2018 ASEE Annual Conference & Exposition
Paper ID #21569

WIP: How Do Visual Representations Affect How Engineering Students Learn and Solve Problems Within and Across Disciplines?

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Introduction and Background

Students struggle to learn fundamental engineering concepts from canonical visual representations (Ferguson & Hegarty, 1995; Litzinger et al., 2008; Nelson, 2014; Stull, Barrett, & Hegarty, 2013). One explanation for this struggle from the visual cognition literature is that students have trouble accessing the important information they need from visual representations (Hegarty, 2013; Kriz & Hegarty, 2007; Ozcelik, Arslan-Ari, & Cagiltay, 2010; Ozcelik, Karakus, Kursun, & Cagiltay, 2009). Studies in multiple engineering disciplines confirm that the design of a representation can affect how students use the representation during problem solving (Hegarty & Just, 1993; A. M. Johnson, Reisslein, & Reisslein, 2014; Nelson, 2014; Rosengrant, Etkina, & Van Heuvelen, 2007; Williamson, Hegarty, Deslongchamps, Williamson K.C., & Schultz, 2013; H.-K. Wu & Shah, 2004). This prior work has culminated in a theoretical framework about how features of a visual representation affect comprehension of static diagrams (Hegarty, 2014). However, Hegarty's framework does not address what happens when students are dynamically modifying the visual representation or are engaged in more complicated problem-solving tasks.

Our study design and analysis were inspired by Hegarty's theoretical framework of multimedia learning. Her framework 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 (Hegarty, 2014)." Features within a representation can be perceptually salient, task relevant, neither, or both. A feature's perceptual salience can be intrinsic or dependent on domain knowledge. Intrinsically perceptually salient objects are features that are quickly noticed by the individual's visual systems and have importance across a wide range of diagram types. Examples of intrinsically perceptually salient objects include a lone red dot on a white map or using arrows to direct a person's attention (Hegarty, 2011). Domain knowledge can increase or decrease how much individuals pay attention to features by guiding the individual's search for information within a representation. For example, physics experts grouped a box and spring problem with a box on a ramp problem in the same category in a card sort activity because the problems are both able to be solved using conservation of energy. Novices in the same study only grouped box-on-a-ramp problems with other box-on-a-ramp problems because they both contained boxes. Thus, experts' domain knowledge made them pay attention to features that indicated the underlying physical principle (Chi, Feltovich, & Glaser, 1981). Without domain knowledge to guide them, novices will naturally pay attention to and talk about the most intrinsically perceptually salient features regardless of whether they are task relevant. We observe this in the Chi, Feltovich and Glaser study when novices justified their groupings by whether the problem depicted a box on a ramp or an object that spins. In another study by Montfort, Herman, Streveler and Brown (Montfort, Herman, Streveler, & Brown, 2012), 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, students said there would be shear forces because there were vertical forces. In this case, the vertical arrow is an intrinsically perceptually salient object that novices used in their reasoning because they didn't have the domain knowledge to guide their search for information.

Changing the intrinsic perceptual salience of features in a display disproportionately aids novice students in their attempts to access the task-relevant information they need but also does not negatively affect more advanced students (Heckler & Scaife, 2015; Heiser & Tversky, 2006; H. K. Wu, Krajcik, & Soloway, 2001). For example, Heiser and Tversky showed that adding arrows to a mechanical system encouraged novice students to talk about the functional nature of the system and make inferences about its performance rather than discuss only physical structures (Heiser & Tversky, 2006) but did not hinder high performing students. Similar expertise-dependent findings have been found in physics (Heckler & Scaife, 2015; Schwartz, 1995), chemistry (H. K. Wu et al., 2001) and anatomy (Stull, Hegarty, & Mayer, 2009). This research has focused primarily on physical science about which novices have intuitions even before formal instruction and exposure to formal notation but has not examined engineering contexts that require students to reason about systems primarily through mathematical models and on those model's notational conventions.

Our theory-building study fills gaps in the visual representations literature by 1) extending analysis of the effect of representational context to problem-solving contexts where students co-create the display (e.g., sketching), 2) identifying how representational context and domain knowledge interact when the representation is the primary way in which students learn about a concept, and 3) identifying categories of features in engineering representations that students have trouble accessing.

