Exploring a Problem Before Instruction Using Graphs versus Tables

Lianda Velić (lianda.velic@louisville.edu)
Department of Psychological and Brain Sciences, University of Louisville
Louisville, KY 40292 USA

Marci S. DeCaro (marci.decaro@louisville.edu)
Department of Psychological and Brain Sciences, University of Louisville
Louisville, KY 40292 USA

Abstract

Traditional education is instructor-centered. Providing exploratory learning activities before instruction typically engages students and improves learning. However, the design of exploratory learning activities can impact learning processes. This study investigated whether using tables or graphs in a statistics activity impacted exploratory learning processes and outcomes. Undergraduate students (*N*=252) in classroom and lab settings were taught about standard deviation. In instruct-first conditions, students received instruction, then an activity including either graphs or tables. In explore-first conditions, students explored either activity before instruction. After exploring, participants in the explore-first condition reported greater knowledge gaps and curiosity than the instruct-first condition. Graphical materials reduced cognitive load compared to tabular. However, instructional order and activity design did not impact learning outcomes (procedural knowledge, conceptual knowledge, representational transfer). Conceptual understanding was highest if students attempted multiple solutions while exploring graphical materials. Depth of exploration may affect conceptual benefits, especially when using graphical materials.

Keywords: exploratory learning; productive failure; statistics learning; graphical representations; STEM

Introduction

In traditional educational settings, instructors often present new material to students first, followed by practice problems. However, many researchers and educators advocate for students to take active roles in building their understanding (Cakir, 2007; Prince, 2004). One such approach is to provide *exploratory learning before instruction,* in which students first explore a novel problem, before they are provided with instruction on the underlying concepts and procedures (DeCaro & Rittle-Johnson, 2012; Weaver et al., 2018). Other instantiations of this general method include *problem solve-instruct methods* (PS-I; Loibl et al., 2017), *productive failure* (Sinha & Kapur, 2021), and *preparation for future learning* (Schwartz & Martin, 2004). These methods have subtle differences, but all include an explore-then-instruct sequence.

Reviews across these areas conclude that reversing the order of activity and instruction results in greater conceptual understanding and learning transfer (González-Cabañes, 2023; Loibl et al., 2017; Sinha & Kapur, 2021). This research suggests that there are three primary mechanisms by which exploring improves conceptual understanding. First, when students *activate prior knowledge* to generate possible solutions during exploration, they begin to integrate the new knowledge with their existing schemas (Kapur & Bielczyzc, 2012; Loibl et al., 2017; Schwartz et al., 2007). Activating prior knowledge also helps students recognize where this knowledge may be incomplete (*knowledge gaps;* e.g., Loibl & Rummel, 2014a; Newman & DeCaro, 2019), and they process canonical solutions at a greater depth (VanLehn et al., 2003). By exploring the problem space, students begin to discern, explain, and organize *deep features* about the target concept (Kapur & Bielaczyz, 2012; Schwartz et al., 2011).

Although research generally finds learning benefits of exploring before instruction, some research does not (e.g., Chase & Klahr, 2017; Fyfe et al., 2014; Nachtigall et al., 2020). More work is needed to better understand how to design exploratory learning materials to promote effective learning processes. Prior research has examined the effects of including contrasting cases within the activities (DeCaro et al., 2024; Loibl et al., 2017), including scaffolding in problem-solving activities (Newman & DeCaro, 2019; Sinha & Kapur, 2021), exploring erroneous solutions as vicarious failure (Kapur, 2016), and changing the exploration prompts (i.e., invent one solution versus generate multiple solutions; Velić & DeCaro, 2025). The current research examines whether altering how data is displayed in an exploratory learning activity (i.e., in a graphical or tabular format) impacts learning processes and outcomes.

Modalities of Exploratory Learning Activities

Many researchers have tested the impact of including visual representations (VR) more generally in various domains (e.g., astronomy, Galano et al., 2018; chemistry, Allen, 2015; mechanical engineering, Mayer, 1989; medicine, Ainsworth & Loizou, 2003). VRs are considered effective methods of presenting and explaining abstract concepts, information, or data, especially in STEM fields (NRC, 2005). Materials integrating VRs typically promote greater learning (Ainsworth, 2006; 2008; Lowrie & Kay, 2001; Mayer, 2014). VRs guide students' perceptual attention, reduce memory demands, and constrain inferences to more efficient conclusions, in turn supporting mental model development (Ainsworth & Scheiter, 2021; Butcher, 2006; Crisp &

In D. Barner, N.R. Bramley, A. Ruggeri and C.M. Walker (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society*

Sweiry, 2006; Mayer, 2002; Sweller et al., 1998). VRs can help students establish connections between concepts and exhibit greater representation use, conceptual understanding, reasoning skills, and problem-solving ability (Boonen et al., 2014; Corter & Zahner, 2007; Debrenti, 2015; Galano et al., 2018; Wu & Shah, 2004; Zahner & Corter, 2010).

Some researchers suggest that VRs are beneficial during novel, difficult, or complex learning situations (Eilam & Poyas, 2008; Lowrie & Kay, 2001; Mayer, 1989). Exploratory learning before instruction might increase such benefits of VR, as it includes a novel, and often complex, learning activity. However, few exploratory learning studies incorporate VRs in their materials (e.g., Bego et al., 2023; DeCaro et al., 2023; Loibl et al., 2020; Schwartz & Martin, 2004; Schwartz et al., 2011). None of these studies compare use of a VR to more textual presentation of information.

Current Research

The current study used learning materials on the concepts and procedures to calculate consistency in statistics (i.e., standard deviation). Between conditions, activity materials presented the same information in two different modalities (i.e., tabular, graphical). Students completed materials in either the *instruct-first condition* (instruction then activity) or *explore-first condition* (activity then instruction).

