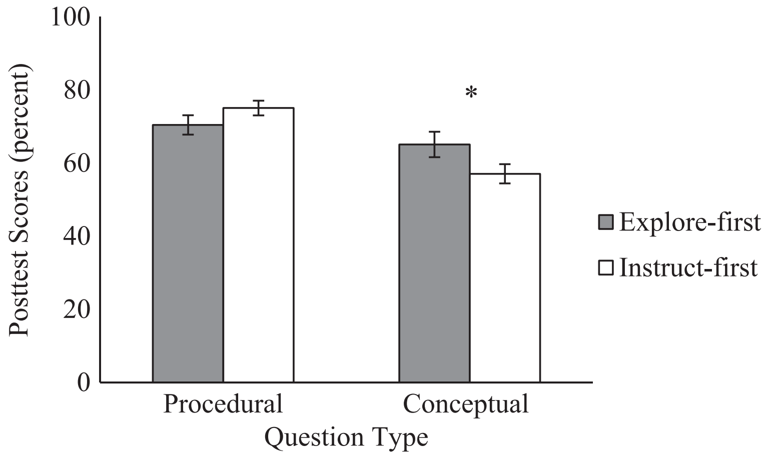


FIGURE 3 Experiment 1 post-test scores by condition. *Note*: Error bars = ±1 *SE*

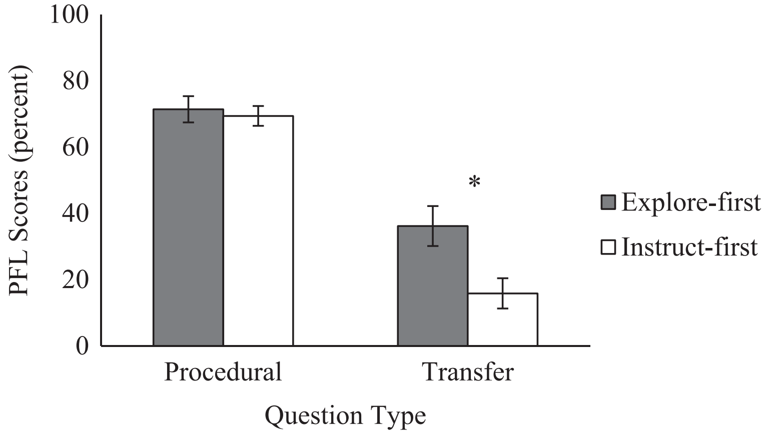


FIGURE 4 Experiment 1 future learning assessment scores by condition. *Note*: Error bars = ±1 SE

students in the instruct-first order (M = 75.07, SE = 2.01, 95% CI [71.09, 79.05]). However, conceptual knowledge was significantly higher for students in the explore-first order (M = 65.11, SE = 3.48, 95% CI [58.23, 71.98]) than for students in the instruct-first order (M = 57.07, SE = 2.63, 95% CI [51.87, 62.28]), d = .36.

Performance on the future learning assessment was also examined using a 2 (*order*) × 2 (*question type*: procedural and transfer) mixed-factorial ANOVA. There was a main effect of the order, $F(1, 127) = 5.20$, $p = .024$. Students in the explore-first condition (M = 53.78%, SE = 3.90, 95% CI [46.06, 61.51]) scored higher overall than students in the instruct-first condition (M = 42.62%, SE = 2.96, 95% CI [36.77, 48.46]), d = .41. There was also a significant main effect of question type, $F(1, 127) = 115.44$, $p < .001$, $\eta_p^2 = .48$, with procedural questions (M = 70.39%, SE = 2.48, 95% CI [65.48, 75.30]) answered more accurately than the transfer question (M = 26.01%, SE = 3.79, 95% CI [18.51, 33.51]), d = 1.32. These effects were qualified by a significant Order × Question Type interaction, $F(1, 127) = 4.91$, $p = .029$, $\eta_p^2 = .04$. As illustrated in Figure 4, students in the explore-first condition scored significantly higher on the transfer question (M = 36.17, SE = 6.04, 95% CI [24.21, 48.13]) than students in the instruct-first condition (M = 15.85, SE = 4.57, 95% CI [6.80, 24.91]), d = .47. Scores on the procedural questions did not significantly differ between students in the explore-first condition (M = 71.40, SE = 3.96, 95% CI [63.57, 79.22]) and students in the instruct-first condition (M = 69.38, SE = 3.00, 95% CI [63.45, 75.30]), d = .05.