We seek to fill this gap in our knowledge using a data-driven qualitative approach. We use the Constant Comparative Method to synthesize findings from two of our previously conducted qualitative research studies, by comparing students' sketching behaviors across domains (Boeije, 2002). This work-in-progress describes one theme that answers the following research question:

Research Question 1: How is the interplay between how information is encoded within representations and students' problem-solving strategies similar and different across sketching tasks from a statics and digital logic course?

Methods

Consistent with the views of Strauss and Corbin (Strauss & Corbin, 1998), we believe interpretation of phenomena across multiple observations and multiple disciplines with researchers of different backgrounds leads to theory that comes close to describing objective reality. We consequently use the Constant Comparative Method, which critiques, extends, or supports data and emerging theory from prior studies through constant comparison with new data (Boeije, 2002) to extend Hegarty's theoretical framework to relatively unexplored contexts.

Data collection

The data in our data-driven approach came from think-aloud interviews with engineering students from either statics or digital logic courses at our institution. 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). We chose these two sets of problems because both types of problems require students to use multiple types of representations - graphical representations (i.e., diagrams that illustrate the relationships between variables), pictorial representations (e.g., schematics), and algebraic representations. Further, both sets of problems require students to translate information from one representation to another multiple times during the problem-solving process. This allowed us to see how they translated information between different types of representations. For details of the specifics of the participant sampling and data collection, please refer to prior publications (Herman & Choi, 2017; Johnson & Herman, 2017). All participants were paid for their participation and gave written consent to be interviewed under IRB approval. The videos were then imported into MaxQDA for qualitative analysis.

Data analysis

In prior studies, we used the Constant Comparative Method to identify patterns and themes in the way that students interacted with visual representations in each discipline individually. The Constant Comparative Method is an effective method to inductively build theory through "categorizing, coding, delineating categories and connecting them" (Boeije, 2002). We established the granularities in advance in order for comparisons between them to be made reliably (Boeije, 2002). The four granularities that we used in prior analysis were subject, problem, translation, and statement. The subject granularity identifies each subject as a weak novice, novice, or advanced novice based on the accuracy of solutions and amount of domain knowledge used. The problem granularity comprised problem-solving strategies students used. The translation granularity comprised the representation students created and what representation they used to create the new one (e.g., schematic to a free body diagram). The statement granularity comprised the statements students made that revealed their conceptual or procedural understanding.

In this study, we conducted comparisons across a new granularity called domain, which constitutes comparing themes that emerged in each dataset. We compared across the domain granularity in two stages. First, we compared the themes generated from the prior studies to each other to determine which themes were common to the disciplines and which were discipline specific. Second, we compared each theme's supporting evidence (constructed from comparisons amongst the other four granularities) to find similar trends in how each theme emerged from the data. The theme "informationally incomplete representations leads to coordinating multiple representations" emerged from the first stage of analysis.

Limitations and why this study is a work in progress

While we did not follow the simultaneous sample and analyze iterative process characteristic of a data driven approach, we followed the other philosophical commitments by initially sampling students that took the course together in a period of two weeks, analyzing data from those students and then determining whether further sampling was necessary. In both datasets, we observed saturation by the eighth interview and thus did not need to do another round of sampling. Additionally, our datasets only encompass two engineering courses. Although statics is a requirement for many engineering disciplines, we don't claim our dataset to represent all those fields. Our data-driven theory will become more robust with further studies (both qualitative and quantitative) and different types of engineering courses/disciplines. The theme presented in this work in progress is intended to become one variable of our data-driven theory and would benefit from the feedback of our community as we develop the rest of our emergent-theory.

The goal of the larger study is to develop data-driven theory that describes the interplay between how information is encoded in a representation, students' problem-solving strategies, and their conceptual knowledge. This paper is work in progress towards that goal because it represents results from an initial analysis in comparing student interviews across different engineering courses.

Theme: informationally incomplete representations leads to coordinating multiple representations

From analyzing the translation codes across the two datasets, we observed qualitative differences in how statics and digital logic students translate representations during problem solving. While both digital logic students and statics students deviate from how experts describe solving problems, statics students deviate more than the digital logic students, doing more translations per problem and using more complicated translation strategies. Statics student performed more translations per problem than digital logic students (5.9 vs. 4.7, respectively). Additionally, statics students used 40 unique translations whereas digital logic students used only 18 different unique translations. In comparison, engineering faculty in both disciplines at our university described 4 necessary translations for their respective sketching tasks.