Many exploratory learning studies investigate learning in the topic of statistics, especially how to understand and compute consistency within or between datasets (variance, standard deviation, mean deviation; e.g., Belenky & Nokes-Malach, 2012; Jarosz et al., 2017; Kapur, 2012, 2014; Loibl et al., 2020; Newman & DeCaro, 2019; Roll et al., 2011; Schwartz & Martin, 2004; Velić & DeCaro, 2025). Some studies include more visual components such as a grid graph (Belenky & Nokes-Malach, 2012; Schwartz & Martin, 2004), or frequency distribution (Loibl et al., 2020; Roll et al., 2011). Others include only a table (e.g., Kapur, 2012, 2014; Loibl & Rummel, 2014b). The current research presented data in the learning activity either using a table (*tabular condition*) or bar graph (*graphical condition*). Bar graphs were used because of their familiarity to learners (see Rau, 2016), and because they have been shown to be useful for discrete comparison (Shah & Freedman, 2009; Tversky et al., 2000).

We assessed three types of learning outcomes. *Procedural knowledge* includes the ability to correctly apply sequential actions of a learned procedure to solve a problem (Rittle-Johnson et al., 2001). *Conceptual knowledge* involves understanding a concept's underlying structure and components, usually reflected in principle-based reasoning or connecting information (Loibl et al., 2017; Rittle-Johnson & Schneider, 2015). *Representational transfer items* included embedded instruction on a new but directly related VR (histograms), followed by items assessing students' competency with the novel representation (Roll et al., 2009).

We also used a questionnaire to assess participants' perceived knowledge gaps, cognitive load (i.e., mental effort), and curiosity, to determine how each component may have a role during the learning process.

Hypotheses

Overall, we predicted higher conceptual knowledge and representational transfer in the explore-first than instruct-first conditions. Prior research using similar materials as the tabular condition has found higher conceptual knowledge, though this work has not assessed representational transfer (e.g., Newman & DeCaro, 2019; Velić & DeCaro, 2025). Typically, procedural knowledge is similar between explore-first and instruct-first conditions (Loibl et al., 2017).

Whether exploring using graphical representations would further increase learning compared to tabular representations was an empirical question. Some prior research has shown benefits of graphical representations, though other research has not (Braithwaite & Goldstone, 2013; Brewer et al., 2012; Labunets et al., 2017; Meyer et al., 1999; Porat et al., 2009; Schonlau & Peters, 2012). If graphical representations help learners focus on the important problem features (e.g., spread in the data), and reduce the material's cognitive complexity, conceptual understanding should benefit. Prior work suggests that conceptual competencies about data visualizations may transfer to new data representations (Baker et al, 2001), and thus could extend to representational transfer.

We also assessed the quality and quantity of solutions that participants generated during the learning activity. Because they were instructed on the standard deviation steps, we predicted that participants in the instruct-first conditions would employ higher quality solutions than in the explore-first conditions (i.e., correctly use more steps of the standard deviation formula). In contrast, we predicted that students in the explore-first conditions would generate a higher quantity of solution attempts. The number of solution attempts may approximate the extent of knowledge activation or search through the problem space (Schneider & Stern, 2010; Sinha & Kapur, 2021; Trninic et al., 2022). VR research suggests that there is a positive relationship between students' transfer ability and the quality and quantity of representations used during problem-solving (Moreno et al., 2011). We investigated whether exploring with graphs or tables impacted the quality or quantity of solutions that were attempted, but did not have prior hypotheses about this factor.

Some research suggests that VRs help students offload cognitive effort (Scaife & Rogers, 1996). We expected cognitive load to be equal or higher in explore-first conditions (Ashman et al., 2020; DeCaro et al., 2024), and potentially lower with graphical materials.

As with prior research, we also predicted that participants who explored first would report greater perceived knowledge gaps (Loibl et al., 2017) and curiosity (Belenky & Nokes-Malach, 2012; Glogger-Frey 2015; Loibl & Rummel 2014) after exploring—regardless of activity modality.

Method

Participants

Participants were undergraduate students (N=252, M_{age}=19.89, SD=3.42, 67% female) enrolled in different sections of psychology statistics courses or who completed a lab study for course credit in Introductory Psychology. Participants were randomly assigned to one of four conditions: *instruct-first tabular* (*n*=68), *instruct-first graphical* (*n*=64), *explore-first tabular* (*n*=66), or *explore-first graphical* (*n*=54). Additional participants were excluded for not speaking English as their native language due to the large amount of reading material (*n*=24), having seen the materials before (*n*=14) or for not completing one of the packet materials (*n*=7).

Materials

Instruction Instruction was provided as a text passage with a worked example explaining procedures and concepts of standard deviation, followed by two practice questions (Newman & DeCaro, 2019).

Problem-Solving Activity The problem-solving activity was a modified version used by Newman and DeCaro (2019; see also Wiedmann et al., 2012), shown in Figure 1. Depending on condition, a data table or three bar graphs were presented showing antioxidants for three different tea growers across five years. In the *instruct-first* conditions, participants were prompted to "use what you have just learned about standard deviation to determine the most consistent tea-grower." In the *explore-first* conditions, participants were prompted to "come up with as many different ways to measure consistency as you can" (modified from Kapur, 2014). All participants were asked to show their work mathematically.