Survey

Seven students did not complete surveys, and one student did not answer the cognitive load question. No effects of the order were found for either the interest and enjoyment scale, $F(1, 121) = 1.79$, $p = .184$, or the cognitive load item, $F(1, 120) = 1.69$, $p = .196$ (see Table 2). Thus, survey responses were similar across conditions, and near the mid-point of the scales, indicating that any additional effort associated with exploring before instruction did not negatively impact cognitive load or interest/enjoyment. This result suggests that our new exploration activity was appropriately difficult and engaging (see Kapur, 2016).

Conclusion

Students who explored contrasting cases scored higher than those who received instruction before the activity on the conceptual knowledge and future learning transfer assessments. Students learned procedural knowledge equally well in both conditions. These findings are consistent with our hypotheses and extend research on exploratory learning in undergraduate classrooms (e.g., Weaver et al., 2018) to a new physics topic. This study is also the first to show that exploratory learning can benefit undergraduate students' transfer.

EXPERIMENT 2

Experiment 2 tested the benefits of exploratory learning using the same topic as in Experiment 1, with a rich dataset instead of contrasting cases in the activity.

Methods

Participants

Participants (N = 92) included all students who attended on the study dates and completed all learning materials, from two introductory physics courses. One course included predominantly premedical students (N = 53), and the other included engineering and physics majors (N = 39). Both courses were conducted in a different semester from Experiment 1. Although the course with premedical students was

TABLE 2 Experiment 1 survey results

	Order	M	SE	95% CI
Interest/enjoyment (of 7)	Explore-first	4.61	.14	[4.33, 4.89]
	Instruct-first	4.92	.18	[4.56, 5.28]
Cognitive load (of 9)	Explore-first	5.53	.17	[5.20, 5.86]
	Instruct-first	5.88	.22	[5.45, 6.31]

different from Experiment 1, all courses had the same instructor of record and received the same overall content along the same timeline throughout the semester.

Materials

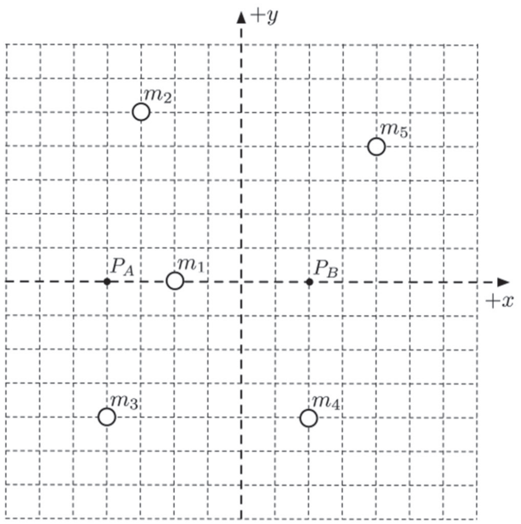
All materials are provided in Figure 5 and the Supplemental Online Materials.

Rich dataset activity

The activity with a rich dataset is shown in Figure 5. This activity consisted of five particles and two points, positioned asymmetrically on a single *xy* plane, and the particle masses and locations were given in a table. The goal of the activity was for students to identify which of the two points was influenced more by the five particles. This activity differed from the activity of the contrasting cases in

Gravitational Field Activity

The figure below on the left shows a series of particles in space, labeled m_1 through m_5, and points in the same space, labeled P_A and P_B. Values for masses and locations for the masses and points are given in the table to the right. The masses are given in kilograms and the x and y components for the locations of both the masses and the points are given in meters.



