Making the Invisible Visible: A New Method for Capturing Student Development in Makerspaces

Richard Lee Davis, Stanford University, rldavis@stanford.edu
Bertrand Schneider, Harvard University, bertrand_schneider@gse.harvard.edu
Paulo Blikstein, Stanford University, paulob@stanford.edu

Abstract: The contribution of this paper is twofold: we introduce a new kind of assessment developed to capture students' learning in makerspaces, and we present a new perspective on how participating in a maker workshop impacts students. As opposed to traditional pen and paper tests, we designed a series of hands-on task that participants complete before and after a maker workshop. In this paper, we contrast high-school students' performance with experts (graduate students in mechanical engineering) and found evidence that the students' behavior became more similar to experts' after participating in a maker workshop. For the scope of this paper, we focus on a single task and describe in detail our coding scheme and analyses. Additionally, we show how a combination of qualitative and computational analysis helped us develop metrics to compare novices' and experts' performances. We conclude by discussing the potential of this type of assessment for supporting students' learning in makerspaces.

Introduction

Informal communities of tinkerers, inventors, hackers, and builders have existed across the world for decades. The most famous of these are practically household names—the Homebrew Computer Club in Silicon Valley, the Chaos Computer Club in Berlin—but the vast majority are small communities meeting in garages, classrooms, basements, and libraries. In the past decade, a common identity has emerged for the members of these disparate groups: the maker. Since the emergence of Make magazine in 2005, the word "make" has become the dominant signifier of this new community. The maker movement is made up of a community of makers, who gather in makerspaces to take part in a common activity: making. As the maker movement spreads widely across the US and Europe, we are beginning to see a growing interest in bringing making into K-12 schools (Halverson & Sheridan, 2014). And rightfully so; many aspects of the maker movement have the potential to disrupt traditional schooling and positively impact K-12 students. The communities of practice that take root in makerspaces are powerful, authentic learning environments (Blikstein, 2013; Halverson & Sheridan, 2014; Peppler & Bender, 2013). The focus on creating complex, personally meaningful artifacts has known learning benefits (Blikstein & Krannich, 2013; Papert, 1980; Piaget, 1973). However, one notable aspect of the maker movement with important educational potential has escaped investigation so far: the maker mindset.

From an educational perspective, the maker mindset is one of the most compelling aspects of the maker movement. Its existence implies that becoming a maker involves more than learning how to create products; it involves a change in one's view of the world. If we wanted to identify the maker mindset, what would we look for? Because the maker mindset has many definitions and descriptions, it is difficult to know where to start. Dale Doherty, the founder and CEO of Maker Media, Inc., defines the maker mindset as a "can-do attitude… an invitation to take ideas and turn them into various kinds of reality… It is a chance to participate in communities of makers of all ages by sharing your work and experience. Making can be a compelling social experience, built around relationships" (Dougherty, 2013). Martin writes that it is "playful, asset- and growth-oriented, failure-positive, and collaborative" (Martin, 2015).

Here, we are interested in a more focused definition of the maker mindset. In previous work, it has been observed that students seem to be more capable of reasoning about and debugging complicated mechanisms after participating in a making workshop (Blikstein, 2013). Fields et al. developed an assessment called a Debuggem to capture this change (Fields, Searle, Kafai, & Min, 2012), finding that after a four-week electronic textiles workshop, students were more able to fix faulty designs like short circuits, poor crafting, and incorrect code. We view this change as part of the shift towards a maker mindset. More specifically, our interpretation of these findings is that after taking part in a maker workshop, some students have learned to think more like engineers. Although this type of thinking is difficult to find in common descriptions of the maker mindset, we feel it is an important outcome with special relevance for K-12 education.

The current study was designed to answer three questions about students' participation in a maker workshop. First, do students think more like engineers as a result of taking part in a long-term maker workshop? Second, is there a way to reliably and efficiently capture this change? And third, if this change in thinking does occur, can we look more closely at the data and begin to understand the specific ways in which the students' thinking changes?

General description of the study

A class of high-school seniors took part in a workshop in our FabLab for several months (Fig. 1). Since the workshop targeted students' understanding of complex mechanical systems, we designed assessments that would capture their ability to build, fix or debug them. Before the workshop, we administered 3 tasks to the high-schoolers and they completed 3 similar tasks after the workshop. Once the workshop was over, we recruited 18 experts (graduate students in mechanical engineering) to complete all six tasks from the pre-test and post-test.