Questionnaire After each of the instruction and activity phases, participants completed a questionnaire. Items assessed perceived *knowledge gaps* (4 items; Cronbach's α=.82–.88; Flynn & Goldsmith, 1999; e.g., "I do not feel very knowledgeable about calculating consistency"), and *curiosity* (3 items; α=.75–.88; Naylor, 1981; e.g., "I felt like seeking information about what I worked on."), intermixed (1=*strongly disagree*; 5=*strongly agree*). A *cognitive load* item (Paas, 1992) asked participants to "Please indicate how much mental effort you invested when solving/studying the problem" on a 9-point scale (1=*very, very low mental effort*; 9=*very, very high mental effort*). On the last questionnaire, participants completed demographic items, an item asking about prior experience with the materials (i.e., "Have you ever seen these specific materials before?"), and self-reported prior knowledge from 0 (not at all) to 4 (very much).

Posttest Posttest items were adapted from exams given by psychological statistics instructors at the same university as participants. *Procedural knowledge* was evaluated as accuracy in executing the correct mathematical sequence to solve an open-ended standard deviation problem (6 points; Rittle-Johnson & Alibali, 1999). *Conceptual understanding* (α=.61) was assessed through nine multiple choice items testing understanding of the underlying principles of standard deviation. To assess *representational transfer* (α=.53), the posttest included an embedded resource explaining histograms, followed by 2 multiple choice items assessing students' understanding of histograms. A new histogram was presented, followed by four *true, false, or unknown* questions about information from the histogram. Then, three multiple choice questions presented a pair of histograms and directed students to select the most accurate statement on the comparison of the two histograms provided.

(a) Tabular Learning Activity

	Tea growers		
Year	Thourbo (Antioxidants per mg)	Dareen	Ging
2017	--	14	9
2018	--	15	13
2019	15	15	14
2020	14	15	21
2021	16	16	19
2022	15	15	14

(b) Graphical Learning Activity

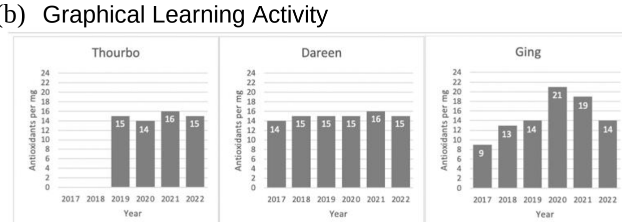

Figure 1: (a) Tabular and (b) graphical versions of the learning activity.

Procedure

Participants from psychology statistics courses completed the study as part of their course lab sessions. Students were told that the activities covered required course content, but their performance would not affect their grade. Participants who completed the study in a lab setting met in a reserved classroom and provided informed consent.

Participants were provided with a calculator and worked individually to complete a timed packet including the instruction, problem-solving activity, and questionnaires. Participants were randomly assigned to condition based on the packet received, interleaved by condition. Participants in the *instruct-first* condition viewed the instruction (14-min), the first questionnaire, problem-solving activity (14-min), then the second questionnaire. Participants in the *explore-first* conditions had the instruction and activity order switched. Then, participants completed a separate posttest packet (17-min). After the study concluded, participants in the lab experiment were debriefed; students in statistics courses were given a debriefing letter later and allowed to exclude their data. All procedures were approved by the university Institutional Review Board.

Results

Preliminary Analyses

Preliminary analyses showed no interaction with study format (class or lab), Fs<1.18, ps>.28, so further analyses were collapsed on this factor.

We examined whether reported prior knowledge differed as a function of condition, using a 2 (instructional order: *instruct-first* or *explore-first*) × 2 (activity modality: *tabular* or *graphical*) between-subjects factorial ANOVA. There was a main effect of modality, $F(1,230)=9.45$, $p=.002$, $\eta_p^2=.039$. Participants with *graphical* materials ($M=1.57$, $SE=0.10$) reported higher prior knowledge than those with *tabular* materials ($M=1.15$, $SE=0.09$). There was no main effect of instruction order, $F<1$, or interaction, $F(1,230)=1.04$, $p=.33$, $\eta_p^2=.004$. Including prior knowledge as a covariate in subsequent analyses did not change the final results, so results are reported without this covariate for simplicity.

Posttest

Each posttest subscale (procedural knowledge, conceptual knowledge, representational transfer) was analyzed using 2 (instructional order) × 2 (activity modality) between-subjects ANOVAs (see Table 1). Due to an error, 18 participants did not receive the procedural knowledge item, and four left it blank. There were no main effects or interactions on any subscale: procedural knowledge: instruction order, $F(1,226)=1.28$, $p=.26$, $\eta_p^2=.006$; representational transfer: instruction order, $F(1,248)=1.85$, $p=.18$, $\eta_p^2=.007$, modality, $F(1,248)=2.29$, $p=.13$, $\eta_p^2=.009$; all other Fs<1.

Table 1: Means (SEs) of posttest scores (%).

Order	Modality	Posttest Learning Measures		
		Procedural	Conceptual	Transfer
Instruct-first	Tabular	87.50 (2.79)	69.77 (2.60)	72.42 (2.39)
	Graphical	85.88 (2.82)	69.79 (2.68)	68.56 (2.46)
Explore-first	Tabular	82.24 (2.77)	66.50 (2.64)	68.94 (2.42)
	Graphical	84.67 (3.06)	69.14 (2.92)	65.28 (2.68)

Activity

Quality of Solution Attempts A similar ANOVA was used to investigate differences in the quality of participants' standard deviation attempts during the activity (i.e., number of correct steps of the formula; 18 points possible; Table 2). There was an effect of order, $F(1,247)=286.21$, $p<.001$, $\eta_p^2=.54$. Participants in *instruct-first* conditions ($M=12.37$, $SE=0.47$) provided more correct steps than in the *explore-first* conditions ($M=0.91$, $SE=0.49$), presumably because they were practicing the formula given. There was no modality effect, $F(1,247)=2.08$, $p=.15$, $\eta_p^2=.008$, or interaction, $F<1$.

