Disentangling Conceptual and Embodied Mechanisms for Learning with Virtual and Physical Representations

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Abstract. Blended educational technologies offer new opportunities for students to interact with physical representations. However, it is not always clear that physical representations yield higher learning gains than virtual ones. Separate lines of prior research yield competing hypotheses about how representation modes affect learning via mechanisms of conceptual salience, embodied schemas, embodied encoding, cognitive load, and physical engagement. To test which representation modes are most effective if they differ in terms of these mechanisms, we conducted a lab experiment on chemistry learning with 119 undergraduate students. We compared four versions of energy diagrams that varied the mode and the actions students used to manipulate the representation. We tested effects on students' learning of three concepts. Representations that induce helpful embodied schemas seem to enhance reproduction. Representations that allow for embodied encoding of haptic cues or makes concepts more salient seem to enhance transfer. Given the high costs of integrating physical representations into blended technologies, these findings may help developers focus on those learning experiences that could most be enhanced by physical interactions.

Keywords: Physical/Virtual modes · Conceptual salience · Embodied cognition

1 Introduction

Educational technologies increasingly blend virtual and physical experiences [1–3]. For instance, problem solving in many STEM domains involves virtual and physical representations [4–6]. Virtual representations appear on a screen and are manipulated via mouse or keyboard. For example, chemistry students may construct a virtual energy diagram by clicking to add arrows that show electrons (Fig. 1(left)). By contrast, physical representations are tangible objects that can be manipulated by hand. For example, students may construct a physical energy diagram by hanging arrows on a board (Fig. 1(right)). While much research has compared virtual vs physical representation modes [1, 2], different lines of research focus on different learning mechanisms [1, 7] and hence offer competing hypotheses about which representation mode is more effective. This poses a challenge to developers of blended technologies

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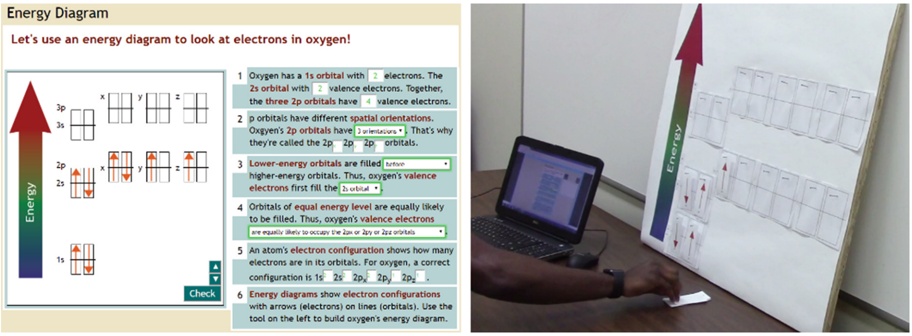
because they are left with little guidance about which learning experiences can be enhanced by physical interactions.



Energy Diagram

Let's use an energy diagram to look at electrons in oxygen!

1 Oxygen has a 1s orbital with 2 electrons. The 2s orbital with 2 valence electrons. Together, the three 2p orbitals have 4 valence electrons.

2 p orbitals have different spatial orientations. Oxgyen's 2p orbitals have 3 orientations. That's why they're called the $2p_x$ $2p_y$ $2p_z$ orbitals.

3 Lower-energy orbitals are filled before higher-energy orbitals. Thus, oxygen's valence electrons first fill the 2s orbital.

4 Orbitals of equal energy level are equally likely to be filled. Thus, oxygen's valence electrons are equally likely to occupy the 2px or 2py or 2pz orbitals.

5 An atom's electron configuration shows how many electrons are in its orbitals. For oxygen, a correct configuration is $1s^2$ $2s^2$ $2p_x^2$ $2p_y^1$ $2p_z^1$.

6 Energy diagrams show electron configurations with arrows (electrons) on lines (orbitals). Use the tool on the left to build oxygen's energy diagram.

Fig. 1. Energy diagram representations: virtual mode (left); physical mode (right).

To our knowledge, no study has systematically contrasted competing hypotheses about representation modes that emerge from theories on physical engagement, cognitive load, embodied encoding, embodied action schemas, and conceptual salience. We address this gap with an experiment that compared these mechanisms. Our findings advance theory by comparing the relative strength of these mechanisms. Our results yield practical advice for choosing representation modes for blended technologies.

