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Watching Hands Move Enhances Learning From Concrete and Dynamic Visualizations

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This article explores the role of sensorimotor engagement in students' learning of a challenging science, technology, engineering, and math-related concept. Previous research has failed to distinguish two features commonly associated with embodiment: sensorimotor engagement and visuospatial concreteness. In the current research, we ask whether sensorimotor engagement—operationalized as watching a video of hands manipulating paper representations—offers unique benefits beyond the visuospatial concreteness of a dynamic visualization of the same process. Participants were randomly assigned to one of three conditions to learn about the shuffle() function in R: a Watch Hands Moving Objects group, which watched a video with hands; a Watch Moving Objects group, which watched a video with a dynamic visualization in which objects moved without hands; or a control group, which watched a live-coding video that did not include either hands or visuospatial representations. Results revealed that only participants in the Watch Hands Moving Objects group demonstrated significantly superior performance compared with both the Watch Moving Objects group and control groups. These findings highlight the unique benefit of sensorimotor engagement for learning, contributing to a deeper understanding of how embodiment can enhance the learning process.

Public Significance Statement

This research investigates the unique contribution of sensorimotor engagement when learning from instructional videos. Students who watched an instructional video in which hands were seen moving objects representing a statistical programming concept learned more than those who watched a video that included the same dynamic visualization but without the hands. The work contributes to the theory of embodied learning and suggests a simple way to improve educational materials.

Keywords: embodied cognition, multimedia learning, dynamic visualization, sensorimotor engagement, data science education

In recent decades, there has been a significant increase in research on embodied cognition, especially in education, where a multitude of studies has demonstrated that learning can be enhanced through various forms of embodiment (see Shapiro & Stolz, 2019, for a review). Both observing and performing bodily movements have been shown to aid student learning (Cook et al., 2017; Goldin-Meadow et al., 2001; Johnson-Glenberg et al., 2014, 2016; Ping & Goldin-Meadow, 2008; Pouw et al., 2016; Tran et al., 2017; Zhang et al., 2022). This benefit has been demonstrated in a variety of science, technology, engineering, and math fields, including

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mathematics (Nathan & Alibali, 2011; M. Novack & Goldin-Meadow, 2015), data science (Zhang et al., 2021, 2022), and physics (Johnson-Glenberg et al., 2014; Johnson-Glenberg & Megowan-Romanowicz, 2017).

Although the beneficial effects of embodiment on learning have been extensively studied, past research has typically compared the impacts of embodied versus nonembodied approaches without further isolating different features of embodiment. Here, we identify at least three important features of embodiment to consider: sensorimotor engagement, visuospatial concreteness, and dynamic quality. *Sensorimotor engagement* refers to the level of involvement of the sensorimotor system during learning. It can range from physically interacting with objects to imitating actions to simply observing someone's gestures or object manipulations. *Visuospatial concreteness* refers to the degree to which a concept or stimulus can be experienced in a material or objectified manner, representing abstract concepts through concrete representations. Last, *dynamic quality* characterizes the degree to which perceptual stimuli move or change during the instruction.

One of the most examined fields of study in embodied learning compares the effect of more embodied learning experiences or materials high on all three of these features against experiences lower on these features. For example, Goldin-Meadow et al.'s (2001) finding that simply allowing learners to gesture during learning improved learning outcomes was based on a comparison of a condition that included more sensorimotor engagement, more visual concreteness, and more movement (or dynamic quality) to one that was low on all three features (i.e., not allowing learners to gesture). Similarly, Johnson-Glenberg et al.'s (2014) finding that moving the learners' entire upper body during instruction benefits learning in science domains was based on a comparison of a condition that included more sensorimotor engagement, more visual concreteness, and more movement (or dynamic quality) to one that was low on all three features (i.e., a regular instruction).

The field of embodied cognition is just beginning to investigate how these features might interact during learning. Learning experiences that involve the body or hands (i.e., high on sensorimotor engagement) are almost always dynamic, but they can vary in their degree of visuospatial concreteness. For example, object manipulation and gesture are two dynamic hand actions commonly leveraged in science education to benefit learners (M. Novack & Goldin-Meadow, 2015; Roberts et al., 2005; Yammine & Violato, 2016). They are both high on sensorimotor engagement, but object manipulation has relatively more visuospatial concreteness (Castro-Alonso et al., 2019). Because object manipulation requires both the movement of hands and concrete objects, it has higher visuospatial concreteness than gesture alone (Chu & Kita, 2008).

Evidence suggests that people interpret hand movements differently in the presence and absence of objects (Schachner & Carey, 2013). When objects are absent, hand movements are interpreted in terms of movement-based goals, and when objects are present, they are interpreted relative to external goals (M. A. Novack et al., 2016). However, in at least one study, such differences do not have implications for learning: Gestures can benefit learners both in the presence and absence of objects (Ping & Goldin-Meadow, 2008). This study can be construed as evidence that a dynamic learning situation with *sensorimotor* features alone was as beneficial as one with *sensorimotor* + *concrete* features. But more research to disentangle these features is needed.

Similarly, dynamic learning experiences can also be high in visuospatial concreteness but low in sensorimotor engagement (e.g., squares moving around in space on their own), or they can be high in both dimensions (e.g., hands moving square objects around). One study found that people learn better from dynamic drawing with a visible hand than from already drawn diagrams (Fiorella & Mayer, 2016). In this case, a *sensorimotor* + *concrete* + *dynamic* presentation of a diagram was better than one that was merely visuospatially *concrete*. Although studies abound that show the benefits of performing actions as well as watching the actions of others (for a review, see Goldin-Meadow & Beilock, 2010), studies of embodied learning interventions, to our knowledge, have not directly examined whether sensorimotor engagement has any added benefits above and beyond that of visuospatial concreteness. That is, how would a *sensorimotor* + *concrete* + *dynamic* presentation compare with one that is *concrete* + *dynamic*? Such evidence is crucial for advancing the field and thus is the focus of our investigation.

One particularly relevant vein of research provides insight into this question by comparing performing versus observing actions. For example, Goldin-Meadow et al. (2012) compared the effects of performing versus observing gestures on a mental rotation task that asked 6-year-olds to judge whether two shapes at different angles of rotation were the same or different. Children who were instructed to perform gestures that mimicked the rotation of the figures performed better on the task than children who simply observed someone else performing similar gestures on a video clip. Performing gestures involves higher sensorimotor engagement than observing them but has the same level of visuospatial concreteness and dynamic quality. Goldin-Meadow et al. have shown a clear effect of a high level of sensorimotor engagement versus a medium level of engagement (observing) but left open the question of whether observing sensorimotor activity benefits learning above a condition with no observable sensorimotor activity.