Quantity of Solution Attempts For the quantity of solutions attempted during the learning activity (Table 2), there was a significant effect of order, $F(1,248)=38.95$, $p<.001$, $\eta_p^2=.14$. As expected, participants in the *instruct-first* conditions ($M=1.09$, $SE=0.06$) attempted fewer solutions than in the *explore-first* conditions ($M=1.66$, $SE=0.07$), $p=.005$. There was no main effect of modality, $F<1$, or interaction, $F(1,248)=1.56$, $p=.21$, $\eta_p^2=.006$.

Table 2: Means (SEs) of activity scores by condition.

	Order of Instruction and Activity Modality			
	IF Tabular	IF Graphical	EF Tabular	EF Graphical
Quality Score	12.76 (0.74)	11.97 (0.85)	1.47 (0.55)	0.33 (0.33)
Quantity Score	1.03 (0.02)	1.16 (0.05)	1.72 (0.13)	1.61 (0.13)

We conducted an exploratory analysis to determine whether any benefits of modality depended on whether students explored multiple solution attempts. Participants were categorized by whether they made a low number of solution attempts (no attempt or 1 solution, $n=188$) or high attempts (2 or more solutions, $n=64$). Separate 2 (activity modality) × 2 (quantity of solutions: *low* or *high*) ANOVAs were conducted for each instruction order (Table 3). For participants in the instruct-first condition, there were no significant effects on any posttest subscale, Fs<1.

Table 3: Means (SEs) of posttest scores (%) as a function of order, modality, and quantity of solution attempts grouping.

Order of Instruction	Activity Modality	Quantity Scores	Posttest Learning Measures		
			Procedural	Conceptual	Representational Transfer
Instruct-First	Tabular	Low	87.36 (2.82)	69.19 (2.54)	72.73 (2.21)
		High	91.67 (15.16)	88.89 (14.56)	62.50 (12.71)
	Graphical	Low	85.33 (3.03)	69.29 (2.78)	70.00 (2.42)
		High	88.89 (7.15)	72.84 (6.87)	59.72 (5.99)
Explore-First	Tabular	Low	77.01 (4.02)	65.69 (3.71)	66.18 (3.59)
		High	86.98 (3.83)	67.36 (3.83)	71.88 (3.70)
	Graphical	Low	81.03 (4.02)	61.95 (3.77)	59.85 (3.64)
		High	89.68 (4.73)	80.42 (4.73)	73.81 (4.56)

For participants in the *explore-first* conditions, for procedural knowledge, there was a main effect of quantity grouping, $F(1,107)=11.78$, $p=.03$, $\eta_p^2=.045$. Participants who attempted more solutions ($M=88.33$, $SE=3.04$) scored higher than participants who attempted less ($M=79.02$, $SE=2.84$). There was no modality effect or interaction, Fs < 1.

For conceptual knowledge, there was no main effect of modality, $F(1,116)=1.34$, $p=.25$, $\eta_p^2=.011$. There was a main effect of quantity of solutions, $F(1,116)=6.25$, $p=.014$, $\eta_p^2=.051$. Participants who attempted more solutions ($M=73.89$, $SE=3.04$) scored higher than those who attempted fewer solutions ($M=63.82$, $SE=2.65$). There was a significant interaction between modality and quantity of solution attempts on conceptual knowledge (Figure 2).

Bonferroni corrected *t*-tests indicated that, in the *explore-first* condition, those who received tabular materials exhibited no difference in conceptual knowledge regardless of solution attempts, $t(65)=-0.31$, $p=.38$, $d=.07$. However, when using graphical materials, those attempted more solutions scored higher than those who attempted fewer (Table 3), $t(52)=-3.07$, $p=.002$, $d=.86$. Of participants who attempted fewer solutions, there were no differences between tabular and graphical conditions, $t(65)=0.68$, $p=.25$, $d=.17$. However, when participants attempted two or more solutions, those using graphical materials scored higher than those using tabular materials, $t(51)=-2.24$, $p=.015$, $d=.63$.

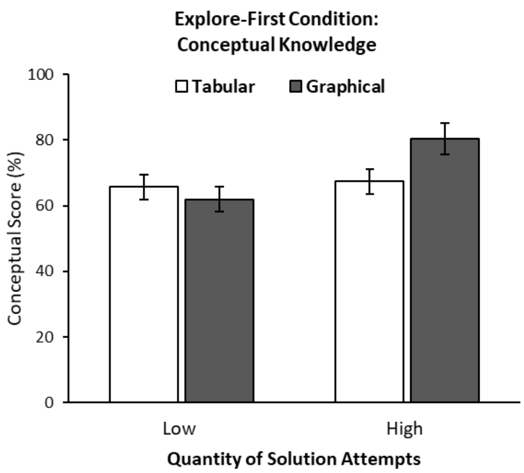

Figure 2: Mean conceptual knowledge scores for participants in the explore-first condition as a function of activity modality and quantity of solution attempts. Error bars = ±SE.

For representational transfer, participants who attempted more solutions ($M=72.84$, $SE=2.94$) scored higher than those who attempted fewer solutions ($M=63.01$, $SE=2.55$), $F(1,116)=6.38$, $p=.013$, $\eta_p^2=.052$. There was no effect of modality or interaction, $F(1,116)=1.13$, $p=.29$, $\eta_p^2=.010$.

Questionnaire

A 2 (order) × 2 (modality) × 2 (questionnaire: *phase one* or *phase two*) mixed-factorial ANOVA was conducted on the questionnaires. Phase was a within-subjects factor (Table 4).