2 Theoretical Background

2.1 Learning with Interactive Visual Representations

Visual representations are powerful tools because they illustrate concepts that are abstract or cannot be directly observed [8–10]. For example, electrons in atoms cannot be observed easily. Scientists often iteratively construct visuals to reflect on difficult and complex phenomena, and then continuously revise them based on their reflections [9]. This iterative representation-reflection process is a key part of STEM practices [11, 12].

Instructional problems with interactive visual representations often mimic iterative representation-reflection processes [2, 5]. Technologies can support such processes by prompting students to construct representations [13], to reflect on how they show concepts [14], and by giving adaptive feedback [15]. While such support is available for virtual and physical representations, it is unclear how to decide whether an instructional activity should include virtual or physical representations.

2.2 Virtual vs Physical Representation Modes

Our review of the literature on learning with virtual and physical representations identified five lines of research that have little overlap and yield competing hypotheses.

Physical Engagement. Proponents of hands-on activities argue that kinesthetic interactions with physical representations are more motivating than virtual ones [16, 17]. Further, physical experiences are concrete, easier to remember, and more connected to real contexts [18]. Hence, physical representations may generally be more effective.

Cognitive Load. In contrast, cognitive load theory recommends eliminating distracting features from the design of visual representations [19, 20]. Because physical representations have richer features that may be distracting, they may increase cognitive load. Further, cognitive load theory recommends designing instructional materials so that students do not have to split their attention between multiple sources of information [19, 20]. In blended educational technologies, students often split their attention between the screen and the physical representation (Fig. 1b). Hence, physical representations have a higher risk of inducing split attention effects. Indeed, studies show that advantages of virtual over physical representations are due to increased cognitive efficiency and attention to target concepts [21–23]. In sum, virtual representations may generally be more effective. However, a limitation of this research is that it has not tested cognitive load effects while systematically varying representation mode.

Embodied Encoding. One line of research on embodied learning proposes that physical experiences provide haptic cues that students can encode through touch, in addition to the visual sense that is engaged in virtual experiences [24, 25]. By experiencing the concepts through additional senses, interactions with physical representations allow for richer, explicit connections between the environment and the concepts [26, 27]. Indeed, embodied experiences that encode haptic cues can reduce cognitive load if students are aware of relations between the cues and the concept [27], which yields higher learning gains than virtual experiences [24, 28]. In sum, physical representations may be more effective if students can explicitly connect embodied experiences to the target concept.

Embodied Schemas. Another line of embodied research focuses on implicit processes that do not require students' awareness [29, 30]. Body actions implicitly affect cognition via metaphors [31, 32] that result from sensory-motor experiences of body movements in the world (e.g., upward movements invoke concepts related to increase [33]). When learning concepts, students form mental simulations that are grounded in embodied schemas [34, 35]. For example, when learning about concepts related to increase, students may mentally simulate upward movements. Indeed, moving the body in ways that are synergistic with mental simulations can enhance learning, even if students are not aware of this relation [36, 37]. Further, virtual representations that are manipulated by synergistic movements enhance learning [3, 34, 38]. In sum, it may not be the representation mode that affects learning. Rather, effects of representation modes may depend on whether they engage students in actions that activate synergistic embodied schemas for the concept. However, this research has not systemically compared modes.

Conceptual Salience. Research on conceptual salience builds on studies that have compared virtual vs physical representations [4, 7, 22]. This research suggests that the effectiveness of a representation does not depend on its mode but on its conceptual salience: the representation that affords an explicit experience of the concept is more effective [4, 7, 39]. For example, research on experimentation skills showed that physical representations make the concept of measurement errors more salient, but virtual representations make concepts of systematic variation more salient [1]. An experiment showed that representations that make the target concept more salient are more effective [1]. However, this research has not tested how effects of conceptual salience compare to effects of embodied schemas. Yet, as we show next, virtual and physical representations often have conflicting advantages for conceptual salience and embodied schemas.

3 Research Questions and Hypotheses

The different theories just reviewed describe mechanisms that may co-occur when students interact with realistic representations. Hence, we investigate: Which representation modes are most effective if they differ in terms of conceptual salience, embodied schemas, embodied encoding, cognitive load, and physical engagement? To this end, we tested hypotheses by the five theories about the effects of two virtual and two physical energy diagrams on learning of three chemistry concepts (see Table 1).

