



Validation of a Mental Model Elicitation Instrument through Deployment of Control Groups in an Undergraduate Engineering Program

Alexander R. Murphy, Georgia Institute of Technology

Alexander R. Murphy is a graduate student at the Georgia Institute of Technology and is pursuing a Ph.D. in mechanical engineering. He was born and raised in Tampa Florida, where he received a B.S. in mechanical engineering with a minor in creative writing from the University of South Florida. He is proud to have received a NSF GRFP fellowship this past spring of 2018. Currently, he is interested in exploring students' and professionals' mental models and how they change during the design process. Specifically, he is investigating the connections between functional decomposition, systems thinking, and mental model representation. His research interests also include investigation into prototyping strategies for engineering design. After completing his graduate degree, Alexander wants to become academic faculty and start a small business as a design consultant.

Henry David Banks, James Madison University

Henry Banks is an undergraduate engineering student at James Madison University. He has been conducting design research as an undergraduate research assistant since 2017 and is currently working towards his honors thesis.

Dr. Matt Robert Bohm, Florida Polytechnic University

Matt Bohm is an Associate Professor of Mechanical Engineering at Florida Polytechnic University (Florida Poly). He joined the University in 2016 after spending 6-years as an Assistant Professor of Mechanical Engineering at the University of Louisville (UofL). Bohm's research examines the intersection of 3 distinct areas, engineering design, engineering education, and big data. Currently, Bohm has an active NSF grant under the Division of Undergraduate Education to examine the effects of systems modeling paradigms with respect to design outcomes and systems thinking and understanding. While at UofL, Bohm was primarily responsible for overseeing the Mechanical Engineering Department's capstone design program. Prior to his position at UofL, Bohm was a visiting researcher at Oregon State University (OSU) after completing his PhD at the Missouri University of Science and Technology (S&T) in 2009. While at S&T, Bohm was also a Lecturer for the Department of Interdisciplinary Engineering and was responsible for coordinating and teaching design and mechanics related courses.

Dr. Robert L. Nagel, James Madison University

Dr. Robert Nagel is an Associate Professor in the Department of Engineering at James Madison University. Dr. Nagel joined James Madison University after completing his Ph.D. in mechanical engineering at Oregon State University. Nagel teaches and performs research related to engineering design. Specifically, through research, Nagel explores how design interventions commonly used to teach design influence student learning.

Dr. Julie S Linsey, Georgia Institute of Technology

Dr. Julie S. Linsey is an Associate Professor in the George W. Woodruff School of Mechanical Engineering at the Georgia Institute of Technological. Dr. Linsey received her Ph.D. in Mechanical Engineering at The University of Texas. Her research area is design cognition including systematic methods and tools for innovative design with a particular focus on concept generation and design-by-analogy. Her research seeks to understand designers' cognitive processes with the goal of creating better tools and approaches to enhance engineering design. She has authored over 150 technical publications including over forty journal papers, and ten book chapters.

First Steps Towards the Validation of a Mental Model Elicitation Instrument in an Undergraduate Engineering Program

Abstract

Mental models of engineering systems contain information about the components, connections, inputs/outputs, and function of a system. It is difficult to study mental models because any mental model elicitation method inherently only provides a representation of the mental model and not a realization of the mental model itself. In order to measure engineering students' understanding of simple systems, a mental model instrument with scoring rubrics has been developed and deployed in undergraduate and graduate engineering classrooms in previous work. The research presented in this paper explores validation of this mental model elicitation approach through two control groups involving the collection of pre- and post-data without intervention. Results from the two control groups are discussed and indicate that without intervention, no learning effects take place. In addition, this work considers the addition of an explanatory example showing exactly how to complete the given tasks. Results concerning the inclusion of this example are inconclusive but give insight into the possible effects for future research. Lastly, unexpected component inclusions/exclusions are discussed as a final point of interest. This work serves as a first step towards validation of this new mental model elicitation method and the related scoring rubrics and is a contribution to ongoing research on mental models of engineering systems. As we continue to explore how students learn about engineering, it is important that educators and researchers have a way to reliably measure student understanding of various systems during their undergraduate and graduate degree programs.