Knowledge Gaps Participants reported greater knowledge gaps after the first phase ($M=3.43$, $SE=0.05$) than the second phase ($M=2.84$, $SE=0.06$), $F(1,242)=153.02$, $p<.001$, $\eta_p^2=.39$. There were no effects of instructional order, $F(1,242)=3.61$, $p=.058$, $\eta_p^2=.02$, or modality, $F(1,242)=2.22$, $p=.14$, $\eta_p^2=.009$. There was a significant phase by order interaction, $F(1,242)=75.69$, $p<.001$, $\eta_p^2=.238$. Participants who explored first reported greater knowledge gaps in phase one than those who received instruction first, $t(245)=-5.82$, $p<.001$, $d=0.82$. During phase two, participants in the instruct-first condition reported greater knowledge gaps than in the explore-first condition, $t(249)=2.02$, $p=.02$, $d=0.93$. There were no interactions, *F*s<2.73, *p*s>.10.

Table 4: Means (SEs) of questionnaire items.

	Condition			
	Instruct-First		Explore-first	
	Tabular	Graphical	Tabular	Graphical
Questionnaire 1				
Knowledge Gaps	3.28 (0.10)	2.97 (0.10)	3.81 (0.11)	3.66 (0.10)
Curiosity	3.38 (0.11)	3.06 (0.11)	3.46 (0.09)	3.63 (0.11)
Cognitive Load	5.69 (0.19)	4.91 (0.21)	5.35 (0.15)	5.27 (0.18)
Questionnaire 2				
Knowledge Gaps	3.07 (0.12)	2.82 (0.12)	2.67 (0.11)	2.78 (0.12)
Curiosity	3.27 (0.12)	3.08 (0.12)	3.52 (0.10)	3.51 (0.12)
Cognitive Load	5.84 (0.19)	5.21 (0.20)	5.97 (0.19)	5.85 (0.20)

Curiosity For reported curiosity, there was no main effect of modality, $F<1$, or questionnaire phase, $F(1,240)=1.05$, $p=.31$, $\eta_p^2=.004$. There was an effect of order, $F(1,240)=9.79$, $p=.002$, $\eta_p^2=.04$. Participants in the explore-first conditions ($M=3.53$, $SE=0.08$) reported greater curiosity than in the instruct-first conditions ($M=3.20$, $SE=0.07$). There were no significant interactions between phase and instructional order or modality, *F*s<1. There was an interaction between phase, order, and modality, $F(1,240)=3.93$, $p=.048$, $\eta_p^2=.016$.

Following up on this interaction, in phase 1, there was no main effect of modality, $F<1$, but there was an effect of order, $F(1,241)=8.96$, $p=.003$, $\eta_p^2=.036$. This effect was qualified by a modality by order interaction, $F(1,241)=5.13$, $p=.02$, $\eta_p^2=.021$. Those in the instruct-first tabular condition reported greater curiosity than instruct-first graphical, $t(123)=2.02$, $p=.023$, $d=.89$; explore-first tabular reported greater curiosity than explore-first graphical, $t(126)=-2.73$, $p=.004$, $d=.83$; and instruct-first graphical reported greater curiosity than explore-first graphical, $t(114)=-3.53$, $p<.001$, $d=.86$. All other comparisons were not significant, *p*s>.06.

For phase 2, there was again no main effect of modality, $F<1$, but there was a main effect of instruction order, $F(1,247)=6.03$, $p=.008$, $\eta_p^2=.028$. Participants in the explore-first condition reported greater curiosity than in the instruct-first condition. There was no interaction, $F < 1$.

Examining the remaining 2×2 analyses separately for order and modality revealed no effects, *F*s<1, *p*s>.10.

Cognitive Load There was a main effect of phase, where lower cognitive load was reported after phase one ($M=5.28$, $SE=0.09$) than phase two ($M=5.72$, $SE=0.10$), $F(1,238)=23.56$, $p<.001$, $\eta_p^2=.09$. There was an effect of modality, $F(1,238)=6.27$, $p=.013$, $\eta_p^2=.026$, where participants with tabular materials ($M=5.71$, $SE=0.12$) reported higher load than those with graphical materials ($M=5.29$, $SE=0.12$). There was no effect of order, $F<1$.

There was no interaction between phase and modality, F<1. There was a phase by order interaction, $F(1,238)=5.60$, $p=.02$, $\eta_p^2=.02$. In phase 1, there were no differences between instruct-first and explore-first conditions, $t(241)=.22$, $p=.41$. In phase two, those in the explore-first conditions reported greater mental effort than instruct-first conditions, $t(249)=-1.79$, $p=.04$, $d=1.56$. There was no order by modality interaction or 3-way interaction, Fs<1.

Discussion

The current study directly compared how using two types of activity modalities (graphical, tabular) impacted learning in a traditional instruct-first order compared to exploring before instruction. Despite participants reporting greater overall awareness of knowledge gaps, curiosity, and engaging in multiple solution attempts, exploration did not benefit learning. Much prior research suggests that exploring before instruction helps improve conceptual understanding, though not all studies show this effect (González-Cabañes, 2023; Loibl et al., 2017; Sinha & Kapur, 2021). This research did find a motivational (curiosity) and metacognitive (awareness of knowledge gaps) boost for students who explored before instruction, which could potentially improve engagement in the topic beyond the learning session (Hidi & Harackiewicz, 2000).

Furthermore, prior research suggests that activity design matters, especially including visual representations (Scaife & Rogers, 1996). However, some research has found no performance differences when learning with specifically tabular or graphical materials (Brewer et al., 2012; Labunet et al., 2017, Experiment 2). The current study did not find a benefit of using graphical materials over tabular, in either instruct-first or explore-first conditions.

Participants who explored a graphical activity and attempted at least two types of solutions did show greater conceptual understanding. Attempting more solutions is thought to indicate greater search of prior knowledge and through the problem space. More work is needed to determine whether prompting students to explore the problem more deeply is key to the benefits to conceptual understanding. It is also possible that there are individual differences in students who are more likely to search and find multiple solutions, who may also be more inclined to engage at a deeper level. More work is needed to also determine whether the graphical materials supported a search of the most important problem features for conceptual understanding. Students may need guidance (e.g., in part, with graphics) in discerning the relevant underlying problem features in order to benefit from exploratory learning.