Mass or Point	Mass (kg)	x coord. (m)	y coord. (m)
m_1	10	−2	0
m_2	20	−3	5
m_3	30	−4	−4
m_4	40	2	−4
m_5	50	4	4
P_A	–	−4	0
P_B	–	2	0

Each row in the table above gives information about the masses or points in space in the diagram. Use the information given in the table to learn about gravitational field $\vec{g}$. The gravitational field $\vec{g}$ is a vector quantity that is related to the gravitational force and represents the influence that masses have on a point in space.

a
- Determine which point (P_A or P_B) is influenced more by the masses (M_1 to M_5) in the figure above.
- Invent a formula or list the steps you might take to determine the influence of the masses (M_1 to M_5) at points P_A and P_B.

b
- Use the mathematical formula you have just learned to calculate the influence of the masses (M_1 to M_5) at points P_A and P_B in the figure above.
- Determine which point (P_A or P_B) is influenced more by the masses (M_1 to M_5).

FIGURE 5 Rich dataset activity used in Experiment 2, with instructions for the (a) instruct-first condition and (b) explore-first condition that the particles and points were not separated or organized around axes, and thus the underlying problem features were hidden. The layout and type of information given were similar to activities given to students in other rich dataset studies (e.g., Kapur, 2014) which allowed students to use different mathematical procedures towards a goal during exploration. Activity instructions mirrored those in Experiment 1 (Figure 2 and 5).

Survey

The survey included the interest/enjoyment and cognitive load scales from Experiment 1. We also added a perceived knowledge gap awareness scale (Cronbach's $\alpha = .87$; adapted from Flynn & Goldsmith, 1999). The scale included four items, with responses on a Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*; e.g., 'I do not feel very knowledgeable about calculating gravitational field'). These items were interleaved with the interest/enjoyment scale, which was modified to Likert 5.

Assessments

Assessments in Experiment 2 were adapted with slight modifications from those in Experiment 1. A section break was added between the procedural assessment (7 items, $\alpha = .69$) and the conceptual assessment (10 items, $\alpha = .41$). In the future learning assessment, conceptual questions were added (4 items, $\alpha = .26$), and the procedural scale was shortened by removing items with low variability (4 items, $\alpha = .59$). Because of (a) the extremely low reliability of the new conceptual scale, (b) the lack of similar data in Experiment 1, and (c) no difference between experimental conditions, analysis of the conceptual scale in the future learning assessment is not included in this article.

Procedure

As in Experiment 1, students were randomly assigned to the instruct-first ($N = 40$) or explore-first ($N = 52$) conditions and worked simultaneously in different active-learning classrooms. The courses met in 50-min sessions, therefore students participated over 2 consecutive class days. On the first day in both conditions, students participated in the activity, survey, instruction and activity review. On the following class day, students completed the assessments within the same, original classroom. The timing of each phase is detailed in Table 3.

Results and discussion

Results were analysed using the same procedures as in Experiment 1.

TABLE 3 Instructional order and timing in explore-first and instruct-first conditions

Day	Phase	Explore-first		Instruct-first	
1	1	Activity	20 min	Instruction	20 min
	2	Survey	4 min	Activity	20 min
	3	Instruction	20 min	Survey	4 min
	4	Activity Review	1 min	Activity Review	1 min
2	5	Assessment Part 1	8 min	Assessment Part 1	8 min
	6	Assessment Part 2	5 min	Assessment Part 2	5 min
	7	Assessment Part 3	15 min	Assessment Part 3	15 min

Learning outcomes

The main effect of the order was not significant, $F(1, 90) = 1.78$, $p = .185$, $\eta_p^2 = .02$. There was a significant main effect of question type, $F(1, 90) = 6.51$, $p = .012$, $\eta_p^2 = .07$. Procedural questions ($M = 71.29\%$, $SE = 2.76$) were answered more accurately than conceptual questions ($M = 65.09\%$, $SE = 1.77$). The Order × Question Type interaction was not significant, $F(1, 90) < 1$, $p = .513$, $\eta_p^2 = .01$ (see Figure 6; procedural knowledge: explore-first $M = 74.73$, $SE = 3.65$, 95% CI [67.48, 81.97]; instruct-first $M = 67.86$, $SE = 4.16$, 95% CI [59.60, 76.11]); and conceptual knowledge: explore-first $M = 66.92$, $SE = 2.33$, 95% CI [62.30, 71.55]; instruct-first $M = 63.25$, $SE = 2.66$, 95% CI [57.97, 68.53].