1. Introduction

All of us have mental models of the world around us. These mental models help us understand how things work, where things are, and what things do. However, we each have unique mental models based on our past experiences, cultural perspectives, innocuous misconceptions, or subjective biases. Measuring these different mental models poses a unique challenge since conceptualizations are held in the mind and any description of them is simply a representation of the mental model and not the mental model itself; in other words, we are seeing a reflection of the mental model through a dirty mirror. In this work, the previously published instruments used to elicit undergraduate students' mental models [1-3] are deployed without intervention to make progress on validation of the instruments for future research studies, therefore cleaning that metaphorical mirror. Despite the impossibility of perfectly representing a mental model, this work takes a step towards the development of a repeatable and reliable experimental instrument for use in academic research and engineering classrooms.

The research presented in this paper is a continuation of a NSF funded project to evaluate the impacts of teaching functional modelling in an engineering design curriculum [4]. During the initial phases of the project, students in engineering design courses were given a series of experimental instruments or homework assignments to assess their ability to recognize product functionality, interpret and understand customer needs, and to explain or decompose a complex system. Students in prior studies had either previously learned functional modeling [3] or were

taught functional modeling as an intervention between different mental model instrument implementations [1, 2, 5]. The investigators slowly adapted these instruments to assess students' systems thinking aptitude and have recently begun to investigate the relationship between mental models, recognition of function, and technology literacy and understanding. This paper reports on mental model data collected from juniors and seniors in a mechanical engineering program and serves as a crucial step towards validating the authors' current mental model instrument [1].

Before moving forward, it is important to define what is meant when referring to “mental models”. In general, no universal definition of “mental models” exists. In one definition, Senge suggests that mental models are deeply held assumptions and generalizations that serve as a reflection of how we perceive the world and what actions we take in that world [6]. One definition that stands out as particularly relevant in the literature was suggested by Markman when he wrote that “mental models of physical systems are internal representations of external systems” [7]. The emphasis on physical systems readily applies to the engineering design context of this research. A third example is offered by Fein et al. where mental models are defined as “knowledge that the user has about how a system works, its component parts, the processes, their interrelations, and how one component influences another” [8]. This definition most closely relates to this work and the reader can assume this definition throughout when we use the terminology.

Mental models give us the necessary scaffolding to make judgements about physical systems [9]. Students studying engineering must have robust mental models in order to make decisions about engineering systems, but it's difficult to know how complete their mental models are—especially for complex systems—through traditional means. The mental model instruments presented in this paper help educators and researchers assess the completeness of their students' mental models. This is particularly important in light of research that shows students' routinely have erroneous mental models of systems, particularly in the domain of physics [10]. As a whole, this research aims to understand how/if these knowledge gaps transfer to engineering systems since the implications could reveal severe deficiencies in students' systems understanding abilities.

The study presented in this paper involved mental model elicitation of three common household products: a hairdryer, a clothes dryer, and a vacuum cleaner. These simple household products give us a window into students' mental models of systems that share similar components or have analogous functionality. Outcomes from this study (and the studies before it) provide insight into how students reason about complex systems and whether or not they can apply the engineering content knowledge they have learned when they encounter new problems or systems.

Validation of the mental model instruments and accompanying scoring rubrics is necessary in order to make strong conclusions about engineering students' ability to reason about systems. The results presented in this paper take a step towards that validation. In order to achieve this, data was collected at two points without intervention to check the mental model instruments for the presence of practice effects on within-subject data. Further details concerning the context of the study are presented in the methodology section after a brief history of research on mental models and related topics.

2. Background

Research that mentions mental models spans across quite a few domains. Out of cognitive psychology, studies on naïve physics [11-17] most strongly influence this work since they often measure mental models with a similar approach. Research on mental models of engineering systems also significantly impacts this work for obvious reasons [18-20]. Other domains that consider mental models include human-computer interactions [8], shared mental models in groups [21, 22], and mental model misconceptions [20, 23-25]. Mental model errors are often caused by perceptual illusions. One example of this is showcased by naïve physics research where participants routinely misjudge the water-level in a cup after it's tilted to an angle [12], attributed to people generally not seeing water in a cup against a larger frame of reference. These kinds of conceptual errors are common in both novices and experts in many different fields.

