# Board 77: Visual Representations Guide Students' Use of Conceptual Knowledge and Problem-solving Strategies

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## Introduction

One of the key findings from the expert-novice transition literature is that experts and novices interpret information from visual representations in different ways [1]. This suggests that what is meaningful to each of these groups is different, and it is so ingrained that experts are able to notice differences between two diagrams shown for 200 ms but only if the differences would change the underlying science [2]. These findings also suggest that the structure of students' conceptual knowledge and how they express it is grounded in visual representations. Some researchers have proposed that one of the reasons students struggle to learn science and engineering concepts, and thus gain expertise, is because students frequently struggle to access information encoded within visual representations [3]–[6] or prioritize what features to focus on [7]. The goal of our work then was to explore how novices engage visual representations in engineering.

Prior research in this area generally examines how well students reason with different types of representations [8] or how different types of features within a specific type of representation influences students' performance on a task. The former has been extensively studied in the math, engineering, and physics education literatures while the latter is relatively unexplored in engineering where students are expected to dynamically modify and create new representations as part of the task. Research in this relatively unexplored area has culminated in a theoretical framework that asserts that successfully comprehending information from visual representations depends on the interplay between students' domain knowledge, the nature of the task, and the perceptual salience of task-relevant information [9]. Studies in multiple domains seem to confirm that the design of a representation can affect how students use representations during problem solving, what information students access, performance on transfer tests, or how students learn the concepts encoded in those representations [5], [10]–[14].

While useful, Hegarty's theoretical framework does not address contexts in which students are dynamically modifying the visual representation or are engaged in more complicated problem-solving tasks that require students to coordinate multiple representations. These processes are cognitively different from those that the framework is built from so it is unlikely that the same theoretical framework can be applied to analyze the contexts we are interested in. Thus, we used Hegarty's theoretical framework to design our study, but we chose a data-driven analysis method to explore how novices engage with visual representations in problem-solving tasks. Additionally, prior studies have yet to explore nuances across disciplines, which could have implications for the kind of pedagogical suggestions this work can make.

To fill these gaps in the literature, we conducted think-aloud interviews of students solving problems. We chose the tasks such that the students were expected to use and generate similar kinds of representations and the representations used in the tasks both contained discipline-specific notational conventions. For example, shear force is denoted as a straight arrow with the letter V in statics and the state in a state diagram is denoted a circle labeled with a state name in digital logic.

## Literature Review

Our work lies at the intersection of the visual representations and conceptual understanding literatures. To limit the scope of this literature review, we summarize relevant findings from these two fields.

### Visual Representations

Prior research in how students engage with visual representations has focused on two types of research questions. The first type of questions asked are: “What types of representations hinder students’ performance” [15]–[18]. The second type of questions asked are: “What is it about a type of representation that hinders students’ performance” [19]–[21]. The former asks about representation type, which we call the macro level view of representations while the later asks about the context of particular types of representations, which we call the micro-level view of representations. While the macro-level view of representations has been extensively studied [16], [17], the micro-level view is relatively unexplored. Thus, in this work, we focused on the micro-level effects of representations on students’ performance in accessing and using their conceptual knowledge. Because we focus on the micro-level view, we will summarize findings from that area only.

In her theoretical framework, Hegarty posits that learning from representations is “an active process of knowledge construction rather than a passive process of internalizing the information presented in an external display.” [22] This process requires people to coordinate information from the representation’s features with their domain knowledge and goals to create a mental model of the concept that the representation encodes.

Based on Hegarty’s work [22], people pay attention to and use the features of a representation depending on how perceptually salient the feature is to them. The perceptual salience of a feature depends on both the brain’s visual system and a person’s level of domain knowledge. Features that have high contrast with their background either by color, shape or motion are readily noticed by visual systems. We call these types of features intrinsically perceptually salient. Examples of these types of features include a lone red dot on a white map or an arrow to indicate what someone should pay attention to [23].

Without domain knowledge to guide them, novices will naturally pay attention to and talk about the intrinsically perceptually salient features regardless of whether they are relevant to the task [24], [25]. For example, one study by Montfort, Herman, Streveler, and Brown [24] showed engineering students often justified there were no shear forces acting on a beam because there were no “vertical forces”. When shown the same beam but rotated to be horizontal instead of vertical, the same students said there would be shear forces because there were now vertical forces. Given how experts and novices justify their answers based on what is perceptually salient to them, there is a need for studies to investigate what types of features novices find perceptually salient and which they do not in visual representations.