Table 1. Overview of competing hypotheses offered by five theories for the two versions of virtual (V_C/V_E) and physical (P_C/P_E) energy diagrams for each concept.

Theory	Concept A	Concept B	Concept C
Conceptual salience	P_C, V_C > V_E, P_E } Action effect	V_C, P_C > P_E, V_E } Action effect	NA } Null effect
Embodied schemas	V_E, P_E > P_C, V_C } Action effect	P_E, V_E > V_C, P_C } Action effect	NA } Null effect
Embodied encoding	P_C, P_E > V_C, V_E } Mode effect	NA } Null effect	NA } Null effect
Cognitive load	V_C, V_E > P_C, P_E } Mode effect	V_C, V_E > P_C, P_E } Mode effect	V_C, V_E > P_C, P_E } Mode effect
Physical engagement	P_C, P_E > V_C, V_E } Mode effect	P_C, P_E > V_C, V_E } Mode effect	P_C, P_E > V_C, V_E } Mode effect

3.1 Concept A: Electrons Randomly Fill Equal-Energy Orbitals

An atom's properties are related to its electrons' energy, which is determined by the electrons' positions in subatomic regions called orbitals. Energy diagrams sort orbitals by energy level (bottom to top). Electrons are more likely to fill low-energy orbitals, but they are equally likely to fill equal-energy orbitals. A common misconception is that electrons fill equal-energy orbitals from left to right, rather than randomly.

To construct physical energy diagram P_C, students move cards from the bottom up to put them in orbitals. P_C makes the *concept more salient* because planning the motor action involved in the vertical action requires attention to the height of the orbital when students put a card in an orbital. To construct virtual energy diagram V_E, students click to put electrons in orbitals, moving the mouse horizontally to click in equal-energy orbitals. V_E makes the *concept less salient* because the horizontal action does not require attention to the orbital's height. To test if these effects are due to the action rather than the mode, we created physical energy diagram P_E so that students hold the cards next to the orbitals and move their hands horizontally to put them in orbitals. This horizontal action makes the *concept less salient*. We created virtual energy diagram V_C so that it asks students to click a button at the bottom each time before moving the hand up to put arrows in orbitals. This vertical action makes the *concept more salient*.

V_E induces *beneficial embodied schemas* for this concept because horizontal action induce a metaphor of equality [33]. By contrast, P_C induces a *suboptimal embodied schema* for this concept because vertical action induce a metaphor of increase [33]. By contrast, the vertical action in V_C invokes a *suboptimal embodied schema*, and the horizontal action in P_E invokes a *beneficial embodied schema*.

Both P_C and P_E allow for *embodied encoding* of the height of equal-energy orbitals because they offer haptic cues through features such as the distance from the bottom of the diagram. Hence, they should be more effective than both V_C and V_E.

Both V_C and V_E yield *lower cognitive load* because they contain fewer distracting details than the physical diagrams and do not require split attention between screen and diagram. Hence, they should be more effective than both P_C and P_E.

Both P_C and P_E *engage students physically* and should yield a more motivating experience than both V_C and V_E. Hence, they should be more effective than V_C and V_E.

3.2 Concept B: Up and Down Spins Have Equal Energy

Electrons in the same orbital have opposite spins, shown by up and down arrows. Up and down spin are equally likely because they do not affect an electron's energy level. A common misconception is that an orbital's first electron always has an up spin.

In V_C, students click to add arrows. The first click adds an up arrow, the second click flips it to a down arrow. V_C makes the *concept more salient* because students have to purposefully flip the arrows to show that the spins are equally likely, which requires explicit attention. In P_E, students pick up cards from a stack that is not sorted, so that up and down arrows are random. P_E makes the *concept less salient* because the spin is already random and does not require attention to a related action. To test if these effects are due to the action rather than the mode, we modified the other version of the diagrams to flip the hypotheses: In V_E, the first click creates an arrow with random spin. The second click flips it. This requires no attention to randomness and makes the *concept less salient*. For P_C, the card stack was sorted so that all cards had an up arrow. Now, students have to purposefully flip the cards, which makes the *concept more salient*.

V_E and P_E induce a *beneficial embodied schema* because the random spin means that it takes the same number of actions and hence the same amount of effort to show up or down spin. V_C and P_C induce a *suboptimal embodied schema* because the fixed spin means it takes two clicks and hence more effort to show a down spin than an up spin.