One study in particular heavily influenced the approach taken in this work that considered mental model differences between experts and novices. Lawson measured mental models of bicycle functionality by asking participants to draw components (the pedals, frame, and chain) on a simple line drawing or to select the correct orientation of these components from a set of options [26]. Results from their study showed that participants—both novices and experts—regularly made errors on both tasks. However, professional cyclists overestimated their ability to complete the task when compared to your everyday bicycle owner. Lawson's study shows that a simple drawing task of system components and connections can elicit mental model errors from both novices and experts. In this paper, the mental model instruments similarly involved the drawing of components on simple line drawings of a product.

Prior research shows that students' systems understanding is not always at an expected proficiency. A study involving graduate students showed that their ability to predict the dynamics of a simple bathtub system was severely lacking [27], where other research claims that systems thinking does not come easily to most [28]. Given these results, educators must ensure that engineering students are developing the skills necessary to create complete and robust mental models of systems. Further, Rozenblit and Keil argue that people are generally overconfident in their ability to understand mechanical systems when the systems' components are visible [29], such as the bicycle problem used by Lawson [26]. Taken together, these studies show the importance of improving students' ability to reason about systems, starting with basic systems and working up to the more complex engineering systems common in industry.

The previously published mental model scoring rubrics used in this study build off of previously published work on functional modeling and decomposition [30-32], and in particular the final 20-question functional modeling rubric [33]. For example, a portion of the mental model rubrics (High-Level Systems Thinking) use similar language to the functional modeling rubric to intentionally measure students' functional understanding of the system, which is an important aspect of a mental model considering the definition provided by Fein et al. [8]. This study is also informed by prior studies using the mental model instrument and accompanying scoring rubrics deployed in this study. Previous work implemented a functional modeling intervention between mental model data collections [1, 2] where results showed improvement in mental model score after learning functional modeling. The functional modeling content delivered to students

involved elements from the FAST method [34], flow-based method [35], and hierarchical method [36]. In addition, the intervention encouraged students to use the functional basis [36-38] to create functional models on assignments.

Results from this prior work showed improved mental models after a functional modeling intervention. However, one concern arose that the improvements may be due to practice effects on the mental model instrument itself. In order to ensure that mental model improvements were not simply practice effects, the study presented in this paper was designed to take a first step towards validating the instruments, accompanying scoring rubrics, and general methodology. The following section outlines the context of the study as well as gives an overview of the experimental materials and procedure used in this study.

3. Methodology

In this section, a description of the university and student body where the study took place is provided followed by a description of the procedure. Examples of the mental model instruments are provided with an additional presentation of the mental model instruments and accompanying scoring rubrics in the Appendix.

3.1 University Context

This study was conducted at a public STEM-centric University in the Southeast United States. The University has a total enrollment of approximately 1,400 students across all academic programs. The mechanical engineering department serves about 375 students enrolled in the ABET accredited degree program (Bachelor of Science in mechanical engineering). The degree program has a curricular focus on project-based learning and engineering design that spans from freshman year to senior year.

Particularly, this study was performed during the fall semester in two different mechanical engineering courses, a two-semester sequence junior lab class and a two-semester sequence capstone design course. Both of these courses are required and focus heavily on the engineering design process. The juniors in the study follow the NASA systems engineering handbook [39] to guide them through the process of designing and building a laboratory experiment. The seniors loosely follow the engineering design processes prescribed by Otto & Wood and Ulman [40, 41], and received formalized functional modelling instruction [42] with related homework assignments prior to the start of the study (not as an intervention). The juniors involved in the study were not taught any formalized functional modelling processes prior to the study.

3.2 Mechanics of the Study

Data was collected at two different points during the semester (three weeks apart) for both the juniors and the seniors (approximately at week 5 and week 8 for both groups). Neither group received any purposeful intervention between the two data collection points. The mental model instruments used for both student groups asked the students to sketch and label the operational components within an outline of three common household products: a hair dryer, clothes dryer, and a vacuum (Figure 1 shows the hair dryer instrument). The instrument for the juniors and seniors were identical except for one small difference. For juniors, the first page of the packet