### Context-dependence of conceptual understanding

In Hegarty’s theoretical framework [22], students integrate both verbal and visuospatial information into a mental model of the concepts encoded within the representation. These findings of the context-dependent nature of comprehension align well with the knowledge in pieces perspective of conceptual change, which posits that students' conceptual knowledge is a collection of pieces that are cued depending on the context of the problem. While there is still considerable debate about whether conceptual knowledge is in pieces or more monolithic [2], [7], [26], [27], we based our project on the knowledge-in-pieces perspective based on its alignment with prior findings in the micro-level view of representations.

The context-dependent nature of cognition has been identified in several studies within a variety of engineering disciplines [28]–[30]. For example, in Herman, Loui, Kaczmarczyk, & Zilles [59], students solved isomorphic logic problems, one time by completing a truth table, one time by selecting images that corresponded to the rows of that truth table, and one time by directly deriving a Boolean expression that expressed the same information as the truth table. Students were often inconsistent in how they revealed their conceptual understanding across these different modalities. While many studies in the conceptual understanding literature have studied the structure of students' conceptual knowledge, these studies focus on introductory courses on mechanics [31], astronomy [6], heat [32] and circuits [33] with only a small number of recent studies in more advanced engineering topics such as shear stress [24], [34], motion in dynamic systems [35] and drift/diffusion [27].

Based on the gaps we identified in the literature, the project's main contributions are to 1) understand how the context of engineering tasks and the visual representations within the task hinder students' ability to learn engineering concepts and apply them during their problem solving and 2) leverage cross-disciplinary analysis so we can move beyond specific mistakes and instead identify potential causes that encourage students to make those mistakes despite direct instruction, which has been identified as a need in prior cross-disciplinary studies [28].

**Methods**

Consistent with the views of Strauss and Corbin [36], we believe interpretation of phenomena across multiple observations and multiple disciplines with researchers of different backgrounds leads to a description that comes close to describing objective reality. Because we were interested in describing the how and why of students' reasoning with visual representations [37], we chose to take a qualitative approach. We consequently use the Constant Comparative Method, a method derived from Strass & Corbin's methodologies. This method critiques, extends, or supports data and emerging theory from prior studies through constant comparison with new data [38]. We also use multiple researchers who work together, challenging each other's interpretations and biases. In our prior studies, the comparisons were within each individual data set [29], [39], [40]. In this study, we conducted comparisons of the themes across each dataset to describe ways in which features of visual representations hinder students' ability to learn engineering concepts.

We used novice-led analysis to further challenge each researcher's biases [28]. The first author began as a novice in qualitative data analysis but had expertise in teaching statics while the second author was an expert in digital logic and had experience with qualitative data analysis. This novice-led approach helps guard the researchers from expert blindspot [41], [42] or inappropriately projecting nascent theories about how students learn that have been gained from informally observing students in the classroom.

**Data Collection**

We selected two sets of problems for the interview protocols: 1) creating shear force and bending moment (SFBM) diagrams for a beam given by its schematic and 2) creating a sequential circuit diagram when given a state diagram for a finite state machine (FSM).

In both the statics and digital logic studies, we conducted 1-hour think-aloud interviews where students sketched either SFBM diagrams (statics) or sequential circuits (digital logic). The two protocols were developed simultaneously to answer similar research questions and with the intention of eventually combining findings from the two datasets. The statics interviews had 15 participants (13 male and 2 female), and the digital logic interviews had 24 participants (17 male and 7 female). For details of the specifics of the participant sampling and data collection, please refer to the prior publications [29], [40]. All participants were paid for their participation and gave written consent to be interviewed under IRB approval (Midwestern University). The videos were then imported into MaxQDA for qualitative analysis.

**Data Analysis**

In prior studies, we used the Constant Comparative Method to identify themes in the way that students interacted with visual representations in statics[40] and digital logic [29]. We generated these themes by making comparisons across different granularities of analysis. These granularities used increasingly smaller units of analysis respectively: each dataset, each problem solved, each new representation drawn, each statement made, or component of a representation drawn. We provide the name of each granularity in bold followed by the unit of analysis, in parenthesis, before describing what types of codes were generated in that granularity.