P_C and P_E do not allow for *embodied encoding* as they do not have haptic cues for spin states. Hence, this hypothesis does not predict an effect of mode. V_C and V_E yield *lower cognitive load*, whereas both P_C and P_E yield *more physical engagement*.

3.3 Concept C: Spins Are Rotational Movements

Electron spins are rotational movements of electrons about their own axis that create a small electromagnetic field with a moment that points up or down. A common misconception is that spins are an electron's directional movement towards or away from the nucleus rather than the rotation around their own axes.

The energy diagram does not explicitly show electron rotations. Hence, no representation makes this *concept salient*. The energy diagram does not require rotational movements. Hence, no representation invokes related *embodied schemas*. Also, no representation offers *embodied encoding* of rotational movements.

However, V_C and V_E yield *lower cognitive load*, but P_C and P_E yield more *physical engagement*. Hence, including this concept allows us to estimate the impact of cognitive load and physical engagement mechanisms on students' learning.

4 Methods

4.1 Participants

We recruited 120 undergraduates from a large university in the US Midwest via email, flyers, and posters for monetary compensation. A screening ensured they had not taken chemistry since high school. One student was excluded because a pretest showed considerable prior knowledge of the target concepts, yielding a sample of $N = 119$.

4.2 Experimental Design

Students were randomly assigned to one of four conditions that varied (1) representation mode and (2) actions required to manipulate the diagrams (see Table 2).

Table 2. Experimental conditions with number of participants (n) that vary representation mode and actions: both versions of virtual (V_C/V_E) and physical (P_C/P_E) energy diagrams.

	Conceptually salient action		Embodied action	
Virtual mode	V_C: $n = 30$	Concept A – Vertical	V_E: $n = 30$	Concept A – Horizontal
		Concept B – Random		Concept B – Fixed
		Concept C – No action		Concept C – No action
Physical mode	P_C: $n = 29$	Concept A – Vertical	P_E: $n = 30$	Concept A – Horizontal
		Concept B – Fixed		Concept B – Random
		Concept C – No action		Concept C – No action

4.3 Materials

Intelligent Tutoring System (ITS). Students worked with an ITS for undergraduate chemistry that has proven effective in prior research [40]. The ITS supports iterative representation-reflection practices by asking students to create energy diagrams to illustrate target concepts. Further, it prompts students to reflect on how the diagrams show the concepts by completing fill-in-the-gap sentences. If students make a mistake on a step, the ITS gives adaptive feedback that targets common misconceptions.

Students worked on eight problems. Each covered all three concepts and asked students to build an energy diagram of an atom. For the virtual conditions, V_C or V_E were embedded in the ITS (Fig. 1a). The ITS gave instruction and feedback on all steps. For the physical conditions, P_C or P_E was placed next to the screen (Fig. 1b). The experimenter gave feedback on the diagrams. The ITS gave all other instruction and feedback.

Assessments. We assessed students' learning of each of the three concepts with a pretest that they completed prior to instruction, an immediate posttest given immediately after instruction, and a delayed posttest given 3–6 days after instruction. For each concept, we assessed reproduction (i.e., recall of information given in instruction) and transfer (i.e., the ability to apply the information to problems not covered in the ITS). As the instruction in the ITS was self-paced, we also measured instructional time.

4.4 Procedure

The experiment involved two sessions in a research lab, 3–6 days apart. In session 1, students completed the pretest, the instruction according to their experimental condition, and the immediate posttest. In session 2, students took the delayed posttest.

5 Results

5.1 Prior Checks

First, we checked for learning gains on each concept using repeated measures ANOVAs with pretest, immediate, and delayed posttest as dependent measures. Results showed significant learning gains for all concepts (*p*s < .01) with effect sizes ranging from p. $\eta^2 = .11$ to p. $\eta^2 = .59$. Second, a multivariate ANOVA showed no significant differences between conditions on any of the pretest measures (*p*s > .10). However, mode affected instructional time, such that physical representations took significantly longer, $F(1, 118) = 14.45$, $p < .01$, p. $\eta^2 = .11$. Because instructional time correlated with the learning outcome measures ($r = -.21$ to $-.25$), we included it as covariate in the analyses below.

5.2 Effects of Representation Mode and Movement

We used a repeated measures ANCOVA model to test the hypotheses in Table 1. The model included mode and action as independent factors, pretest scores and instructional time as covariates, and immediate and delayed posttest scores as dependent measures. Figure 2 shows a summary of the results.