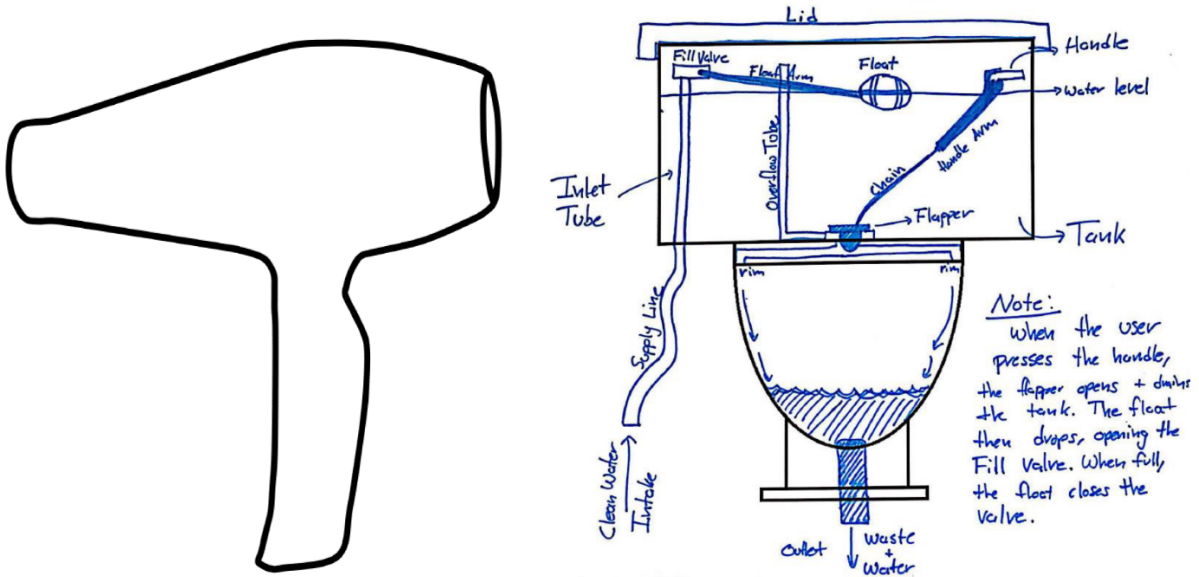


Figure 1: An example of the blank hair dryer instrument (left) that students fill out and the completed toilet example (right) provided to students during the study.

contained an example of how to use the instrument by providing an outline of a toilet with necessary components, inputs & outputs, and connections between these elements (Figure 1).

Data was scored using mental model rubrics that correspond to each of the three products: the hair dryer, the clothes dryer, and the vacuum cleaner. Mental models are awarded points based on a series of questions, where each question earns either 0, 0.5, or 1 points depending on correctness (some questions can only earn 0 or 1 points because the component the question refers to is either present or not). These rubric questions were created by experts conducting research in the field of engineering design theory and education and have been used to score similar data in previously published work [1, 3]. Note that while these rubrics are not immediately generalizable, there is significant similarity between the different rubrics that can be easily adapted to other products. Before scoring, data was deidentified and randomized with a non-descriptive code to help remove bias during the scoring process. A mental model's score is calculated by simply summing the points awarded to the student on each rubric question.

Since this study is investigating the possibility of practice effects when completing the task, lecture content is described during the three weeks between data collections to show that function or functional modeling was not taught and to document any other material that may have had any unexpected effect on changes in mental model score. For seniors, lecture content focused on optimization, trade-off analysis, and failure mode analysis between the two points of data collection. Homework assignments consisted of developing and assessing proof-of-concepts for their overall capstone project. For juniors, lecture content focused mostly on Labview (a software used by systems engineers for testing, measurements, and control of hardware [43]) and how to interface with and interpret data from physical hardware. Homework assignments focused on Labview to interface and record data from existing physical systems. While this

content is related to engineering design, the authors do not believe any of this material would have an effect on their mental model scores.

In summary, seniors with knowledge of functional modelling were given the instrument without an example of how to use the instrument. Juniors with no formalized functional modelling instruction were given the instrument with an example of how to use instrument. Juniors and seniors received the exact the same packet during initial data collection and then again during the second data collection three weeks later. The authors recognize that the experimental design is not particularly exciting. However, data collection from this study is useful when combined with previous data collection efforts to understand practice effects, intervention effects, and to help move towards instrument validation.