**Domain (each dataset)** includes the themes generated in the prior studies, which were constructed by comparing across the four smaller granularities of analysis. For example, we compared the findings that supported the creation of the digital logic theme (Reliance on Origin + Transition=Destination heuristic) and the statics theme (Reliance on Object Translation heuristic). These two themes suggested that students generally used the same heuristics within a domain and that these heuristics were generally useful, but they failed students. Comparing when and how these heuristics failed, we identified new domain-general patterns (e.g., theme 1: students conflate concepts that share perceptual features) that did not rely on domain-specific heuristics.

**Problem (each problem solved)** includes a description of the overall strategies participants used when solving each problem. For example, did the student analyze external and internal equilibrium or just external equilibrium? Did the student analyze the output separately from analyzing next-states?

**Translation (each new representation drawn)** includes when a student uses information from one representation to sketch another. This granularity identifies which translations students performed so we could compare what knowledge students used or features they noticed during each translation. For example, a student uses a state diagram to construct a circuit diagram, or a student uses a free body diagram and algebraic expressions to construct their shear force diagram.

**Statement (each statement or component of a representation)** includes correct and incorrect statements students made while sketching, their auditory explanation of their sketches, or the contents of what they sketched. We use these statements to document what students are paying attention to and how they are using that information. For example, a student might use knowledge of specific joint types to determine start and end points for their shear force diagrams. Alternatively, a student might refer to the output of the circuit (O) as next state (Q+) revealing a conflation of the two ideas.

We identified the emergent themes across the two datasets in two stages. First, we compared the themes generated from the prior studies to each other to determine which themes were domain-general and which were domain-specific. Second, we compared each theme's supporting evidence (constructed from comparisons amongst the three other granularities) to find similar trends in how each theme emerged from the data. Similar trends in each theme's supporting evidence were grouped and renamed to describe the trend, which resulted in three themes.

### Limitations

While the goal of our work is to identify the patterns and nuances in students' interactions with visual representations across engineering disciplines, our study only examines two disciplines due to the intensely time-consuming nature of this analysis. However, because students from a majority of engineering majors take either statics or digital logic and these two courses explore dramatically different types of engineering (i.e., analysis of physical systems based on laws of nature vs. design of systems based on man-made conventions), we believe that the comparisons of these two datasets represent a vital first step in identifying ways in which visual representations hinder students' ability to learn engineering concepts. Future studies in more disciplines will be needed to further refine the findings from this project.

## Results

### Theme 1: students conflate concepts that share perceptual features (perceptually similar concepts)

Students in both the statics and digital logic datasets commonly conflated concepts. We coded a conflation when students either consistently used the wrong word to describe the concept or their drawings indicated they conflated the concept. Theme 1 describes how students conflated concepts when the concepts shared features and did not conflate concepts when features were distinct.

### Statics example of a conflation

Sixty-six percent of students who conflated shear force with external forces demonstrated this conflation by sketching a profile of the external forces acting on the beam as their shear force diagram (see Figure 1). First, notice the red triangles. In this region, there is a 20 N point load pointing in the negative y-direction (Figure 1). In the same region, the student draws a line at -20 N on their shear force diagram (Figure 1). Next, notice the region indicated by the green circle. In this region, there are no arrows indicating applied loads. The student drew a line at 0 N on their shear force diagram in this region. Finally, notice the blue squares. In this region, there is a distributed load of 1 N/m pointing in the negative y-direction, resulting in a cumulative 10 N. In this region, the student drew a line at -10 N on their shear force diagram.

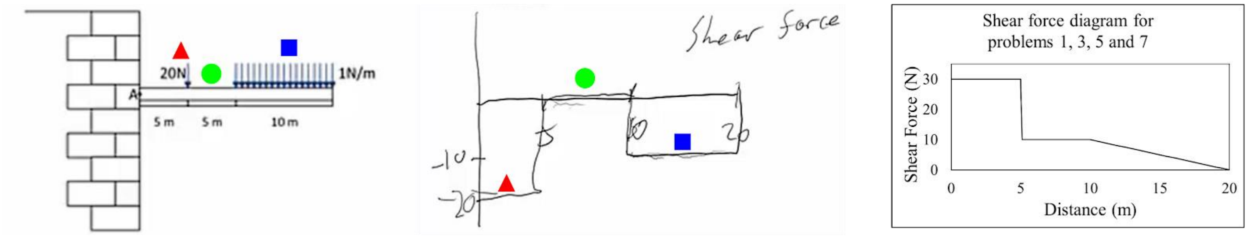


Figure 1: Shear force diagram from a student showing that each segment of the shear force diagram matches the magnitude and direction of applied forces in each segment.