On the future learning assessment, the main effects were not significant for order, $F < 1$, or question type (procedural and transfer), $F(1, 90) = 2.43$, $p = .123$, $\eta_p^2 = .03$. The Order × Question Type interaction was also not significant, $F < 1$, $p = .696$, $\eta_p^2 < .01$ (see Figure 7): procedural knowledge, explore-first order ($M = 43.27$, $SE = 3.10$, 95% CI [37.12, 49.42]) and procedural knowledge, instruct-first order ($M = 43.75$, $SE = 3.53$, 95% CI [36.74, 50.76]); transfer, explore-first order ($M = 36.54$, $SE = 6.67$, 95% CI [23.48, 49.79]) and transfer, instruct-first order ($M = 32.50$, $SE = 7.61$, 95% CI [17.39, 47.61]).

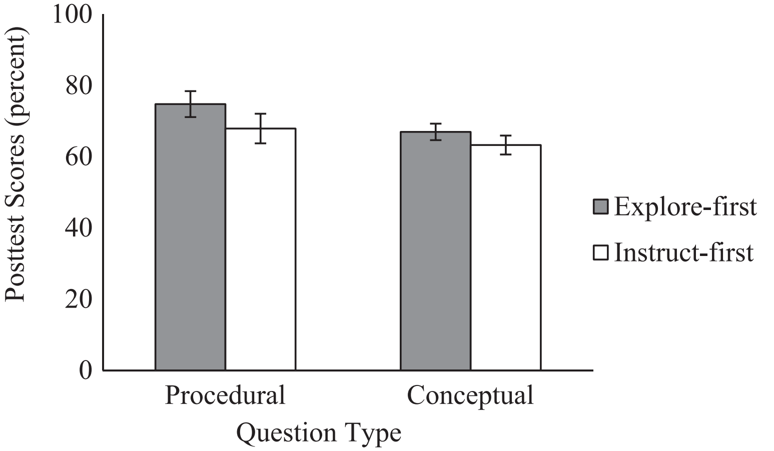


FIGURE 6 Experiment 2 (rich dataset) post-test scores as a function of order and question type. *Note*: Error bars = ±1 *SE*

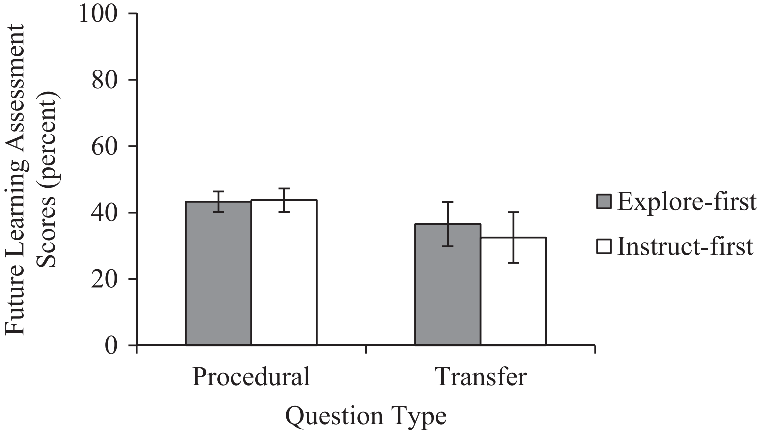


FIGURE 7 Experiment 2 future learning assessment scores by order and question type. *Note*: Error bars = ±1 *SE*

Survey

One student was missing data on the knowledge gap awareness scale. No significant order differences were found for interest/enjoyment, $F(1, 90) = 1.75$, $p = .189$, or cognitive load, $F < 1$. Again, responses were near the mid-point of the scales, indicating that any additional effort associated with exploring before instruction did not negatively impact cognitive load or interest/enjoyment. Knowledge gap awareness, however, was significantly higher for students in the explore-first condition than students in the instruct-first condition, $F(1, 89) = 15.16$, $p < .001$, $\eta_p^2 = .15$ (see Table 4).

Conclusion

Learning outcomes were consistent with our second set of hypotheses: there were no differences in procedural or conceptual knowledge or future learning between the explore-first and instruct-first conditions. Merely reversing the order of instruction and activity with a rich dataset did not provide learning benefits.

GENERAL DISCUSSION

We tested the causal impact of reversing the order of instruction and activity on learning and transfer in undergraduate physics classrooms. We also varied the activity design between the two experiments. Activities differed in whether important problem features were made salient, with examples presented as contrasting cases (Experiment 1) or a rich dataset (Experiment 2).