4. Results

This section describes analysis of the pre- and post-data collections to determine whether or not practice effects are present. In addition, a few interesting tendencies for component inclusion/exclusion are shown at the end of this section. The mental models were scored by a Ph.D. student conducting research in the field of engineering design and an undergraduate student at a different university trained to use to the mental model scoring rubrics. All data was deidentified and masked so that the scorers did not know what groups (pre- or post-data, junior or senior) the mental models belonged to. The undergraduate student scored a random sample of 25% of the data (or 60 mental models) for inter-rater reliability. Analysis shows a percent agreement of 78.65%, as an initial measure of agreement. In addition, a Pearson's correlation of 0.90 was obtained for total mental model scores. Finally, as a measure of agreement that takes the possibility of random chance agreement into consideration, a Cohen's kappa [44] of 0.64 was obtained, which indicates substantial agreement. Disagreement (while small) most likely occurs because of the slightly subjective but necessary approach used to score the students' hand-drawn mental models. These high inter-rater values indicate good agreement between raters as a point of validation when interpreting results from this study.

Analysis included 20 juniors and 20 seniors each with two mental model instrument packets from the pre-data collection and post-data collection. Further, each student completed all three mental model instruments (the hair dryer, the clothes dryer, and the vacuum cleaner) on both the pre- and post-data collections. In total, each student participant generated 6 total mental models over the course of the study (3 during the pre-data collection and 3 during the post-data collection), which ultimately resulted in 240 total elicited mental models that were hand scored by the research team. As shown in Figure 2, average mental model scores as percentages were sorted after scoring into their appropriate groups (pre- vs. post-data, juniors vs. seniors). Various aspects were checked for statistical significance using a two-sample t-test assuming equal variance. In order to show the absence of practice effects, no significance differences between pre- and post-pairs of data should occur. To determine this, two-tailed p-values were calculated as shown in Table 1.

Table 1: Collection of two-tailed p-values calculated using two-sample t-tests assuming equal variance to check for significance and the presence of practice effects. All calculations have 38 degrees of freedom.

Group	Product	t-stat	p-value	Significant?
Juniors	HD	1.560	0.127	No
Juniors	CD	-0.169	0.867	No
Juniors	VAC	-0.545	0.589	No
Seniors	HD	-0.079	0.938	No
Seniors	CD	-1.643	0.109	No
Seniors	VAC	-0.944	0.351	No

As shown, no significant practice effects are evident for the junior or senior groups when considering average scores on pre- and post-mental model data (Table 1). However, one significant difference in average score was calculated. For post-data collection hair dryers between juniors and seniors, there is a significant difference in the average mental model scores ($t(38) = -2.409, p = 0.021$). Despite this single point of significance, it is unclear what effect the inclusion of the toilet example has on the data since there are no significant differences between juniors and seniors overall (juniors received the toilet example, seniors did not) and requires further investigation. This idea and the difference in post-hair dryer scores are explored in detail in the following discussion section.