**Digital logic example of a conflation**

In a circuit diagram, state should be stored inside the system with flip-flops while inputs are provided from outside the system and are typically drawn on the far left of the diagram. Next-state is calculated from the state and input and is drawn as entering the left side of the flip-flops while output is calculated solely from the state and is drawn on the far right of the diagram. When students maintained a conceptual distinction between these two concepts, they generally began their drawings by first drawing their flip-flops to store their state (See first frame of Figure 2) and then drew inputs on the far left and then used next-state logic to calculate their next state (see middle frame of Figure 2). Similarly, when students maintained a conceptual distinction of next-state and output, their drawings separated next-state logic from their outputs on the far right (see last frame of Figure 2).

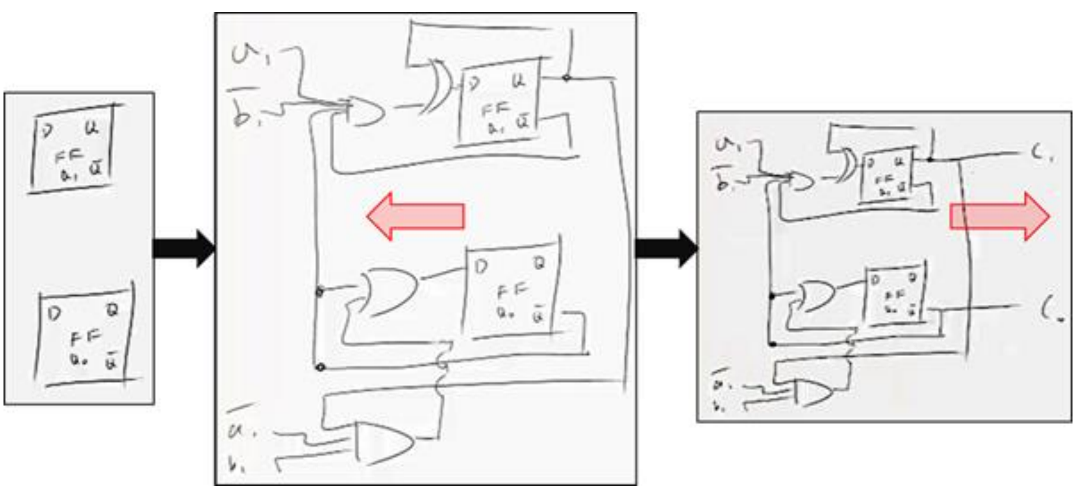

Figure 2: Student draws flip-flops first and then added inputs and next-state logic and then outputs. This student maintained critical conceptual distinctions.

When students conflated state with input, they visually revealed this conflation by failing to draw flip-flops and drawing both state and input variables as inputs on the left of their circuit diagram (see first and middle frames of Figure 3). Drawing state in this way reveals that the student, for a time, conceptualized state as coming from outside the system rather than inside. When students conflated next-state with outputs, they drew both next-state and outputs on the far right of their circuit diagram (see last frame of Figure 3). These drawings revealed that students treated output as a function of state and input rather than as a function only of state, conflating the next-state and output.