With dynamic learning stimuli such as those found in instructional videos, it is difficult to disentangle the role of sensorimotor engagement from visuospatial concreteness. Our approach compares an embodied intervention, operationalized as an instructional video with both sensorimotor engagement and visuospatial concreteness, against a similar video that preserves the visuospatial concreteness but reduces sensorimotor engagement. We designed dynamic instructional videos to teach students learning about randomness in statistics how to use the shuffle function (from the programming language R), which randomly reorders individual elements (either rows or cells in a data set). In the embodied intervention, students are shown a video of hands physically cutting up a data set printed on article and reordering cells. This intervention involves both sensorimotor engagement, through the instructor's hand movements, and visuospatial concreteness, through physical article objects and spatial manipulation of those objects. In the less embodied version, the video shows the data set being split up and reordered without the involvement of any hands. The objects simply move on their own.

The current research aims to investigate whether sensorimotor engagement, such as watching the hands physically manipulate article, offers unique benefits beyond representational concreteness in dynamic learning videos. After all, concrete representations may benefit learning without a sensorimotor component. For example, the moving data frames and cells may facilitate learning by associating abstract ideas (such as "variables" and "values") with more concrete visuospatial objects (such as columns and cells, respectively). Such representations can implicitly represent abstract properties in an analog fashion (Goldstone & Barsalou, 1998) without the need for explicit statements and memorization of assumptions (e.g., when cells of a data frame are being moved around in space, students can see that cells are not being added or taken away). Prior research has shown that concrete objects are particularly beneficial for young children and novices (Fyfe et al., 2014; Montessori, 1917; Piaget, 1970; Uttal et al., 2006) presumably because they have less background knowledge and need to use concrete features to build up a basis for understanding new abstract concepts. This has led to the concreteness-fading hypothesis, which hypothesizes that instruction should transition from concrete to abstract for optimal learning (Fyfe et al., 2014). Many studies have demonstrated the efficacy of such an instructional sequence, demonstrating the benefits of visuospatial concreteness early in the learning process (e.g., Fyfe et al., 2015).

Beyond concreteness, are there additional learning benefits of engaging the sensorimotor system in a dynamic learning video? If sensorimotor engagement is not found to add additional value beyond visuospatial concreteness in dynamic learning stimuli, it may challenge a fundamental tenet of embodied cognition that the body plays a unique role in cognitive activities. Therefore, the present study aims to disentangle the effects of visuospatial concreteness and sensorimotor engagement in embodied learning research. Compared with more abstract instruction, does concreteness per se lead to better learning, or do we need both concreteness and sensorimotor engagement to see benefits to learning?

The Present Study

The present study is based on a previous study (Zhang et al., 2022) in which college students were randomly assigned to watch an instructional video featuring either hands-on demonstrations or live coding in R prior to watching a second live-coding video using a larger data set. The results showed that students who watched a hands-on demonstration before watching a live-coding video learned more than those who watched two live-coding videos in a row.

However, the hands-on video used in that study involved both visuospatial concreteness (i.e., pieces of paper to represent data) and sensorimotor engagement (i.e., hands shuffling the paper). In the present study, we will refer to this as the Watch Hands Moving Objects (WHMO) condition. We also will introduce a new condition that has visuospatial concreteness without any hand movements, which we will refer to as the Watch Moving Objects (WMO) condition. In this condition students saw visuospatial representations of the data set and cells moving around dynamically, but without being manipulated by the instructor's hands. Although this condition might still involve some sensorimotor engagement (via the presentation of visuospatial objects), it is at a lower level than the hands-on video, making it suitable for addressing our research question. We also included Zhang et al.'s (2022) control condition, which showed the same concepts being taught through live coding alone. Table 1 summarizes how the three conditions vary on three key features: sensorimotor engagement, visuospatial concreteness, and dynamic quality.

Table 1
Summary of the Three Conditions Based on the Three Features

Condition	Sensorimotor engagement	Visuospatial concreteness	Dynamic quality
Control (live coding)	Low	Low	Medium
Watch Moving Objects	Low	High	High
Watch Hands Moving Objects	High	High	High

The embodied cognition view would be that sensorimotor engagement confers a unique benefit to learning. This view would expect that the type of instructional video students are exposed to before the abstract live-coding video would significantly impact their subsequent learning outcomes. In the present study specifically, we hypothesize that students who first watch a hands-on video, which involves sensorimotor engagement, visuospatial concreteness, and dynamic qualities, will perform better than those who watch videos with only visuospatial concreteness and dynamic qualities, or the control (i.e., the live coding).

Beyond exploring whether sensorimotor engagement leads to better learning, we also wish to understand the potential mechanisms by which embodiment causes better learning. What are the mental representations that result from a more embodied learning experience? To explore this question, at the end of our study, we will ask participants to describe whether they thought about the contents of the video while answering the posttest questions and, if so, what they thought about. Specifically, we are interested in whether their recalls were visuospatial (e.g., recall learning that data frames are made up of rows, columns, and cells and that R code can change the arrangement of these elements).

If watching sensorimotor activity changes the quality and content of mental representations, as several studies in gesture have demonstrated (e.g., Alibali et al., 2000; Brooks et al., 2018; Rimé et al., 1984, Wagner et al., 2004), participants in the WHMO condition should stand apart from those in the other two conditions in both the quantity and quality of their recall of the learning videos. For example, they may be more likely to recall that cells are "moving," even though the cells are moving in both the WHMO and WMO conditions. If this were the case, we would have evidence that sensorimotor engagement even by watching sensorimotor activities uniquely leads to different mental representations.

If, on the other hand, the quantity and quality of recall look similar across the WHMO and WMO conditions, yet different from the control condition, we might conclude that it is the dynamic and concrete qualities of the representations that impact learning and not the sensorimotor engagement.

For the quality of their recall, we asked specifically whether the elements recalled were visuospatial. This is an important question because past research has revealed mixed evidence of whether the effect of gesture is visuospatial or propositional (Alibali et al., 2000; Wagner et al., 2004). If we observe participants reporting more visuospatial recall in the WHMO condition, this might provide support for a visuospatial representation that underlies embodiment. However, if we only see differences in a general recall, but no difference when it comes specifically to visuospatial recall between the WHMO condition and the other two conditions, we might lean toward a propositional representation.

Method

Transparency and Openness

The way we determined our sample size, excluded participants, all manipulations, and measures followed the Journal Article Reporting Standards (Kazak, 2018). All data are available at https://osf.io/y795h/?view_only=c8c8ad03fe74462397e85ef84708e4d3 (Zhang, 2024). Analysis code and research materials are available upon request. Data were analyzed using R, Version 4.0.0 (R Core Team, 2020), and data visualizations using the package ggplot2, Version 3.2.1 (Wickham, 2016). Neither the study's design nor its analysis was preregistered.

Participants

Participants were 153 undergraduate students taking an introductory psychological statistics course at a large public research institution. They took the course either during the summer of 2022 or the winter of 2023. These students were selected to participate in the study because they had already been introduced to the shuffle function from the mosaic package in R (v1.8.4; Pruim et al., 2017) as part of their coursework. Mastery of the shuffle function, which instantiates the process of randomness, was integral to understanding further course topics, such as the sampling distribution.