It is possible that the time allotted for each phase was not sufficient for students to explore, practice, or learn from the materials, as tables and graphs require different comprehension times (Braitwaithe & Goldstone, 2013; Brewer et al., 2012). Furthermore, the simplicity or complexity of visualizations can impact learning. Galano and others (2018) found that VRs that are oversimplified may not effectively communicate concepts. However, Rau (2016) discussed that students must understand what makes a representation meaningful before they attempt to connect the visual features with conceptual understanding. Previous research suggests that students struggle with underlying structures of graph types on the topic of variability while comparing groups (Cooper, 2018). The design of the visual, or graph, can have greater variability in what aspects can be effective or disruptive toward learning, while tables vary little in their design features.

The assessment is another possible reason our results differed from prior work. Our conceptual and transfer subscales had low internal consistencies (Cronbach's αs<.61). We used items that assessed broad conceptual understanding, from actual statistics exams at our university. However, there was variety in the specific learning outcomes assessed. For example, some conceptual items targeted knowledge that standard deviation measures how scores vary from the mean on average. Other items required participants to interpret standard deviation scores. Other items assessed understanding of different parts of the standard deviation formula. There may have been some misalignment between the learning objectives targeted by the learning activity and assessment.

Limitations

As noted above, two potential limitations to this study include the potential complexity of the graphical materials, and the alignment of the assessment with the learning objectives targeted by the activity. Another general limitation is that this study was conducted on only two types of formats and with only undergraduate psychology students. More work is needed to generalize. For example, future work could examine how design elements of the visual representations vary in how they affect the learning process, including organizational complexity (Novick & Fuselier, 2019), fluency or sensemaking aspects (Rau, 2017), or overall simplicity (Tversky et al., 2002). Altering graphical elements in graphical representations in relation to the problem features may restrict, or enforce, different interpretations (Scaife & Rogers, 1996). Finally, the study relied on self-report of prior knowledge rather than a pretest, though pretests can serve as exploration activities, limiting their use in this work (Newman & DeCaro, 2019).

Conclusion

Educators and researchers should carefully consider the design of their learning processes and materials, as it can impact students' awareness of knowledge gaps, curiosity, and ability to discern the features most important to understanding the underlying concepts. Outside of these motivational and metacognitive benefits, we found no evidence supporting either exploring before instruction or using graphical over tabular presentation of the learning materials. More work is needed to determine whether other methods, such as encouraging students to further explore the problem space, would lead to stronger effects.

References

Ainsworth, S. (2006). DeFT: A conceptual framework for learning with multiple representations. *Learning and Instruction, 16,* 183-198.

Ainsworth, S. (2008). The Educational Value of Multiple-representations when Learning Complex Scientific Concepts. *Theory and Practice in Science Education. Models and Modeling in Science Education, 3,* 191-208.

Ainsworth, S. E., & Scheiter, K. (2021). Learning by drawing visual representations: Potential, purposes, and practical implications. *Current Directions in Psychological Science, 30(1),* 61-67.

Ainsworth, S., & Th Loizou, A. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science, 27*(4), 669-681.

Allen, E. C. (2015). Picture this: The Value of Multiple Visual Representations for Student Learning of Quantum Concepts in General Chemistry. Boston University.

Ashman, G., Kalyuga, S., & Sweller, J. (2020). Problem-solving or explicit instruction: Which should go first when element interactivity is high?. *Educational Psychology Review, 32*(1), 229-247.

Baker, R. S., Corbett, A. T., & Koedinger, K. R. (2001). Toward a model of learning data representations. In *Proceedings of the 23rd annual conference of the Cognitive Science Society,* 45-50.

Bego, C. R., Chastain, R. J., & DeCaro, M. S. (2023). Designing novel activities before instruction: Use of contrasting cases and a rich dataset. *British Journal of Educational Psychology, 93*(1), 299-317.

Belenky, D. M., & Nokes-Malach, T. J. (2012). Motivation and transfer: The role of mastery-approach goals in preparation for future learning. *Journal of the Learning Sciences*, *21*(3), 399-432.

Boonen, A. J., van Wesel, F., Jolles, J., & van der Schoot, M. (2014). The role of visual representation type, spatial ability, and reading comprehension in word problem solving: An item-level analysis in elementary school children. *International Journal of Educational Research, 68,* 15-26.

Braithwaite, D. W., & Goldstone, R. L. (2013). Benefits of graphical and symbolic representations for learning and transfer of statistical concepts. In *Proceedings of the Annual Meeting of the Cognitive Science Society, 35*(35).

Brewer, N. T., Gilkey, M. B., Lillie, S. E., Hesse, B. W., & Sheridan, S. L. (2012). Tables or bar graphs? Presenting test results in electronic medical records. *Medical Decision Making, 32*(4), 545-553.

Butcher, K. (2006). Learning from text with diagrams: Promoting mental model development and inference generation. *Journal of Educational Psychology, 98,* 182-197.

Cakir, M. (2007). Constructivist Approaches to Learning in Science and Their Implications for Science Pedagogy: A Literature Review. *International Journal of Environmental and Science Education, 3*.

Chase, C. C., & Klahr, D. J. (2017). Invention versus direct instruction: For some content, it's a tie. *Journal of Science Education and Technology*, *26*, 582–596.

Cooper, L. (2018). Assessing Students’ Understanding of Variability in Graphical Representations that Share the Common Attribute of Bars. *Journal of Statistics Education*, *26*(2), 110–124.