For *reproduction of Concept A*, results showed a main effect of action, *F*(1, 113) = 4.94, $p = .03$, p. $\eta^2 = .04$, favoring horizontal over vertical actions. This effect aligns with the embodied schema hypothesis. There was no main effect of mode, *F*(1, 113) = 1.65, $p = .20$, nor an interaction effect ($F < 1$).

For *transfer of Concept A*, there was no significant main effect of action, *F*(1, 113) = 1.14, $p = .29$. A main effect of mode, *F*(1, 113) = 6.37, $p = .01$, p. $\eta^2 = .05$, favored physical over virtual representations. This effect aligns with the embodied encoding and the physical engagement hypotheses. There was no interaction effect ($F < 1$).

For *reproduction of Concept B*, there was a significant main effect of action, *F*(1, 113) = 5.30, $p = .02$, p. $\eta^2 = .05$, favoring a random number of actions over a fixed number of actions. This aligns with the embodied schema hypothesis. There was no main effect of mode, *F*(1, 113) = 1.64, $p = .20$, nor an interaction effect ($F < 1$).

For *transfer of Concept B*, there was a significant effect main of action, *F*(1, 113) = 4.40, $p = .04$, p. $\eta^2 = .04$, such that a fixed number of actions yielded higher gains than a random number of actions. This effect aligns with the conceptual salience hypothesis. There was no effect of mode, *F*(1, 113) = 2.60, $p = .11$, or an interaction effect ($F < 1$).

For *reproduction and transfer of Concept C*, no effects were significant (*F*s < 1).

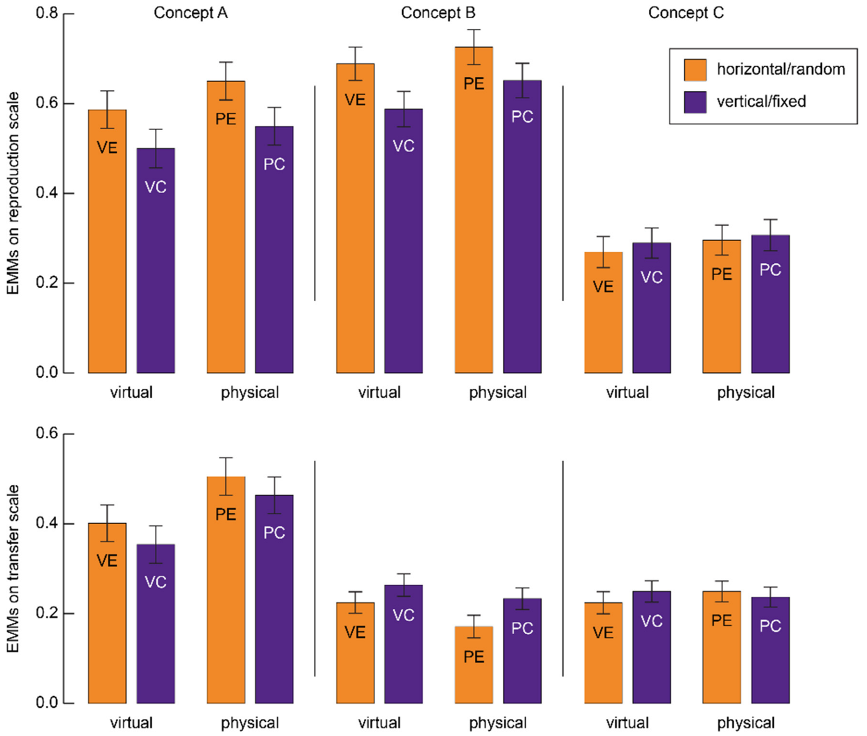


Fig. 2. Estimated marginal means (EMMs) for reproduction and transfer averaged across immediate and delayed posttests, controlling for pretest and instructional time.

6 Discussion and Conclusion

While much prior research has compared virtual vs physical representations, separate lines of research have focused on different mechanisms that yield competing hypotheses for their effectiveness. This leaves developers with little guidance for choosing appropriate representation modes. To address this issue, we investigated which representation modes are most effective if they differ in terms of conceptual salience, embodied schemas, embodied encoding, cognitive load, and physical engagement. Because prior research provides evidence for these mechanisms, it seems likely that they co-occur when students interact with realistic representations. Hence, our goal was not to confirm or refute the theories, but rather to examine which mechanism prevails when students learn abstract concepts. To our knowledge, our study is the first to integrate these theories by systematically comparing effects of representation mode and actions.