Three participants were excluded because they took more than 5 hr on the study survey, indicating that they did not complete the study in one sitting as required. This resulted in a final sample size of 150 students. The gender and ethnic composition of the sample matched that of the course. The sample contained 120 females and 30 males. The racial/ethnic breakdown was as follows: 64 Asian, six Black or African American, one Native Hawaiian or other Pacific Islander, 32 other or mixed race, and 47 White. This information was collected through self-reports. Students who participated in the study received a small amount of extra credit (0.5%) toward their course grades and also may have derived educational benefits from their participation. The study was reviewed and approved by the university's institutional review board.

A power analysis was conducted using the pwr package in R (Champely et al., 2017; Cohen, 1988). Based on Cohen's f of 0.3, with an α of .05 and a power of .85, the minimum sample size needed with this effect size is 42 per group. The power analysis indicated that the sample is sufficiently large to detect a medium effect size.

Design and Procedure

The study was hosted on Qualtrics, and students participated online. Participants received an email from their professor with the Qualtrics link to the study. They volunteered to participate by clicking on the link, upon which Qualtrics randomly assigned participants to one of the three conditions: *control* ($n = 47$), *WMO* ($n = 52$), and *WHMO* ($n = 51$).

After answering some basic demographic questions, participants responded to five open-response questions designed to assess their existing understanding of probability and the shuffle function. Subsequently, they viewed two intervention videos, detailed below. The first video varied according to experimental conditions, while the second video was identical across the three conditions. After watching the second video, participants answered 22 posttest questions. They then answered two additional questions about how often they thought about the content of the videos during the time they were answering the posttest questions and, if they did think at all about the videos, what they were thinking about specifically.

Intervention Videos

Students started by watching one of three versions of an instructional video. It is worth highlighting that although some students watched videos that included hands-on activities, participants in this study did not perform any hands-on activities themselves, a fact that is reflected in our naming of the conditions (the "W" stands for "watching"). Although the format differed, the content of the videos was carefully matched across versions. All three versions of the video explained the use of the shuffle function to simulate randomness by showing what a small artifactual data set would look like after shuffling rows versus cells within columns. A screenshot from each video is shown in Figure 1.

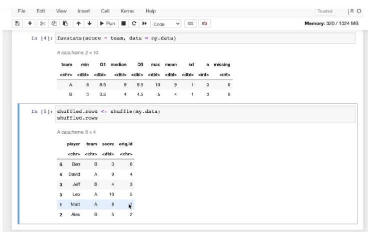
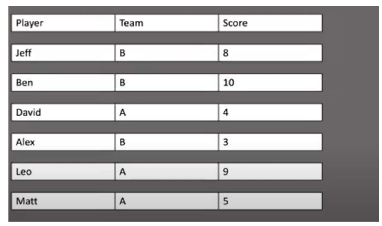
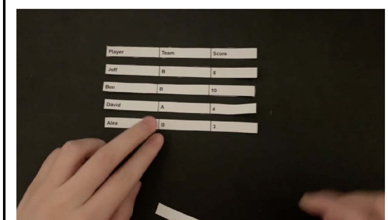
Students in the WHMO condition watched a video, shot from above, of the instructor's hands as she cut a printed data table into pieces and then randomly rearranged the pieces. In other words, the pieces of the data sets were cut and moved by the instructors' hands. This approach provided a concrete and sensorimotor representation of what the shuffle function does. As the pieces of data were manually shuffled, the narrator explained what was being done.

Students in the WMO condition heard the same narration as those in the *WHMO* condition, but instead of watching a person cut and shuffle pieces of paper, they saw animated visualizations of the data table being separated and shuffled. The animations, which were generated by PowerPoint, were matched with the movements of the physical data set in the *WHMO* video but, critically, did not show any hands manipulating the data set. Our goal was to simulate the WHMO experience but without the hands, thus minimizing the activation of sensorimotor systems.

Students assigned to the control condition saw a computer screen recording of R code being typed and executed to perform the same shuffles as those enacted in the WHMO and WMO videos. The narration was the same, except that it referred to the code being run instead of the visuospatial movements described in the other two videos. The control condition provided a less perceptually concrete experience because the pieces of the data sets were not being cut out or moved around as in the other two conditions. The data set would simply appear or change after the code was run. However, it is worth noting that this condition was also dynamic because of the live coding—it was just less dynamic than the two experimental conditions. It was not entirely abstract either, as the instructor wrote code to print out the data set before and after running the shuffle function to show changes in the data set, thereby retaining a degree of visuospatial concreteness in the learning experience.

After watching their assigned version of the first video, students in all three conditions watched a live-coding video, which was similar in format to the live-coding video described above. In this second video, the live coding involved applying concepts learned in the first video to a larger data set adapted from a real experiment. The descriptions of the WHMO condition and the control condition have been published previously by Zhang et al. (2022).

Figure 1
Screenshots of Each Video From the Three Conditions

Control	WMO	WHMO
		

Note. WMO = Watch Moving Objects; WHMO = Watch Hands Moving Objects. See the online article for the color version of this figure.

Measures

Pretest

Participants' knowledge before watching the videos was measured on a pretest consisting of five open-response questions (Appendix A).

Posttest

Participants' knowledge after watching the videos was measured using a combination of eight multiple-choice questions and 25 open-response questions. The questions were designed to evaluate students' understanding of the shuffle function, the concept of randomness, and how to use the concept of randomness to make statistical inferences (a complete list of the questions is presented in Appendix B).

Both pre- and posttest questions were graded by two trained coders based on a predetermined rubric. The two coders were blind as to the experimental condition from which each response came. Each question was given a maximum of 1 point. Partial credit of 0.5 was given to open responses that were missing parts or showed minor misunderstandings. The possible total score ranged from 0 to 32 (Cronbach's α = .89).

Recall of Instructional Videos During Problem Solving

General Recollection of Video Content. After completing the posttest questions, participants were asked: "When you were answering the posttest questions, how often did you think about the content in the videos?" Responses were coded on a 5-point scale based on a predetermined rubric, with answers indicating *not at all/never/none of the questions* scored as 0, *not often/only one or two questions* as 1, *sometimes/a couple questions* as 2, *often/half of the questions* as 3, and *all the time/every question* as 4. After all responses were coded by one experimenter, another trained experimenter coded 20% of the responses to establish interrater reliability (Cronbach's α = .98).

Visual Recall of the Video. A follow-up question asked, "If you did think about the video, what did you think about specifically?" A trained experimenter coded whether participants referenced visual elements from the video or not. For example, mentions of specific actions like "cutting up paper and 'shuffling' data" or recalling distinct images such as histograms from the video were dummy coded with 1, signifying visual recall. In contrast, references to abstract concepts or nonvisual elements, like the idea of "shuffling to break the relationship" or the importance of "running a function multiple times to explain variation," were coded as 0, no visual recall. A second experimenter coded 20% of the responses to this question (Cronbach's α = .86).