Average Pre- and Post-Mental Model Scores

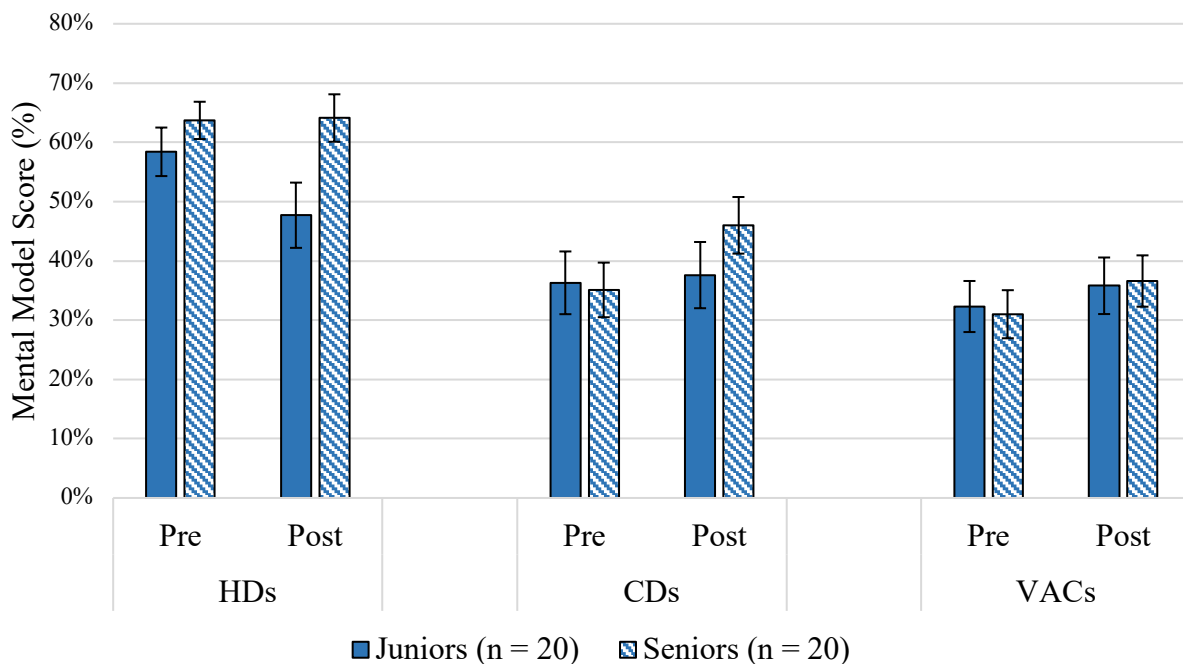


Figure 2: Comparison of junior and senior average mental model scores from the pre- and post-data collection with error bars of +/- 1 standard error. The hair dryer (HD), clothes dryer (CD), and vacuum cleaner (VAC) are all included.

Considering Figure 2 again, there appears to be a general trend downwards in average score across the three products. This might indicate effects of fatigue while completing the mental model instruments since they have always been presented in the same order. In future implementations, it would be beneficial to vary the instrument order for consistency.

Next, scores for the component section of the rubric were considered across all scored mental models aggregated by product to see what components students typically include and exclude on their various mental model representations. For the question that asks, “Is there a fan, air compressor, or air moving device?”, 98% of students included this on the hair dryer while only 33% indicated the presence of a motor. This indicates either that these students don’t know that there is a motor in the product, or more likely that students deem it unnecessary to include a motor (such as assuming it is obvious) because they are reasoning at different levels of abstraction depending on the product. However, it’s surprising that on the clothes dryers, 65% of students actually include a motor of some kind even though these two tasks occur directly after one another in the experiment packet (55% students included a motor on the vacuum cleaners). Further, while 98% of students indicated a fan on the hair dryers, only a mere 19% indicated a fan or air moving device on the clothes dryer (63% indicated a fan on the vacuum cleaners). This seems shocking and suggests that students are not considering similarity between these products despite the research team specifically choosing them to have analogous functionality. As two final points of interest, only 28% of students included an air filter or lint collector on their clothes dryers (despite this being one of the only components users routinely interact with) and the component with the highest inclusion rates on the vacuum cleaners was a debris brush at 90%, more than a power cord/supply (74%) or an air moving device (63%). Possible causes and implications from these results and the average score comparisons are explored further in the following discussion section.

5. Discussion

Taken as a whole, the results suggest that practice effects are not present when implementing the mental model instruments, which answers the original question that motivated the study. This helps to validate the instrument for future studies, as well as validate the authors’ previously published work [1-3, 5]. From a broad perspective, this project aims to understand the role of function in systems understanding, students’ ability to communicate their knowledge about systems through mental model representations, and to find avenues for bringing technological literacy into both engineering and non-engineering classrooms. The creation of a robust and reliable mental model elicitation instrument is crucial for the success of this project. The results presented in this paper show a step towards that validation through the confirmation that practice effects are not present when collecting mental model data in this manner, along with a few unexpected insights into how students reason about systems as described by the quirky inclusion and exclusion of various product components.

Across all three products and both experimental groups (juniors and seniors), no significant differences in mental model score were present (Table 1). A secondary motivation for this study was to try and determine how the presentation of the toilet example (shown to juniors, Figure 1) affects results compared to no example of instrument completion. Results are inconclusive since

there are no significant differences between the two groups in general while acknowledging the significant difference in post-hair dryer mental models between the groups, which is attributed to differences in motivation. Specifically, the decrease in pre- to post-scores on the hair dryer by juniors, while not statistically significant, is rather unexpected and can really only be attributed to motivation issues. It is possible that the benefits afforded to the juniors by the toilet example are equal to the benefits afforded to the seniors by prior experience with functional modeling (as described in the methodology). Future work will attempt to uncover whether or not the toilet example adds value to the study procedure.