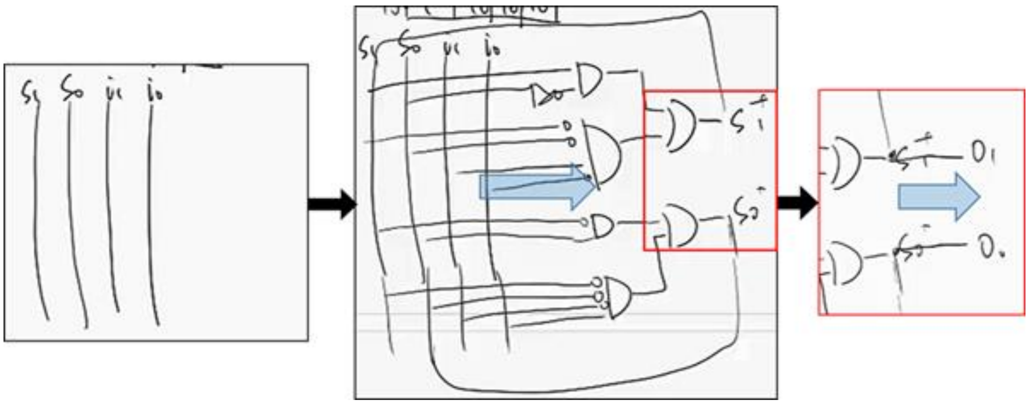

Figure 3: Student draws state and input as inputs (conflation) and next-state and output as outputs (conflation) after solving a Karnaugh map. Student fails to draw flip-flops. An example of a correct solution can be seen in Figure 2.

**Comparing and contrasting the observations across the datasets**

We observed that when students in both datasets conflated two concepts, the concepts shared similar features in the visual representation. Some concepts shared more similar features than distinct features. For example, bending moment and external moment share both symbolic and arrow conventions while shear force and external force share only arrow conventions. The more similar features the two concepts shared, the more students we saw conflate them. For example, sixty percent of statics students conflated shear force with external force while eighty-seven percent of statics students conflated the concept of bending moment with external moment. We observed a similar trend in conflations within the digital logic dataset. Figures 4 and 5 show how concepts share perceptually similar features.

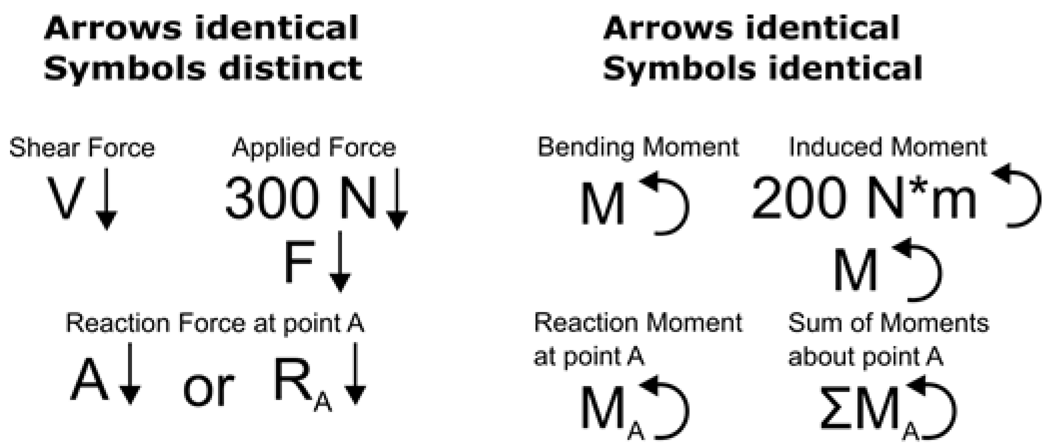


Figure 4: Symbol and arrow conventions for forces and moments. Forces have distinct symbols but identical arrow types while moments have identical symbols and arrow types.