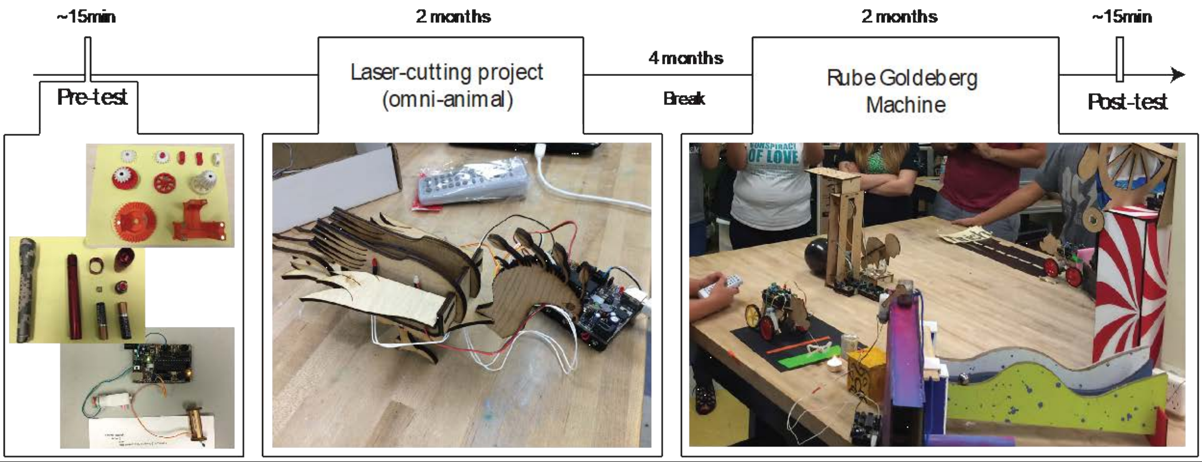


Figure 1. Timeline of the study. On the left, three examples of tasks used before and after the workshop to assess its effect on students' mindset (described in details in the methods section). In the middle, an example of an Omni-Animal laser cutting project. On the right, the final Rube Goldberg machine.

Hypotheses: We expect to see three trends in our data based on participants' performances at the pre- and post-test: 1) novices should improve from pre to post-test; 2) experts should perform significantly better than novices; and 3) novices' behavior should become more similar to experts at the post-test.

Methods

Subjects

20 high-school seniors (4 males, 16 females) from a low-SES school took part in a workshop organized in our FabLab. Three female students had to be excluded from our analyses because they dropped out of the workshop. 18 graduate students (9 females and 9 males, mean age=24.67, SD=2.13) in mechanical engineering from an R1 university were asked to complete the study tasks as a comparison group. They received a $20 gift card for their participation. We will refer to high-schoolers as "novices" and mechanical engineers as "experts" henceforth.

Intervention

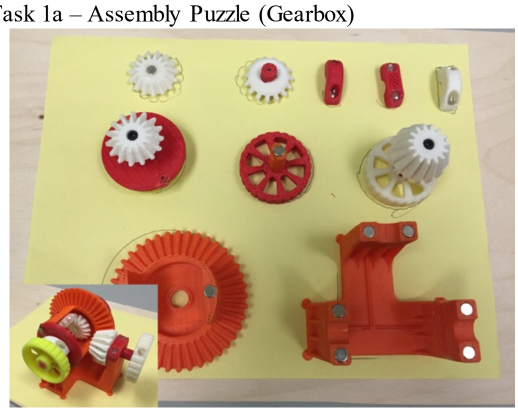
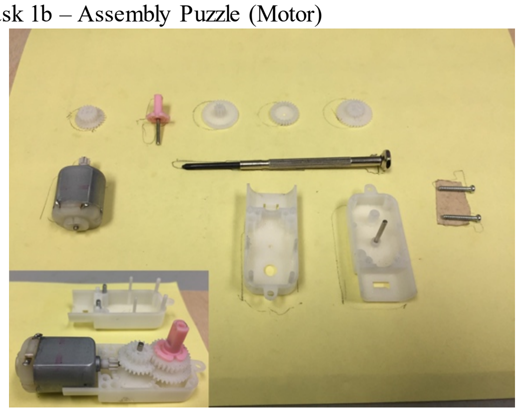
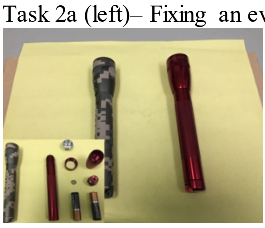
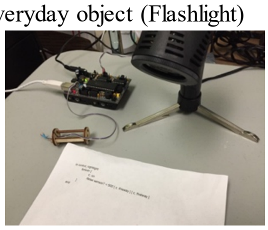
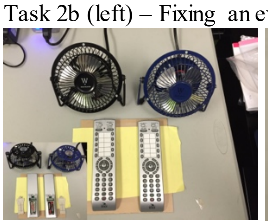
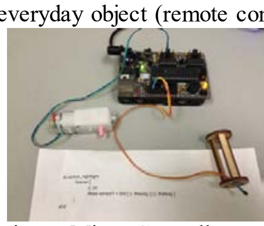
The students took part in a year-long workshop in our FabLab that stretched across two two-month blocks (Figure 1). During each block, the students worked in the lab for 1.5 hours per day, two times a week. In the first two months, the students worked in pairs on a project called the Omni-Animal. During this project students learned how to design their own three-dimensional creature using computer-aided drawing (CAD) software (Figure 1). Each creature was constructed from 6-14 individual pieces, which the students cut out of a piece of plywood using the laser cutter. Due to the difficulty of translating between two and three dimensions, none of the students' initial designs were successful. The students encountered problems like making slots too wide, failing to take the thickness of the material into account, and making pieces too big or too small. All of the students iterated on their initial designs multiple times and ultimately completed a successful Omni-Animal. In the second two-month period, the students worked in groups to create an electro-mechanical Rube Goldberg machine (Figure 1). The students worked in groups of two to three with each group working on one part of the machine. Each group created a laser-cut mechanism paired with a microcontroller platform called the GoGo board (Sipitakiat et al., 2004) to add motion, react to the environment, or create an effect.