Results

Posttest Performance

Figure 2 shows the distribution of students' performance on the posttest questions by condition. Students in the WHMO group scored higher on average than did students in either of the other two groups.

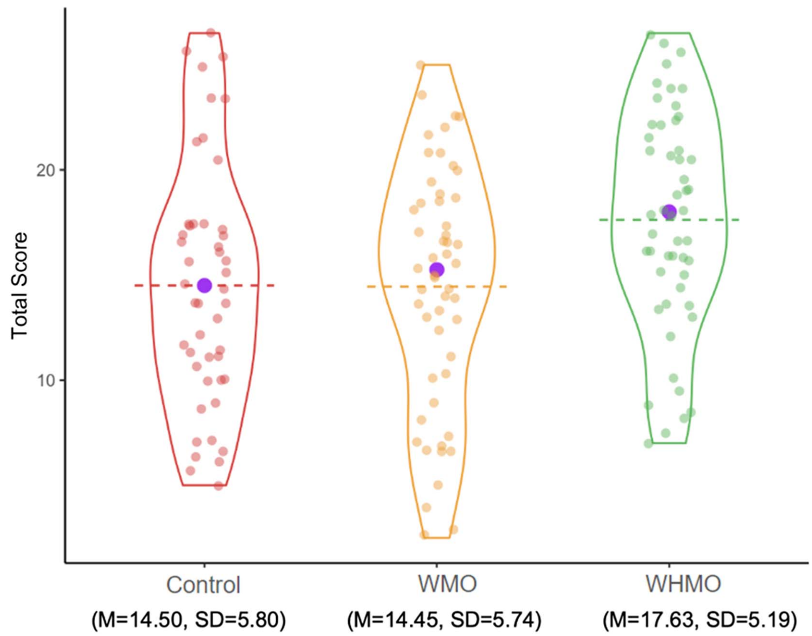
An analysis of covariance, which modeled posttest performance as a function of experimental condition while controlling for pretest performance and study cohort (summer vs. winter), revealed that the overall effect of condition significantly impacted posttest performance (Table 2).

Post hoc comparisons showed that students in the WHMO group (M = 17.63, SD = 5.19) outperformed both those in the WMO group, M = 14.45, SD = 5.74; $t(146)$ = 5.10, $p_{adj.} < .001$, and those in the control group, M = 14.50, SD = 5.80; $t(146)$ = 4.89, $p_{adj.} <$ .001. (Note: The error variance is pooled across all groups and then weighed to the groups being compared to offer a more robust error term; the p values were adjusted for multiple comparisons using Bonferroni correction.)

Did Participants' Visual Recall of the Video During Problem Solving Differ by Condition?

Figure 3 shows the number of participants who self-reported having a visual recall of the video during problem solving broken down by condition. A logistic regression showed that participants in the WMO group were 152% more likely to think back to visual components than those in the control group (log odds = 0.92, OR = 2.52, p = .109). Participants in the WHMO group were 590% more likely to think back to visual components than the control group (log

Figure 2
Violin Plots of Students' Posttest Performance by Condition



Note. Dashed lines are means; purple dots are medians. WMO = Watch Moving Objects; WHMO = Watch Hands Moving Objects. See the online article for the color version of this figure.

odds = 1.93, *OR* = 6.90, $p < .001$) and 174% more likely than the WMO group (log odds = 1.01, *OR* = 2.74, $p = .020$).

Did Visual Recall of the Video Predict Participants' Posttest Performance?

Figure 4 shows violin plots and descriptive statistics of participants' posttest performance separated by whether or not they reported a visual recall of the videos. An independent sample *t* test showed that posttest performance of participants who mentioned a visual recall of the video was significantly higher than that of participants who did not recall visual components of the videos, $t(148) = 3.89$, $p < .001$.

Did Visual Recall of the Video Mediate the Effect of Condition on Learning?

Because the mediator is binary, we used a causal mediation analysis to evaluate whether the effect of condition on posttest performance was significantly mediated by whether participants reported visual recall of the instructional videos during the posttest assessment. Because the predictor variable (i.e., condition) was multicategorical with three levels, we fitted three mediation models.

The effect of the WHMO condition versus the control condition on participants' posttest performance was significantly mediated by participants' self-reported visual recall (Figure 5; average causal mediation effect = 1.22, 95% CI with 5,000 nonparametric bootstrapping [0.32, 2.12], $p = .004$). The effect of the WHMO condition versus the WMO condition on posttest performance was also significantly mediated by visual recall (Figure 6; average causal mediation effect = 0.81, 95% CI with 5,000 nonparametric bootstrapping [0.02, 1.67], $p = .037$). The effect of the WMO condition versus the control condition on posttest through visual recall was not significantly mediated (see Appendix C for complete results).

Table 2
Analysis of Covariance Results

Predictor	*df*	*F*	PRE	η_p^2	95% CI for η_p^2	*p*
Model (error reduced)	5	19.64	0.41			<.001
Condition	2	6.38	0.08	0.10	[0.02, 0.20]	.002
Pretest performance	1	79.92	0.36	0.36	[0.24, 0.47]	<.001
Time (winter/summer)	2	0.07	0.00	0.00	[0.00, 0.00]	.934

Note. *df* = degrees of freedom; PRE = Proportion Reduction of Error; CI = confidence interval.

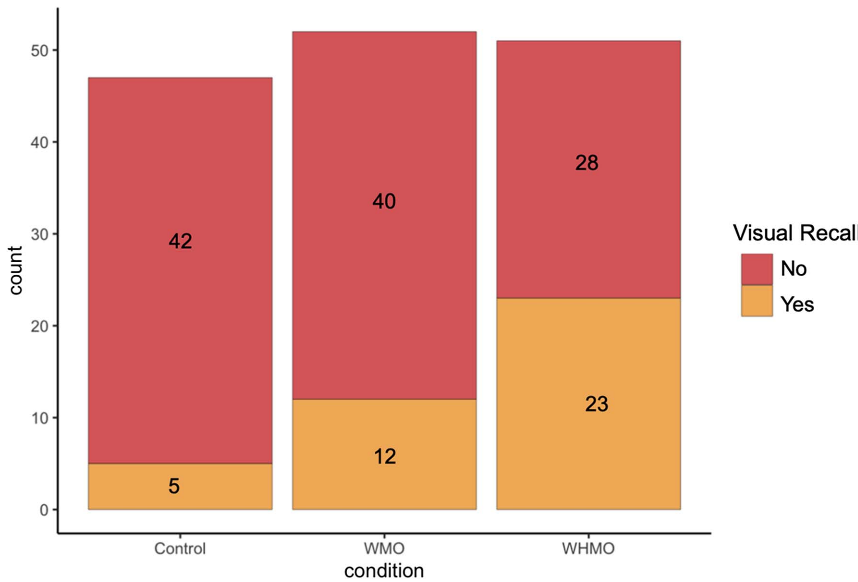
Did Participants' General Recollection of the Video During the Posttest Differ by Condition?