Corter, J. E., & Zahner, D. C. (2007). Use of External Visual Representations in Probability Problem Solving. *Statistics Education Research Journal, 6*(1). 22-50.

Crisp, V. & Sweiry, E. (2006). Can a picture ruin a thousand words? The effects of visual resources in exam questions, *Educational Research, 48*(2). 139-154.

Debrenti, E. (2015). Visual Representations in Mathematics Teaching: An Experiment with Students. *Acta Didactica Napocensia, 8*(1), 19-25.

DeCaro, M. S., Bego, C. R., Velić, L., & Newman, P. M. (2024). Increasing contrasting cases during exploration or practice problems given before or after instruction. *Instructional Science*, 1-30.

DeCaro, M. S., Isaacs, R. A., Bego, C. R., & Chastain, R. J. (2023). Bringing exploratory learning online: problem-solving before instruction improves remote undergraduate physics learning. In *Frontiers in Education*, 8, p. 1215975.

DeCaro, M. S., & Rittle-Johnson, B. (2012). Exploring mathematics problems prepares children to learn from instruction. *Journal of Experimental Child Psychology, 113,* 552–568.

Eilam, B., & Poyas, Y. (2008). Learning with multiple representations: Extending multimedia learning beyond the lab. *Learning and Instruction, 18*(4), 368-378.

Flynn, L. R., & Goldsmith, R. E. (1999). A short, reliable measure of subjective knowledge. *Journal of Business Research, 46*(1), 57-66,

Fyfe, E. R., DeCaro, M. S., & Rittle-Johnson, B. (2014). An alternative time for telling: When conceptual instruction prior to exploration improves mathematical knowledge. *British Journal of Educational Psychology, 84,* 502–519.

Galano, S., Colantonio, A., Leccia, S., Marzoli, I., Puddu, E., & Testa, I. (2018). Developing the use of visual representations to explain basic astronomy phenomena. *Physical Review Physics Education Research, 14*(1).

Glogger-Frey, I., Fleischer, C., Grüny, L., Kappich, J., & Renkl, A. (2015). Inventing a solution and studying a worked solution prepare differently for learning from direct instruction. *Learning and Instruction, 39,* 72-87.

González-Cabañes, E., Garcia, T., Chase, C., & Núñez, J. C. (2023). PROTOCOL: Problem solving before instruction (PS-I) to promote learning and motivation in child and adult students. *Campbell Systematic Reviews, 19*(3), e1337.

Hidi, S., & Harackiewicz, J. M. (2000). Motivating the academically unmotivated: A critical issue for the 21st century. *Review of Educational Research, 70*(2), 151-179. doi:10.3102/00346543070002

Jarosz, A. F., Goldenberg, O., & Wiley, J. (2017). Learning by invention: Small group discussion activities that support learning in statistics. *Discourse Processes, 54*(4), 285–302.

Kapur, M. (2012). Productive failure in learning the concept of variance. *Instructional Science, 40,* 651–672.

Kapur, M. (2014). Productive failure in learning math. *Cognitive Science, 38,* 1008–1022.

Kapur, M. (2016). Examining productive failure, productive success, unproductive failure, and unproductive success in learning. *Educational Psychologist, 51*(2), 289– 299.

Kapur, M., & Bielaczyc, K. (2011). Classroom-based experiments in productive failure. In *Proceedings of the annual meeting of the Cognitive Science Society, 33*(33).

Kapur, M., & Bielaczyc, K. (2012). Designing for productive failure. *Journal of the Learning Sciences, 21,* 45–83.

Labunets, K., Massacci, F., & Paci, F. (2017). On the equivalence between graphical and tabular representations for security risk assessment. In *Requirements Engineering: Foundation for Software Quality: 23rd International Working Conference,* REFSQ 2017, Essen, Germany, February 27–March 2, 2017, Proceedings 23 (pp. 191-208). Springer International Publishing.

Loibl, K., Roll, I., & Rummel, N. (2017). Towards a theory of when and how problem solving followed by instruction supports learning. *Educational Psychology Review, 29*(4), 693-715.

Loibl, K., & Rummel, N. (2014a). Knowing what you don't know makes failure productive. *Learning and Instruction, 34,* 74–85.

Loibl, K., & Rummel, N. (2014b). The impact of guidance during problem-solving prior to instruction on students' inventions and learning outcomes. *Instructional Science, 42*(3), 305-326.

Loibl, K., Tillema, M., Rummel, N., & van Gog, T. (2020). The effect of contrasting cases during problem solving prior to and after instruction. *Instructional Science, 48*.

Lowrie, T., & Kay, R. (2001). Relationship between visual and nonvisual solution methods and difficulty in elementary mathematics. *The Journal of Educational Research, 94*(4), 248-255.

Mayer, R. E. (1989). Systematic thinking fostered by illustrations in scientific text. *Journal of Educational Psychology, 81*(2), 240–246.

Mayer, R. E. (2014). Cognitive theory of multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (2nd ed., pp. 43–71). Cambridge University Press.

Meyer, J., Shamo, M. K., & Gopher, D. (1999). Information Structure and the Relative Efficacy of Tables and Graphs. Human Factors: *The Journal of the Human Factors and Ergonomics Society, 41*(4), 570–587.

Moreno, R., Ozogul, G., & Reisslein, M. (2011). Teaching with concrete and abstract visual representations: Effects on students' problem solving, problem representations, and learning perceptions. *Journal of Educational Psychology, 103*(1), 32–47.

Nachtigall, V., Serova, K., & Rummel, N. (2020). When failure fails to be productive: Probing the effectiveness of productive failure for learning beyond STEM domains. *Instructional Science,* 651-697.

Naylor, F. D. (1981). A state-trait curiosity inventory. *Australian Psychologist, 16*(2), 172-183.