One unexpected result was the presence of what seems to be the effects of fatigue while completing this task. Considering Figure 1, scores seem to decrease as students get further through the packet since the three products have always been presented to the students in the same order (hair dryer, clothes dryer, vacuum cleaner). In future studies, the order of the three products should be varied in order to control for the effects of fatigue. Another solution could be to simply reduce the number of products to two (or even one). It is important to mention that the hair dryer has always shown the highest scoring mental models in almost every implementation of the instruments, so it may be that the scores on each product are not related to fatigue and are actually typically representative of students' understanding of these three systems. Further research is necessary to determine if this is the case.

The large sample size of mental models (240 mental models, 120 for each of the three products, and 40 students consisting of 20 juniors and 20 seniors) allowed us to take a look at other aspects of the mental model activity that we had not previously considered. By looking at component inclusion/exclusion frequencies, we have a first glimpse at student abstraction of component architecture as related to product complexity. As mentioned, these products were specifically chosen because of their analogous functionality, yet students do not seem to be making the expected analogous leaps between the systems. Consider the inclusion/exclusion of the fan or air moving device on the hair dryer (98% inclusion) vs. the clothes dryer (19%) vs. the vacuum (63%); all three products facilitate the movement of air, yet students either do not seem to recognize this or do not feel it important enough for explicit indication. These preliminary results prompt exciting questions for future research with the implementation of these further validated mental model instruments.

The research presented in this paper fits into a larger frame of research on students' ability to understand systems. Recently, this research includes analogical reasoning [2, 5] and the impact of functional modeling and decomposition training on systems representation [1, 3], while historically, efforts were focused on methods for teaching function to undergraduate students [1, 31-33, 45-51]. The more recent inclusion of studies including graduate students [1] and non-engineering students (in progress) are helping the authors explore different ways to bring technology literacy into both engineering and non-engineering classrooms. While these results are specific to the three chosen products (a hair dryer, a clothes dryer, and a vacuum cleaner), they reveal some interesting phenomena beyond a simple description of systems thinking ability. For example, these results show that further research is needed to fully understand why students choose to include or exclude certain components. In addition, results from this kind of work offer

a novel way to measure analogous reasoning in engineering design. Understanding these principles at this low level of abstraction with simple household products will help researchers start to understand similar phenomena that occur in industry by professional engineers.

The work presented in this paper is a steppingstone toward these larger research goals by exploring instrument validation through the inclusion of a control group into the larger body of work. More focused controlled groups, confirmation of the effectiveness of the toilet example, and improved experimental procedures are left to future work.

6. Conclusion

The study presented in this paper has shown that practice effects are not present when using the implemented mental model instruments and accompanying scoring rubrics. However, results also suggest potential issues with student fatigue while completing the task as they move through the three products. Results were inconclusive on whether or not the toilet example has a significant effect on students' understanding of how to complete the given task. Finally, large sample sizes allowed for a closer look at students' system abstraction in regard to product complexity through component inclusion/exclusion that showed surprising results across both student groups. This has evoked interesting new research questions about students' abstraction of these systems that will be explored in future studies.

Systems understanding and communication is crucial for industry engineers. The development of an instrument to measure engineering students' ability to reason about systems is critical for educators and researchers alike that are trying to prepare students for a rapidly changing industry landscape in the field of engineering. More and more universities are incorporating design theory education into their engineering curriculum to respond to these changes. Systems thinking and system abstraction are skills that allow professional engineers to respond to dynamic situations, complex systems, and new technologies effectively over time. The work presented in this paper takes us closer to understanding how to develop these skills for students as they become professional engineers.