To explore whether how often participants thought about the content in the videos differed by conditions, we performed a one-way analysis of variance. The one-way analysis of variance did not reveal a significant difference between the three conditions in terms of their general recollection of the video during the posttest, $F(2, 147) = .95$, $p = .389$ (Figure 7).

Did Participants' General Recollection of the Video Predict Their Posttest Performance?

There was no significant correlation between general recollection of video and posttest performance, $t(148) = -0.08$, $p = .931$.

Figure 3
Participants' Thinking Back to Visual Components by Condition

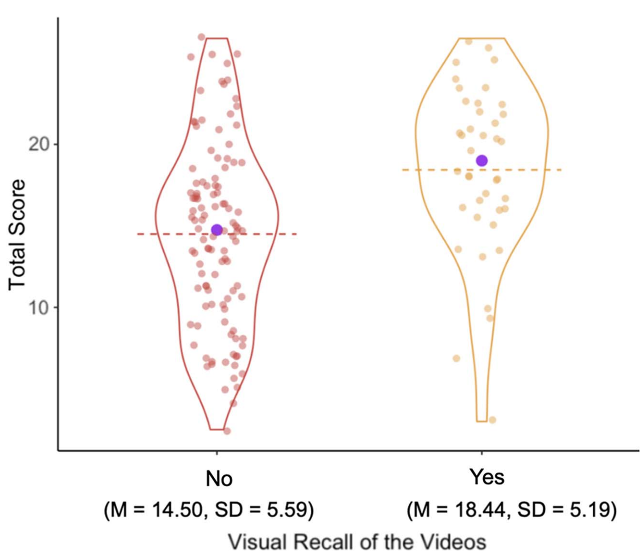


Note. WMO = Watch Moving Objects; WHMO = Watch Hands Moving Objects. See the online article for the color version of this figure.

Discussion

The present study explored whether sensorimotor engagement confers unique learning benefits over and above those provided by concreteness. Consistent with the embodied cognition theory, the findings showed that the WHMO group outperformed the WMO group and the Control group. This distinction between visuospatial concreteness alone and the addition of sensorimotor engagement enable us to see that sensorimotor engagement confers a distinct advantage on top of visuospatial concreteness in promoting learning outcomes, whereas concreteness by itself, as implemented in the dynamic visualizations, is no more helpful than abstract demonstration. The mediation analyses further suggest that one potential mechanism for this effect might be that the hands-on demonstrations enabled students to more easily activate visual memories of the demonstrations and then use these visual representations during problem solving.

Figure 4
Violin Plots of Posttest Score by Whether Participants Reported Having Visual Recall of the Videos



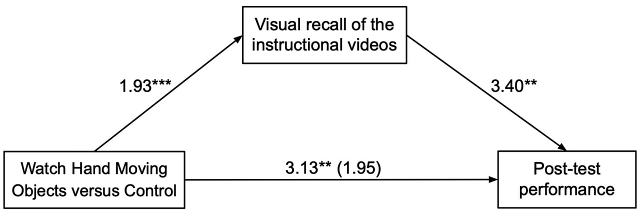
Note. Dashed lines are means; purple dots are medians. See the online article for the color version of this figure.

Beyond theories in embodied cognition, our findings also align with the dual-coding theory. Dual-coding theory posits that because mental representations are established through a combination of verbal and nonverbal processing, learning through multiple modalities is beneficial (Clark & Paivio, 1991). In particular, the theory identifies concrete sensorimotor experiences as a key input to provide meaning and grounding to verbal information. Although the connection between dual-coding theory and embodied learning has mostly been studied in the context of reading comprehension and writing (e.g., Sadoski & Krasny, 2018; Sadoski & Paivio, 2013), the present study suggests a link to the learning of abstract concepts in the domain of statistics and data science: Sensorimotor inputs can also provide meaning and grounding to representations such as computer programming functions and the concept of randomness.

Our findings also advance the dual-coding theory by proposing a mechanism by which these sensorimotor representations facilitate information processing. The dual-coding theory (Clark & Paivio, 1991) posits that links between verbal and nonverbal (e.g., sensorimotor) representations lead to more robust mental models of concepts. Our finding that participants who saw sensorimotor representations were more likely to draw upon these representations during testing provides support for the idea that sensorimotor experiences are a unique contributor to robust mental representations.

Figure 5

Diagram Showing Visual Recall of Videos as a Mediator of the Effect of Watching Hands Moving Objects (vs. Control) on Posttest Performance



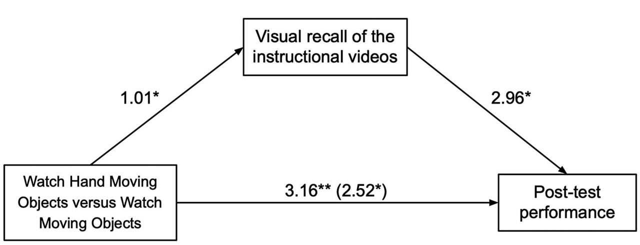
Note. The estimate for the path (i.e., the effect of condition on visual recall) is in the form of log odds.
** $p < .01$. *** $p < .001$.

It is also interesting that students' performance after viewing the *concrete + dynamic* representations without hands (i.e., the WMO) was almost identical to their performance after viewing the live-coding control, which was both less concrete and less dynamic. In computer science education, live-coding demonstrations are thought to be better than simply showing students a large block of code on a slide. In live coding, instructors dynamically write and run each line of code one at a time, modeling how coding behaviors unfold over time (Bennedsen & Caspersen, 2005). It is possible that because the live-coding videos dynamically showed the process of generating each line of code and how an output changed (e.g., printing out a changed data set), this experience may be sufficient to produce a learning benefit. Therefore, adding an additional dose of concreteness may not have added more value beyond what live coding already offers.

Previous research has produced mixed findings regarding the effectiveness of dynamic visualizations. Concerns have been raised regarding the cognitive load imposed by dynamic visualizations (Hegarty, 2004; Tversky et al., 2002). On one hand, the dynamic visualizations in the WMO and WHMO stimuli may have been quite similar in cognitive load because the content was highly similar. On the contrary, it may be that the embodiment involved in seeing the hands moving the objects made it easier for students to generate and sustain the visual and dynamic representations and to use them in problem solving (de Koning & Tabbers, 2011; Zhang et al., 2022).

Figure 6

Diagram Showing Visual Recall of Videos as a Mediator of the Effect of Watching Hands Moving Objects (vs. Watching Moving Objects) on Posttest Performance



Note. The estimate for the path (i.e., the effect of condition on visual recall) is in the form of log odds.
* $p < .05$. ** $p < .01$.