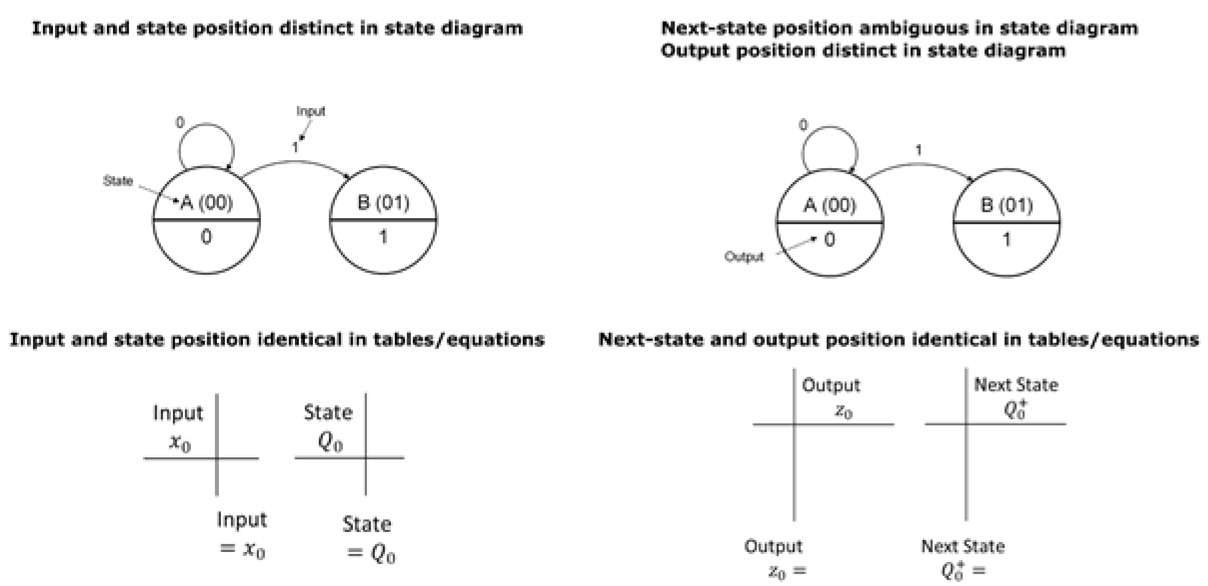


Figure 5: Symbol and variable conventions for state, input, next-state, and output. State, input, next-state, and output have appearance matches in tables and equations, but state and input are distinct in state diagrams.

**Theme 2: students coordinate multiple representations during translations when the starting representation is informationally incomplete (informationally incomplete representations)**

From analyzing the translation granularity codes across the two datasets, we observed qualitative differences in how each discipline translates representations during problem solving. Theme 2 describes how differences in whether a representation contains all the task-relevant information results in students coordinating multiple representations.

Both digital logic students and statics students deviated from how experts describe solving problems (i.e., 4 translations), but statics students deviated more than the digital logic students. Statics students performed 5.9 translations per problem on average when sketching their SFBM diagrams while digital logic students performed 4.7 translations per problem on average when sketching sequential circuits. Additionally, we coded 40 unique types of translations for the statics students whereas we only coded 18 unique types of translations for the digital logic students.

Bigger qualitative differences emerged from the data when we looked at the types of translations present in both codebooks. In the statics codebook we found more of what we call hybrid translations. We define a hybrid translation as whenever students coordinated information from multiple representations to create a new representation. For example, when statics students used information from the schematic and their shear force diagram to construct their bending moment diagram. We coded a translation as a hybrid translation when students verbalized using information from multiple representations or when they scrolled their screen between two representations when translating to a new representation. Hybrid translations occurred more frequently in the statics dataset as compared to the digital logic data set with both in the percentage of unique translation codes in the codebook (42% of translation codes vs. 4% of translation codes respectively ) and percentage of total instances of translation codes (20% of translations vs. 1% of translations respectively).

## Discussion

### Implications for the debate on the context-dependence nature of knowledge

As mentioned in the literature review, there is a debate over the structure of students' knowledge in engineering and how to change that structure from novice-like to expert-like [2], [4], [7]. Findings from this project suggest that students apply their knowledge differently depending on the context of the problem, which supports the knowledge in pieces perspective [7] and corroborates findings from other engineering education studies that show context-dependence in students' knowledge [29].

In the knowledge-in-pieces perspective, diSessa claims that students' knowledge structures are broken into pieces that are cued depending on the context. From this work, we believe that Theme 1 could represent one such piece of knowledge that students have about how to interpret information from visual representations (i.e., "two objects that look the same are the same"). If two concepts are represented using similar features, this could lead to students incorrectly categorizing two concepts as the same thing, hindering them from forming nuanced distinctions. For example, in statics, bending moment and applied moment are both moments, but they are distinct because applied moments are external to a system and the bending moment is a material's response to external stimuli. In our study, students failed to make this distinction and commonly referred to bending moment as "force times distance", which suggests students treat these two types of moments as fundamentally the same concept.