In Experiment 1, students who explored contrasting cases before instruction demonstrated equivalent procedural knowledge and greater conceptual knowledge, compared to students who completed the activity after instruction. These results align with the majority of studies in the growing exploratory learning literature (Loibl et al., 2017; Sinha & Kapur, 2021), supporting the idea that there are beneficial learning mechanisms invoked by reversing the common tell-then-practice order. In addition, students who explored before instruction showed greater transfer to a new, related topic – extending prior research (e.g., Schwartz & Martin, 2004) into undergraduate STEM disciplines. This result underscores the potential for exploratory learning to benefit generalized domain understanding. It is critical in advanced STEM degrees that students connect earlier and later concepts throughout multiple semesters and adapt and apply known procedures to novel questions. Therefore, instructional methods that facilitate conceptual understanding may be especially useful in these disciplines.

The results from Experiment 2 differed from Experiment 1. Students who explored a rich dataset showed similar learning outcomes as students in the instruct-first condition. The null finding for conceptual knowledge contradicts some prior studies using activities with rich datasets before instruction (e.g., Kapur, 2008, 2012, 2014). One possible reason for this inconsistency may be that many prior studies did

TABLE 4 Experiment 2 survey results

	Order	*M*	SE	95% CI
Interest/enjoyment (of 5)	Explore-first	3.89	.09	[3.70, 4.07]
	Instruct-first	3.70	.11	[3.49, 3.91]
Cognitive load (of 9)	Explore-first	6.39	.16	[6.06, 6.71]
	Instruct-first	6.35	.19	[5.98, 6.72]
Knowledge gap awareness (of 5)	Explore-first	3.30	.11	[3.08, 3.52]
	Instruct-first	2.64	.13	[2.38, 2.89]

not experimentally control the learning materials given between instruct-first and explore-first conditions. Thus, a factor other than the order of instruction may have led to the benefits of exploring rich datasets. More importantly, prior studies using rich datasets often include instruction on common student solutions for the explore-first condition, whereas we did not. Loibl et al. (2017) found that prior studies using rich datasets that did include such instruction were more likely to show the benefits of exploring before instruction (e.g., Loibl & Rummel, 2014). Instruction on student errors may serve to highlight problem features in the instruction as opposed to during the activity. More research is needed to test whether methods that highlight common student errors have similar benefits as using contrasting cases in the exploration activity. Such findings would indicate that highlighting the problem features is key, whether it occurs during the activity or instruction. Contrasting cases during the activity may be one way to accomplish this goal, and highlighting student solutions in the instruction may be another way.

Together, the learning outcomes from Experiments 1 and 2 indicate that the design of exploration activities may impact the benefits of exploratory learning by activating different learning mechanisms. We assume that activities given prior to instruction, with either contrasting cases or a rich dataset, encourage students to activate their prior knowledge and become aware of their knowledge gaps. Although we did not measure knowledge gap awareness in Experiment 1, perceived knowledge gaps were higher following the activity in the explore-first condition than instruct-first condition in Experiment 2. However, given the null results in Experiment 2 (rich datasets), it seems likely that prior knowledge activation and knowledge gap awareness do not alone lead to the benefits of exploratory learning. Instead, our results suggest that discernment of problem features is also required (Newman & DeCaro, 2019). Our results support the idea that many learning mechanisms work together to benefit learning outcomes (Loibl et al., 2017) and suggest that contrasting cases help complete the set of learning mechanisms required by encouraging students to identify problem features.

Cognitive load and engagement

The survey results demonstrated that exploration was not more cognitively demanding or less interesting/enjoyable than solving a problem after instruction. Cognitive load was rated right around the mid-point of the scale in both studies, demonstrating that the task was not overly difficult for students. Activities with high element interactivity can be perceived as more difficult (i.e., cognitively demanding), and in such contexts, instruct-first conditions have been shown to lead to better learning than explore-first conditions (e.g., Ashman et al., 2020). This idea aligns with the findings of Loibl et al. (2020), who compared the use of contrasting cases and rich datasets in exploration activities and found a benefit of instruct-first conditions. Future exploratory learning studies may benefit from measuring cognitive load to continue to explore perceived cognitive load as a potential moderator.