Only a few studies of embodied cognition have experimentally examined the intersection of sensorimotor engagement, visuospatial concreteness, and dynamic visualization, and each has focused on slightly different combinations of these features (e.g., Congdon et al., 2018; Fiorella & Mayer, 2016; Goldin-Meadow et al., 2012). Ours kept visuospatial concreteness and dynamic quality relatively constant while manipulating levels of sensorimotor engagement. This manipulation is similar to the comparison of performing versus observing gestures (e.g., Goldin-Meadow et al., 2012), but ours is the first to our knowledge to demonstrate the unique benefit of observing sensorimotor activities over concrete dynamic visualizations. Others have kept sensorimotor engagement and dynamic quality constant and manipulated levels of concreteness (e.g., Ping & Goldin-Meadow, 2008).

Beyond these few studies, other combinations of these three features of embodiment also merit attention. For example, we need studies that keep sensorimotor engagement and concreteness constant while manipulating the dynamic quality of the representations. Would participants benefit more from a video of an instructor's hand drawing a diagram than from a video in which the instructor's hand simply pointed to parts of an already finished drawing? We have begun to explore this possibility by teaching students about the normal distribution in statistics—a diagram that instructors commonly draw and point to as they teach students (Zhang et al., 2024). Future research could also investigate *how much* of these features are needed to benefit learning. In the present study, we included only the hands in our sensorimotor engagement condition; would including the entire body result in different benefits?

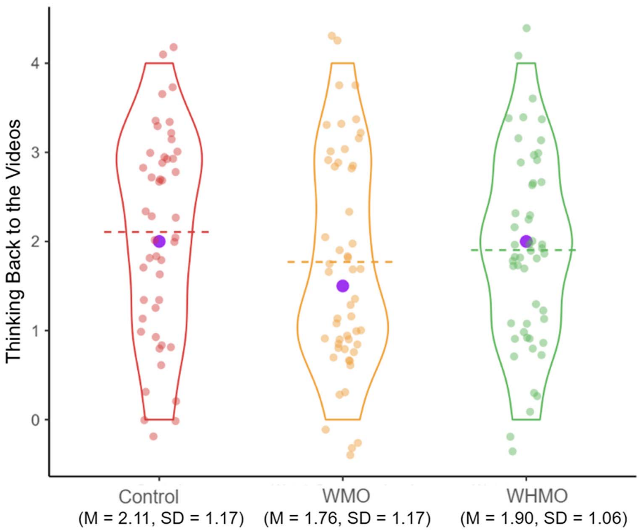
The disentanglement enabled by the present study highlights the need for a more nuanced understanding of what we mean when we say "embodied learning experiences." The three features we have proposed are only a starting point to finding the best ways to characterize a construct as complex as embodied learning. Whether embodiment should be categorized in types or considered on a continuum, ranging from purely abstract representations to somewhat embodied ones (e.g., observing actions) to strongly embodied ones (e.g., performing actions), varies depending on the theory and remains a subject of inquiry (e.g., Johnson-Glenberg & Megowan-Romanowicz, 2017). Additionally, it remains unclear whether the learning benefits of embodiment increase linearly with the levels of embodiment.

When there are learning benefits of embodiment, what are the mechanisms underlying the effect? The robustness and content of mental representations may be one potential mechanism for the benefits of embodied learning. This study not only narrowed in on the causal relationship between sensorimotor engagement and learning benefits but also revealed that sensorimotor engagement prompted learners to activate and use visuospatial mental representations, ultimately resulting in enhanced learning outcomes. Recognizing that sensorimotor engagement provides a distinct benefit has the potential to reshape instructional practices and curriculum development, moving beyond a narrow emphasis on visuospatial concreteness and expanding to incorporate deliberate engagement of the body and physical experiences in the world.

Constraints on Generality and the Importance of Replications

Given the novelty and importance of this study's findings, it is essential for the field to critically assess and replicate our findings to

Figure 7
Participants' Thinking Back to the Video by Condition



Note. WMO = Watch Moving Objects; WHMO = Watch Hands Moving Objects. See the online article for the color version of this figure.

validate and extend their applicability. Replication is crucial, as highlighted by Camerer et al. (2018), for confirming the robustness of these results and furthering the advancement of the field. Importantly, the participants in this study are students from a highly selective public university learning coding and statistics. Compared with the general student population in the United States, they are high achieving and have relatively high content knowledge. Future studies might want to replicate the present study using a similar design but involving students from more diverse educational backgrounds. Further research is also needed to explore the implications of sensorimotor engagement and perceptual concreteness in domains beyond coding and statistics.

In conclusion, this study highlights that students exposed to hands-on representations exhibited superior learning outcomes because of the unique contribution of sensorimotor engagement beyond perceptual concreteness and dynamic quality. By exposing the role of mental representations in embodied benefits to learning, this study sheds light on the processes underlying embodied learning. Finally, the practical implications for teaching are noteworthy. As educators face daily decisions regarding the integration of different types of representations and activities into their lessons, this study advocates for the inclusion of bodily movements, even in lessons that are already perceptually concrete.

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Appendix A

Pretest Questions

1. In your own words, explain what the shuffle() function does.
2. In your own words, explain when you would use the shuffle() function.
3. Which process do you think will create a more random result? Shuffling once or 10 times? Explain your answer.
4. Given a specific data set, would the number of observations in the condition variable (either experimental or control) increase, decrease, stay the same, or we cannot know until after we see the shuffled result after the condition column is shuffled?
5. Suppose you roll a dice four times, which is more likely to occur and why: See the numbers 6, 6, 6, and 6 in order; see the numbers 1, 2, 3, and 4 in order; or see the numbers 3, 4, 1, and 6 in order.

(*Appendices continue*)

Appendix B

Posttest Questions

Now, you will answer some questions based on the videos you have watched.

The laptop_data data set contains data from an experiment on the effect of laptops on student learning. Undergraduate students were randomly assigned to one of two conditions: view or no-view. In the view condition, students attended a 40-min lecture and were allowed to keep their laptops open. In the no-view condition, students attended the same lecture but were asked to keep their laptops closed. At the end of the lecture, students took a test on the lecture content and rated how distracted they felt during class.

There are three variables in this data set:

- Condition: The condition students were randomly assigned to either view or no-view.
- Total: The percentage of questions students answered correctly on the postlesson assessment.
- Distracted: Students' self-reported rating of how distracted they were in class.