Thus, future studies on conceptual understanding should consider the context of the representation when analyzing student responses during problem solving, specifically how disciplinary conventions within visual representations might contribute to conflations. For example, a recent study by Brown et al [34] found that students consistently associated the concept of shear force with vertical forces in visual representations. As an alternative to Vosniadou's framework theory, our findings suggest that a knowledge-in-pieces perspective can equally explain this result. Findings from our prior statics study [40] similarly showed that students who could identify shear forces for horizontal beams with vertical loading struggled to identify these forces for vertical beams that were isometrically loaded with horizontally loads.

This struggle may not be grounded so much in a robust misconception but rather the perceptual features of the visual representations that may be prompting and reinforcing this incorrect reasoning. While studying only two courses is not sufficient for claims of generalizability, the fact that we see this context-dependence across very different engineering disciplines suggests this could be a pervasive problem in engineering education.

One weakness of the knowledge in pieces literature is that it so far has not presented a pedagogical structure through which instructors could improve students' learning. In contrast, naïve theory and ontological research use domain-general approaches such as cognitive conflict and ontological training respectively. Additionally, knowledge in pieces research tends to be domain-specific, or even concept-specific, and has been criticized for its lack of a domain-general perspective [43]. This lack of domain-general understanding has made it difficult to develop instructional practices or changes to visual representations that could help students across contexts. This project is among the first to our knowledge that uses the knowledge in pieces perspective across multiple domains simultaneously, enabling us to make domain-general pedagogical suggestions.

## Preliminary suggestions for instruction based on our findings

### Altering notation to decrease conflations

Based on our findings, we propose that students' conceptual understanding and problem-solving performance may be affected in part by how many similar features two distinct concepts share. These observations corroborate Genter's [44] study of appearance matching where people group concepts together based solely on how similar their features are. In addition to corroborating past studies, our findings imply that representing concepts using several similar features may hinder how students develop strong, appropriate conceptual distinctions over time and how they use their conceptual knowledge during problem solving. Careful consideration of how to visually distinguish two concepts may help students more easily gain appropriate conceptual knowledge and help them in the early stages of problem solving. For example, instructors could consider requiring all state and next-state variables be labeled with accent symbols or with Greek letters in contrast to lowercase or latin letters for input and output to help students maintain a conceptual distinction between next-state and output. Ideally, as students develop these conceptual distinctions, their ability to access their conceptual knowledge will be more robust against similarities in notational conventions. Future research could try modifying course notation to see its effect on students' learning and problem-solving performance.

## Future work based on findings from this project

The findings outlined in this work indicate several areas of future work. First, our findings were built from qualitative studies of two engineering disciplines. While that choice allowed us to build preliminary comparisons, we would need data from more disciplines to explore the nuances of these findings. Second, quasi-experimental follow-up studies are needed to explore the generalizability of these findings. We recently conducted such a study exploring the generalizability of an additional finding that we did not report in this paper. Preliminary findings from that study indicate that making the joints within schematics of beams more perceptually salient improved students' scores when drawing shear force and bending moment diagrams. Finally, given these preliminary findings, future studies could explore the use of scaffolding in visual representations. Similar to the idea of scaffolding tasks, initial courses at the sophomore level where students are first exposed to core concepts would use representations that have a lot of visual scaffolding with each subsequent course having less structuring. What constitutes "a lot" and how much to take away at each subsequent course could be the subject of these future research studies.

## Conclusion

One critique for the knowledge-in-pieces perspective on conceptual change has been that "if students' use of knowledge is unpredictable and subject to contextual cues, how do we design instructional interventions that help students across contexts?" By combining a data-driven approach with the knowledge-in-pieces framework and Hegarty's theoretical framework, we have identified promising pathways for designing instructional interventions to address students' conceptual difficulties and avenues for future research in conceptual understanding. Ultimately, our data suggests that the way we design our visual representations may play a major role in helping students identify when and where to use their conceptual knowledge. If students struggle with conflating distinct concepts, are there ways that our notational standards reinforce these conflations by presenting distinct concepts as similar? If we can accelerate the creation of these distinctions, we can transition students back to traditional representations after their conceptual knowledge is robust enough to guide them. Our themes of perceptually similar concepts, perceptually obscure concepts, and informationally incomplete representations suggest clear avenues for investigating what types of perceptual cues may hinder students' ability to develop or use appropriate conceptual knowledge. As engineers, we can use this knowledge to potentially design new notations or new pedagogical techniques that can help students recognize and overcome the ways our notation may currently be failing to help students learn.

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