Newman, P. M., & DeCaro, M. S. (2019). Learning by exploring: How much guidance is optimal?. *Learning and Instruction, 62,* 49-63.

National Research Council, Division on Earth, Life Studies, Board on Earth Sciences, Geographical Sciences Committee, Committee on Support for Thinking Spatially, & The Incorporation of Geographic Information Science Across the K-12 Curriculum. (2005). *Learning to think spatially*. National Academies Press.

Novick, L. R., & Fuselier, L. C. (2019). Perception and conception in understanding evolutionary trees. *Cognition, 192,* 104001.

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive load approach. *Journal of Educational Psychology, 84,* 429-434.

Porat, T., Oron-Gilad, T., & Meyer, J. (2009). Task-dependent processing of tables and graphs. *Behaviour & Information Technology, 28*(3), 293–307.

Prince, M. (2004). Does Active Learning Work? A Review of the Research. *Journal of Engineering Education, 93,* 223-231.

Rau, M. A. (2016). A framework for educational technologies that support representational competencies. *IEEE Transactions on Learning Technologies, 10*(3), 290-305.

Rau, M. A. (2017). Conditions for the Effectiveness of Multiple Visual Representations in Enhancing STEM Learning. *Educational Psychology Review, 29*(4), 717–761.

Rittle-Johnson, B., & Alibali, M. W. (1999). Conceptual and procedural knowledge of mathematics: Does one lead to the other? *Journal of Educational Psychology, 91*(1), 175–189.

Rittle-Johnson, B. & Schneider, M. (2015). Developing conceptual and procedural knowledge of mathematics. In R. Cohen Kadosh & A. Dowker (Eds.), *The Oxford handbook of numerical cognition.* Oxford University Press.

Rittle-Johnson, B., Siegler, R., & Alibali, M. (2001). Developing conceptual understanding and procedural skill in mathematics: An iterative process. *Journal of Educational Psychology, 93,* 346-362.

Roll, I., Aleven, V., & Koedinger, K. R. (2009). Helping students know 'further'-increasing the flexibility of students' knowledge using symbolic invention tasks. In *Proceedings of the 31st annual conference of the Cognitive Science Society*. 1169-1174.

Roll, I., Aleven, V., & Koedinger, K. (2011). Outcomes and mechanisms of transfer in invention activities. In

Proceedings of the Annual Meeting of the Cognitive Science Society, 33(33).
Scaife, M., & Rogers, Y. (1996). External cognition: how do graphical representations work?. *International journal of human-computer studies, 45*(2), 185-213.
Schneider, M., & Stern, E. (2010). The cognitive perspective on learning: Ten cornerstone findings (pp. 69-90). *The nature of learning: using research to inspire practice.*
Schonlau, Matthias & Peters, Ellen. (2012). Comprehension of Graphs and Tables Depend on the Task: Empirical Evidence from Two Web-Based Studies. *Statistics, Politics, and Policy, 3.*
Schwartz, D. L., Chase, C. C., Oppezzo, M. A., & Chin, D. B. (2011). Practicing versus inventing with contrasting cases: The effects of telling first on learning and transfer. *Journal of Educational Psychology, 103,* 759–775.
Schwartz, D. L., & Martin, T. (2004). Inventing to prepare for future learning: The hidden efficiency of encouraging original student production in statistics instruction. *Cognition and Instruction, 22*(2), 129–184.
Schwartz, D. L., Sears, D., & Chang, J. (2007). Reconsidering prior knowledge. *Thinking with data,* 319-344.
Shah, P., & Freedman, E. G. (2011). Bar and line graph comprehension: An interaction of top-down and bottom-up processes. *Topics in Cognitive Science, 3*(3), 560-578.
Sinha, T., & Kapur, M. (2021). When problem solving followed by instruction works: Evidence for productive failure. *Review of Educational Research, 91,* 761-798.
Sweller, J., van Merrienboer, J. J. G. & Paas, F. G. W. C. (1998). Cognitive Architecture and Instructional Design. *Educational Psychology Review, 10,* 251–296. https://doi.org/10.1023/A:1022193728205.
Trninic, D., Sinha, T., & Kapur, M. (2022). Comparing the effectiveness of preparatory activities that help undergraduate students learn from instruction. *Learning and Instruction, 82,* 1-12.
Tversky, B., Zacks, J., Lee, P., & Heiser, J. (2000). Lines, blobs, crosses and arrows: Diagrammatic communication with schematic figures. In *Theory and Application of Diagrams: First International Conference,* Diagrams 2000 Edinburgh, Scotland, UK, September 1–3, 2000 Proceedings 1 (pp. 221-230). Springer Berlin Heidelberg.
VanLehn, K., Siler, S., Murray, C., Yamauchi, T., & Baggett, W. B. (2003). Why do only some events cause learning during human tutoring? *Cognition and Instruction, 21*(3), 209–249.
Velić, L., & DeCaro, M. S. (2025). Comparing effectiveness of exploratory learning activities given before instruction: generating multiple strategies vs. inventing one strategy. *Instructional Science,* 1-36.
Weaver, J. P., Chastain, R. J., DeCaro, D. A., & DeCaro, M. S. (2018). Reverse the routine: Problem solving before instruction improves conceptual knowledge in undergraduate physics. *Contemporary Educational Psychology, 52,* 36-47.
Wiedmann, M., Leach, R. C., Rummel, N., & Wiley, J. (2012). Does group composition affect learning by invention? Instructional Science, 40(4), 711–730.
Wu, H. K., & Shah, P. (2004). Exploring visuospatial thinking in chemistry learning. Science education, 88(3), 465-492.
Zahner, D. & Corter, J. E. (2010). The Process of Probability Problem Solving: Use of External Visual Representations. Mathematical Thinking and Learning. 12(2). 177-204.