1. What would you expect to happen to the value of *condition* for Row 1 if we ran the code below?

   laptop_data$condition ← shuffle(laptop_data$condition)

   ____.

2. What would you expect to happen to the value of condition for Row 1 if we instead ran the code below?

   laptop_data$total ← shuffle(laptop_data$total)

   ____.

3. We ran this code to create a table that shows the number of observations in each condition.

   tally(~ condition, data = laptop_data)

   ```
   condition
   no-view    view
        19      19
   ```

   Now, imagine we run this code:

   laptop_data$condition ← shuffle(laptop_data$condition)

   tally(~ condition, data = laptop_data)

   What would happen to the number of observations in the view condition?

   a. The number of observations would increase.

   b. The number of observations would stay the same.

   c. The number of observations would decrease.

   d. The number of observations would increase, decrease, or stay the same, but it is impossible to tell which.

4. Explain your answer to the previous question.

   ____.

We used the code below to create a faceted histogram showing the distribution of total in each condition. The vertical lines represent the mean total scores for the two conditions. Again, you can see that the participants in the no-view group scored higher, on average, than participants in the view group.

stats ← favstats(total ~ condition, data = laptop_data)

gf_dhistogram(~ total, data = laptop_data) %>%

gf_vline(xintercept = ~mean, data = stats, color = "blue") %>%

gf_facet_grid(condition ~.)

5. Sometimes groups differ just because of randomness. Do you think the group difference in the histogram above could be due to randomness?

   a. Yes, it must be due to randomness.

   b. No, it cannot be due to randomness.

   c. Maybe, need to further investigate.

6. Explain your answer to the previous question.

   ____.

7. If you wanted to investigate whether this difference could be due to randomness, what would you do? Please be as specific as possible in your response.

   ____.

8. Alex thinks she only needs to shuffle once to see if the difference between conditions on total could be due to randomness by comparing the shuffled result with the original data. Mary thinks she needs to shuffle more than once to be able to see if the difference could be due to randomness. Do you agree with Alex or Mary? Explain your answer.

   ____.

Take a look at each line of code below. For each line, *explain (a) what the code is doing* and *(b) why someone would write that code*.

laptop_data$condition.shuffle ← shuffle(laptop_data$condition)

9. What is this line of code doing?

   ____.

(*Appendices continue*)

10. Why would someone write this line of code?

____.

laptop_data$total.shuffle ← shuffle(laptop_data$total)

11. What is this line of code doing?

____.

12. Why would someone write this line of code?

____.

13. Look at the two examples of codes below. Examples 1 and 2 each produce a faceted histogram. In what ways would the two-faceted histograms be similar?

Example 1:

```
gf_dhistogram(~ distracted, data = laptop_data) %>%
gf_facet_grid(shuffle(condition) ~.)
```

Example 2:

```
gf_dhistogram(~ shuffle(distracted), data = laptop_data) %>%
gf_facet_grid(shuffle(condition) ~.)
```

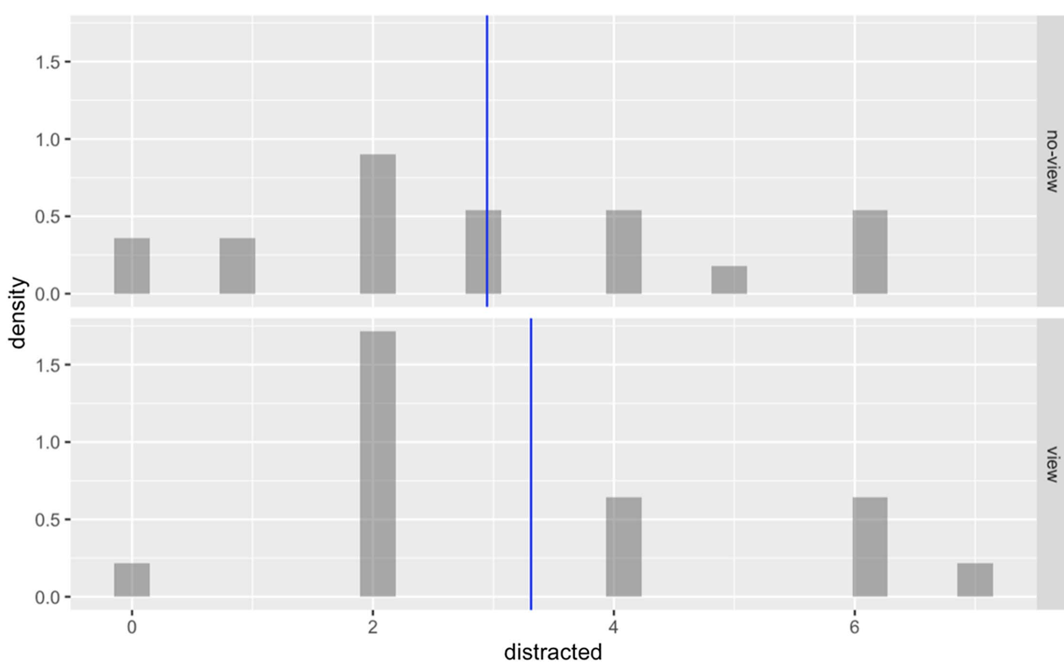
____.

14. Would one histogram be more random than the other one? If yes, which one is more random and why? If not, why not?

15. Would the two histograms look exactly the same or different? Explain your answer.

We ran this code to create the graph below. We added a line in each condition to represent the mean of *distracted* of that *condition*. Notice that the average *distracted* rating in the *no-view condition* is lower than the average *distracted* rating in the *view condition*.

```
stats ← favstats(distracted ~ condition, data = laptop_data)
gf_dhistogram(~ distracted, data = laptop_data) %>%
gf_vline(xintercept = ~mean, data = stats, color = "blue") %>%
gf_facet_grid(condition ~.)
```



Note. See the online article for the color version of this figure.

(*Appendices continue*)

16. Sometimes groups differ just because of randomness. Do you think the group difference in the histogram above could be due to randomness?

    a. Yes, it must be due to randomness.

    b. No, it cannot be due to randomness.

    c. Maybe, we need to further investigate.

17. Explain your answer to the previous question.

    ____.

18. If you run the code in the previous question again, do you think it would produce the same output?

    a. Yes

    b. No

    c. It is possible, but not likely.

19. Explain your answer to the previous question

    ____.

We revised the code from the previous question to create the graph below. We added a line to represent the mean of *distracted* for each *condition*. Notice that the average *distracted* rating in the *no-view condition* is higher than the average *distracted* rating in the *view condition*.