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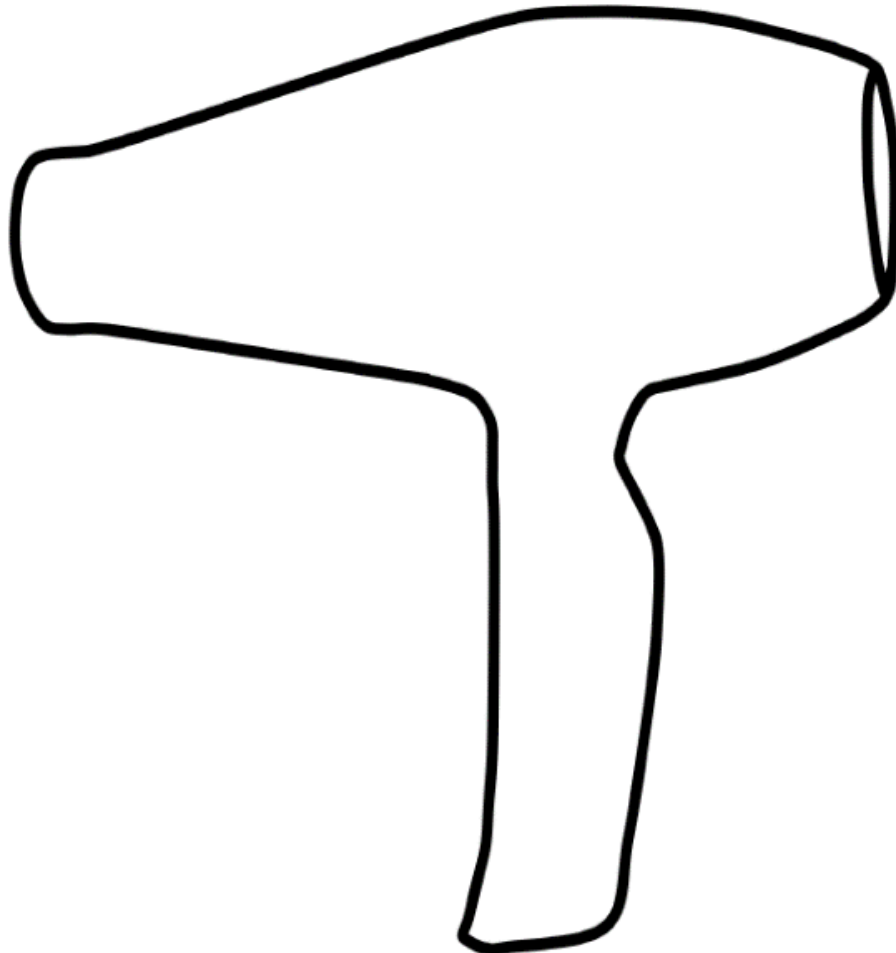
Appendix

Please contact the authors for the complete set of mental model instruments and scoring rubrics. The following abbreviated materials have been provided for convenience and reference.

Abbreviated Hair Dryer Instrument

For the following outline of a common household product, please fill in the **components**, the **connections** between those components, and the **inputs** and **outputs** that allow the system to complete its primary functionality: **Dry Hair**. You are encouraged to use a combination of **drawing, labeling, and text** for clarity. Please incorporate enough **detail** to explain how this product works to someone else.

1. What is the product commonly called? _____
2. Have you ever used this product? (Circle) Yes / No
3. Do you use this product monthly? (Circle) Yes / No
4. Have you ever taken this product apart? (Circle) Yes / No



Abbreviated Hair Dryer (HD) Rubric

1. Is energy conserved across the system boundaries?
2. Is energy changed, converted, or transferred AND conserved within the system?
3. Is material conserved across the system boundaries?
4. Is material changed, converted, transferred AND conserved within the system?
5. Are signals used appropriately throughout the system?
6. Are correct inputs recognized?
7. Are correct outputs recognized?
8. Overall, does the model represent functional understanding of the system?
9. Is there an electric plug or alternate power source?
10. Is there a fan, air compressor, or air moving device?
11. Is there a heating element?
12. Is there a motor, engine, or similar device?
13. Is there an On/Off or power switch?
14. Is there a component for the control of the heating element?
15. Is there a component for the control of the fan/air moving device?
16. Is the internal wiring complete/present?
17. Is the motor, engine, or similar device powered?
18. Is the fan/air compressor/air moving device connected to the motor, engine, or similar device?
19. Is the heating element powered?
20. Is the motor, engine, or similar device properly regulated?
21. Is the heating element properly regulated?
22. Does the model account for the movement of air through the system?
23. Does the model account for the transfer of heat to air within the system?
24. Does the model account for the control of electricity within the system?
25. Does the model account for varying modes of operation?