Limitations

Despite the many factors that were the same between Experiments 1 and 2, there were differences that limit our ability to fully compare the results of exploring with contrasting cases with rich datasets. In Experiment 1, students were in different types of classrooms for the two experimental conditions; in Experiment 2, students in both conditions were in the same type of classroom. However, it seems unlikely that the physical environment fully accounts for our results in Experiment 1, given the consistency with many other studies examining exploratory learning. Also, the reliability of the conceptual scale was low in Experiment 2 ($\alpha = .41$), and not in Experiment 1 ($\alpha = .76$), which could have limited our ability to detect significant differences between conditions. Although the procedural and conceptual knowledge items were the same between experiments, these subscales were split into different timed segments in Experiment 2, potentially impacting students' responses. The samples were also slightly different between experiments. Experiment 1 included primarily engineering students, whereas Experiment 2 included both engineering and premedical students. Due to the length of class periods (75 vs. 50 min), Experiment 1 was conducted in a single class period, whereas Experiment 2 was conducted over two class periods. Although the null results in Experiment 2 could be driven by the delay in the assessment, prior studies have found benefits of exploring even with a delay (e.g., Kapur, 2012; Weaver et al., 2018). Finally, in designing activities that use contrasting cases versus rich datasets, the problems students were exposed to in the activities were not exactly the same. Thus, we cannot say for certain whether it was the use of contrasting cases, or some other change in the content, that led to the different pattern of findings between experiments. Certainly, additional studies are needed to replicate and extend our findings on the effect of activity type, with students randomly assigned to both order of instruction and activity type conditions.

Another limitation concerns the interpretation of the findings for the contrasting cases conditions (Experiment 1). Our experiments were designed to test how the order of the activity (i.e., before or after instruction) impacted students' learning. Thus, we controlled for other factors, including the materials given to the students. We can conclude that students in the explore-first condition scored higher on conceptual and transfer assessments than students in the instruct-first condition. But we cannot determine which condition drove this effect. Students in the explore-first condition might have benefitted from the activity, or students in the instruct-first condition might have been hindered by the activity. For example, students in the instruct-first condition were taught the mathematical procedure in the instruction right before the activity and therefore, might have approached our more conceptually oriented activity in a more procedurally oriented way (e.g., by doing complex math rather than thinking deeply about the concepts). Indeed, students often apply the rote procedures they learn in instruction to practice problems; exploratory learning might help to avoid a more superficial approach to the problems (Bonawitz et al., 2011; Schwartz et al., 2012). However, more research is needed to examine these ideas.

Relatedly, the final limitation of this study was that the procedural knowledge assessment did not include any problems with complex math (vector addition). These types of problems take longer to solve, and we decided to instead include multiple, more concise items on the procedural scale. It is therefore possible that we may have missed an effect in procedural knowledge either in favour of the explore-first group or instruct-first group. However, prior research has indicated that switching the order of instruction does not often impact procedural knowledge (Loibl et al., 2017). Additionally, vector addition was a relatively common procedure used in this physics course and was not specific to this topic. Therefore, it was expected that students would be able to complete this procedure regardless of condition.

CONCLUSION

There is currently a strong push to use active learning methods in undergraduate education. Exploratory learning is a promising method due to the observed benefits of conceptual understanding and transfer, both of which are critical for students to connect and apply their learning to novel problems. However, more work is needed to fully investigate the potential boundary conditions and moderators of this method. The current findings indicate that including contrasting cases in the activity may facilitate learning from exploring. Our results suggest that different learning mechanisms might be activated by different activity designs. A good goal is to design activities that enable students to activate their prior knowledge, become aware of gaps in their knowledge and discover problem features for themselves.

AUTHOR CONTRIBUTIONS

Campbell R. Bego: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; validation; visualization; writing – original draft. **Raymond J. Chastain:** Conceptualization; investigation; project administration. **Marci S. DeCaro:** Conceptualization; data curation; formal analysis; investigation; methodology; supervision; writing – review and editing.

CONFLICT OF INTEREST

We have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available through the Open Science Foundation at https://osf.io/hf5bc/.

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SUPPORTING INFORMATION

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

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