20. What caused the difference in the means represented in the graphs below?

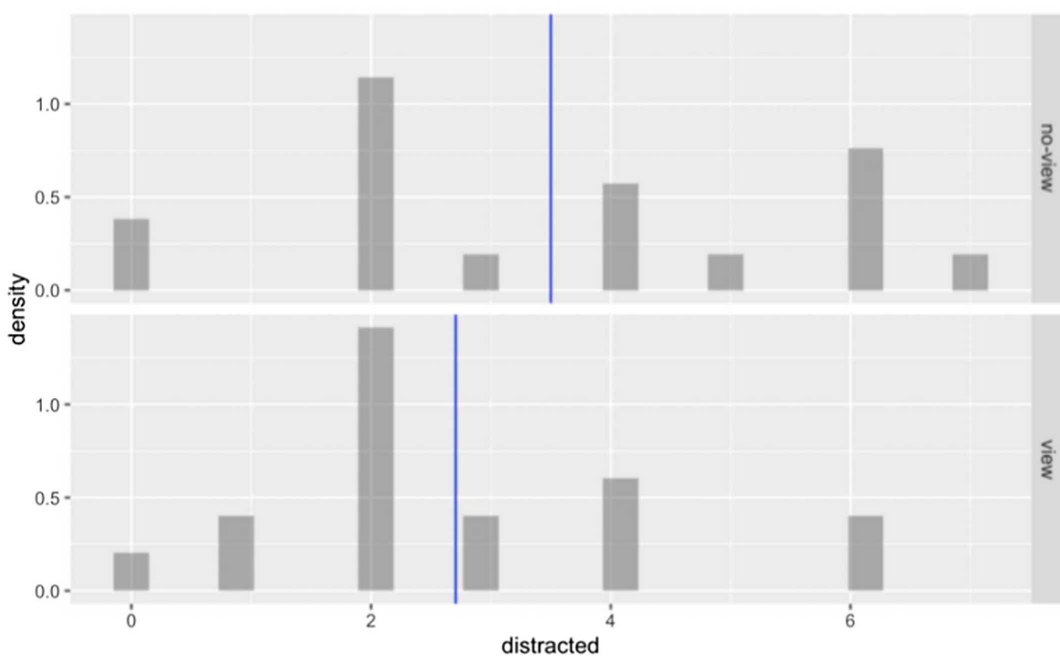
    laptop_data$condition.shuffle ← shuffle(laptop_data $condition)

    stats ← favstats(distracted ~ condition.shuffle, data = laptop_data)

    gf_dhistogram(~distracted, data = laptop_data) %>%

    gf_vline(xintercept = ~mean, data = stats, color = “blue”) %>%

    gf_facet_grid(condition.shuffle ~.)



Note. See the online article for the color version of this figure.

(*Appendices continue*)

____.

21. Sometimes groups differ just because of randomness. Do you think the group difference in the histogram above could be due to randomness?

    a. Yes, it must be due to randomness.

    b. No, it cannot be due to randomness.

    c. Maybe, need to further investigate.

22. Explain your answer to the previous question.

____.

23. If you run the code in the previous question again, do you think it would produce the same output?

    a. Yes

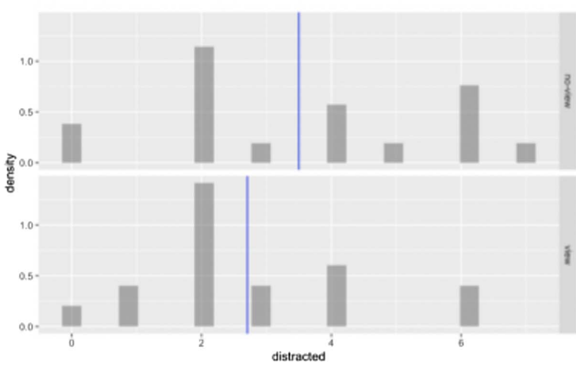
    b. No

    c. It is possible, but not likely.

24. Explain your answer to the previous question.

____.

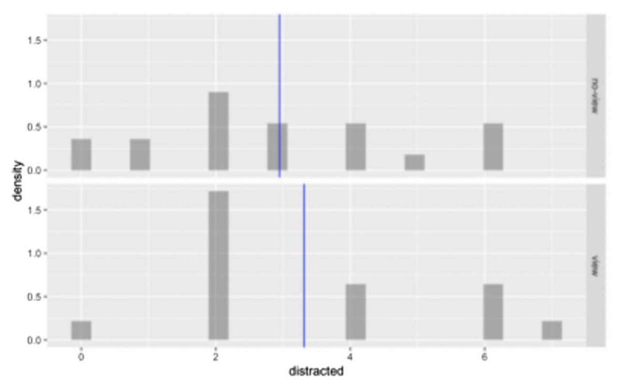
Look at the two-faceted histograms below, along with the code that produced each (the code might be a bit hard to read; feel free to zoom in to get a better read):




```
laptop_data$condition.shuffle <- shuffle(laptop_data$condition)

stats <- favstats(distracted ~ condition.shuffle, data = laptop_data)

gf_dhistogram(~distracted, data = laptop_data) %>%
gf_vline(xintercept = ~mean, data = stats, color = "blue") %>%
gf_facet_grid(condition.shuffle ~ .)
```




```
stats <- favstats(distracted ~ condition, data = laptop_data)

gf_dhistogram(~ distracted, data = laptop_data) %>%
gf_vline(xintercept = ~mean, data = stats, color = "blue") %>%
gf_facet_grid(condition ~ .)
```

Note. See the online article for the color version of this figure.

(*Appendices continue*)

25. Why do the two-faceted histograms look different?

    ____.

26. Based on what you have learned from these two histograms, do you think being able to view or not view a laptop during class (condition) affects students' self-reported rating of how distracted they were in class (as measured by distracted score on a postlesson assessment)? Why or why not?

    ____.

    Imagine we run the code below:

    laptop_data$distracted.shuffle ← shuffle(laptop_data$distracted)

    mean(laptop_data$distracted.shuffle)

    mean(laptop_data$distracted)

27. How would the mean of distracted.shuffle compare with the mean of distracted?

    a. The mean of distracted.shuffle would be larger.

    b. The mean of distracted.shuffle would be smaller.

    c. The two means would be the same.

    d. It is impossible to tell.

28. Explain your answer to the previous question.

    ____.

29. What will the distribution of the variable, distracted.-shuffle, look like compared with the distribution of the variable, distracted?

    a. Wider

    b. Narrower

    c. The same

    d. Not sure. It will vary randomly.

30. Explain your answer to the previous question.

    ____.

Imagine now we have a new variable, gender, so that we have four variables in the data set:

Gender: the gender students self-identify with

Condition: the condition students were randomly assigned to, either view or no-view

Total: the percentage of questions students answered correctly in their final exam

Distracted: students' self-reported rating of how distracted they were in class

31. If we now shuffle the column of gender, what would happen to the relationship between condition and total? Explain your answer.

    ____.

32. What do you think the purpose of the shuffle() function is?

    ____.

33. In your own words, explain when you would use the shuffle() function.

    ____.

Appendix C

Mediation Analysis for the Effect of Watching Moving Objects versus Watching Live-Coding on Posttest Performance Through Visual Recall

The indirect effect of watching moving objects without hands versus watching live coding on participants' posttest performance through participants' self-reported visual recall was not statistically significant (indirect effect = 0.29, 95% CI with 5,000 nonparametric bootstrapping [−0.20, 1.34], p = .16).

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