Altogether, for *reproduction of knowledge*, our results suggest that the *embodied schema mechanism* outweighs the other mechanisms. The embodied schema hypothesis predicted an advantage of horizontal and random actions for Concepts A and B, and both effects were confirmed for the reproduction scales of these concepts. Hence, representations that are manipulated via body actions that induce beneficial embodied schemas seem to enhance students' ability to recall information covered in instruction.

By contrast, for *transfer of knowledge*, our results suggest that the *embodied encoding mechanism* outweighs the other mechanisms if it applies. The embodied encoding hypothesis predicted an advantage of both physical representations only for Concept A, and this effect was confirmed for the transfer scale of this concept. Hence, physical representations that offer haptic cues for the target concept seem to enhance students' ability to apply their knowledge to novel situations. However, if the representation does not contain haptic cues for the concept, as in the case of Concept B, the *conceptual salience mechanism* appears to outweigh the other mechanisms. This finding suggests that transfer is more affected by conceptual salience than by embodied schemas.

The complexity of embodied schemas, embodied encoding, and conceptual salience mechanisms may explain differences between reproduction and transfer. The embodied schema mechanism describes a simple, implicit process that does not require awareness [36]. Information recall involves simple knowledge structures that have one-on-one question-response mappings [41]. Thus, representations that engage students in simple embodied mechanisms seem to enhance learning of simple knowledge structures.

By contrast, both the conceptual salience and the embodied encoding mechanisms describe complex, explicit learning processes. The conceptual salience mechanism describes how students map visual cues of representations to concepts. Arguably, the embodied encoding mechanism is yet more complex because it describes how students connect haptic *and* visual cues to concepts. Because transfer of knowledge requires many-to-many mappings between question and response, it assesses complex knowledge structures [41]. Thus, representations that engage students in complex mechanisms seem to enhance learning of complex knowledge structures, especially when the representations offer opportunities for embodied encoding of haptic cues.

We found no evidence for the *cognitive load* and *physical engagement* hypotheses. In light of the null effects for Concept C, which were predicted by the other three hypotheses, we can conclude that cognitive load and physical engagement mechanisms either were negligible or cancelled each other out. This also allows us to rule out that cognitive load or physical engagement could have distorted the effects for the other three mechanisms on Concepts A and B. In fact, the only result in line with the physical engagement hypothesis was the advantage of physical representations on transfer of Concept A, but this effect was also predicted by the embodied encoding hypothesis.

In sum, our study suggests that developers may prioritize embodied schema mechanisms if the goal is to enhance reproduction. To enhance transfer, they may choose a physical representation if it offers haptic cues for the concept. Otherwise, they may choose the representation that makes the concept more salient. These considerations should outweigh considerations of cognitive load or physical engagement. Given that the integration of physical representations into educational technologies is costly, these findings may help developers of blended technologies focus on learning experiences where physical representations have the highest impact on learning outcomes.

Our results should be interpreted in light of several limitations. First, we focused on particular concepts, representations, and population. Future research should test if our findings generalize more broadly. Second, while we purposefully selected concepts for which the five theories made conflicting predictions, we did not test all possible conflicts. For example, future research should test cases where conceptual salience and embodied schemas align but conflict with embodied encoding. Third, our intervention was relatively short. Over longer learning periods, it is possible that sequence effects emerge, such that one mechanism prevails at first and another mechanism later. Specifically, we found that embodied schema mechanisms enhance reproduction but embodied encoding and conceptual salience mechanisms enhance transfer. Given that instruction often moves from simple to complex concepts, it is possible that embodied schema mechanisms should be prioritized early and embodied encoding and conceptual salience mechanisms later. Testing such effects may yield new insights into embodied grounding of conceptual knowledge [42] and may provide insights into the concrete-abstract debate [18], which has not accounted for embodied mechanisms.

In conclusion, blended educational technologies offer new opportunities to combine virtual and physical modes, for example, by integrating physical representations into ITSs. However, physical representations are not always more effective than virtual ones. Our study reveals the relative strength and scope of multiple mechanisms that have been examined by thus far separate lines of research even though they likely co-occur when students learn with representations. Further, our results may provide practical advice for developers to choose representation modes for blended technologies.

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