Bigger differences emerged from the data when we looked at the types of translations present in both codebooks. Subjects in the statics dataset often coordinated multiple representations when sketching a new representation, which we call a hybrid translation. For example, we observed a statics subject use both the schematic and shear force diagram to sketch their bending moment diagram. For reference, students in statics courses are often taught to just use the shear force diagram to translate to the bending moment diagram. Hybrid translations predominantly occurred in the statics dataset both in percentage of unique codes in the codebook (Figure 1a) and the percentage of total instances of translation codes (Figure 1b).

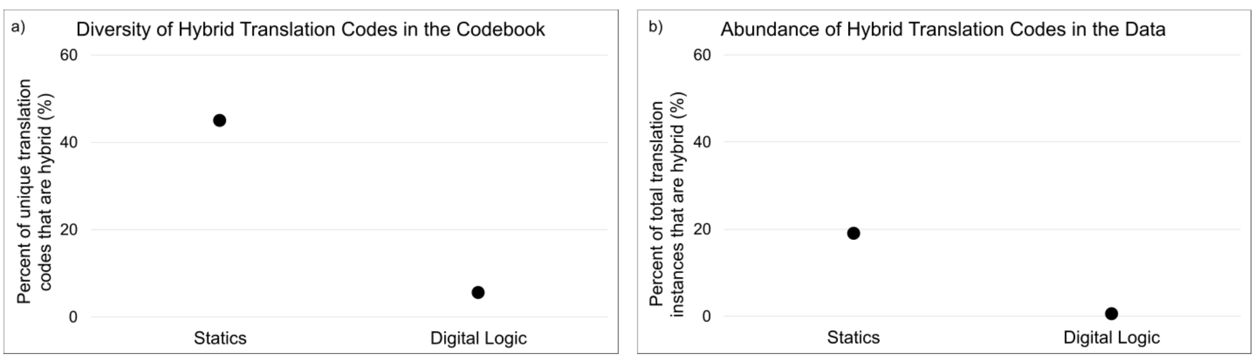

Figure 1: Percentage of a) total unique translation codes and b) total translation code instances that are hybrid translations.

Discussion

When we noticed the qualitative difference in how subjects used representations in the statics dataset versus the digital logic dataset, we looked back at the interview protocols and how experts describe solving their sketching task. During this analysis, we noticed that the shear force representation in the statics dataset does not contain all the information necessary for a student to translate from the shear force to the bending moment diagram. This makes the shear force diagram what we're calling informationally incomplete. Rather than information being perceptually missing but ultimately accessible through domain knowledge, the shear force diagram simply does not encode the presence or value of discontinuities in the bending moment diagram created by applied moments, including reaction moments. The location of applied moments can be identified or inferred in the schematic or free-body diagrams but not in the shear force diagram. Thus, students who sketched their bending moment diagram by integrating their shear force diagram to coordinate multiple representations to sketch a correct diagram. 33 of 39 hybrid translation code instances that ended with the bending moment diagrams were of the form other + shear force → bending moment where other includes the algebraic, extended free body diagram (EFBD), free body diagram, or schematic representations. Additionally, we observed hybrid translations for representations that are informationally complete and thus don't need coordination from multiple representations (e.g., schematic + free body diagram → shear force). In comparison, the digital logic problems do not contain any informationally incomplete representations, which explains why we only coded one hybrid translation in the digital logic codebook.

The prevalence of hybrid translations and doing more translations per problem suggests that statics students are coordinating more information than digital logic students during problem solving. More broadly, our results suggest that problem-solving tasks that require students to use informationally incomplete representations could result in students experiencing a higher cognitive load. Our results extend Hegarty's framework by showing how problem-solving behavior (hybrid translations) can be tied to how the representation encodes information (informationally incomplete). Further analysis is needed to examine how our work extends other claims in Hegarty's theoretical framework to the problem solving and engineering education spaces.

Conclusion

This work-in-progress demonstrates that cross-disciplinary analysis within problem solving and visual cognition research is a valuable tool for researchers to more deeply probe potential causes of students' problem-solving behavior both across and within disciplines. Without comparing across disciplines, we likely would not have identified informationally incomplete representations as the source of the hybrid translations prevalent in the statics dataset. While further analysis is needed, our data suggests that how information is encoded or present at all affects the way students use representations and access information during problem solving, which could have implications for engineering education research and practice.

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