Materials

We used three tasks as a pre-test and three tasks as a post-test. The first set (A) is shown in the first column of Table 1, and the second set (B) is shown in the right column. Task 1 is about rebuilding a gear system: 1a is a differential, and 1b a motor. Task 2 is about fixing a broken system: 2a is a flashlight where the bulb is broken and the batteries are inverted; 2b is a remote control where the batteries and spring are inverted, the fan is switched off. Task 3 is about reconfiguring a micro-controller: the sensor and actuator are plugged into the wrong ports.

Those tasks went through several iterations before we were confident that they could capture students' learning. More specifically, since the laser cutting project was about creating three-dimensional creatures from flat pieces of wood, we expected that students would increase their ability to assemble complex mechanical objects from their individual pieces. They also learned to use the GoGo board, which is an easy to use micro-controller with plug-and-play sensors and actuators and block-based programming environment. Since many everyday devices include a similar input-output structure (e.g., a button / light sensor / motion sensor detects an event, a few lines of code analyze the data, and the system triggers a response with a motor or a speaker), we hypothesized that the students would be better equipped to reason about, troubleshoot, and repair everyday devices. Finally, the Rube Goldberg project was designed to convey the idea that complex systems are more than the sum of their parts: during the workshop, each group built one step of the machine using the laser cutter and a GoGo board. All six tasks described in Table 1 tried to capture those three aspects to various extent.

Table 1: the six tasks given to our participants (a smaller image on the bottom left shows the final product for task 1 or a step toward fixing the system for task 2). For the scope of this paper, we focused on task 1a.

Task 1a – Assembly Puzzle (Gearbox) 	Task 1b – Assembly Puzzle (Motor) 
Task 2a (left)– Fixing an everyday object (Flashlight)   Task 3a (right)– Reconfiguring a Micro-Controller	Task 2b (left) – Fixing an everyday object (remote control)   Task 3b (right) - Reconfiguring a Micro-Controller

Design

Half of the novices completed set A as a pre-test and set B as a post-test. We counter-balanced those tasks for the other half of the participants. In other words, half of the novices completed tasks 1a, 2a and 3a for the pre-test and tasks 1b, 2b and 3b for the post-test. The other half of the novices completed tasks 1b, 2b and 3b for the pre-test and tasks 1a, 2a and 3a for the post-test. The experts completed all six tasks in a single session, and we also counter-balanced set A and B for them.

Procedure

Novices were asked to leave the workshop for a short period of time to complete the study. Because of time constraints, they were run in pairs sitting side by side at a 3' by 6' table. Each participant was given their own puzzle to work on. They were instructed not to work together on the puzzles or to look at what the other person was working on. First, an *Assembly Puzzle* was placed in front of each participant on a wooden board (task 1). The participants were told that the object in front of them had been disassembled, that it was their job to try and put it back together in five minutes, and that they should try their hardest and not be frustrated if they were unable to solve the puzzle. They were not given any further information about the object (i.e., no instructions on how to assemble the object). Participants were instructed not to touch the puzzle until the timer was started. Once the timer was started they had five minutes to try and solve the assembly puzzle. When the time expired, the puzzle was removed from the table. Next, the repair puzzle was placed in front of the participant (task 2). The participants were given four minutes to work on this puzzle. When the timer expired, the repair puzzle was removed from the table, and the reconfiguration puzzle was placed on the table (task 3). They had three minutes to work on the reconfiguration puzzle. When the time expired, the participants were thanked for their time and left the room.

Since there was no time constraint associated with participating to a workshop, experts were run one at a time and worked through all six tasks in a single session. Half of the experts worked on the tasks from set A first, followed by the tasks from set B (1a-2a-3a-1b-2b-3b), while the other half did the tasks from set B followed by set A (1b-2b-3b-1a-2a-3a). The time-per-task was the same for experts and novices. Video, audio, and body position (using a Kinect sensor) were recorded for the duration of the study.

Video coding

We had two major goals which resulted in the development of two distinct video coding schemes. First, we needed a way to determine how close participants came to the correct solution. The 11-point assessment scale was developed for this purpose. Second, we needed a way to model the participants' full sequence of meaningful actions as they worked through each puzzle. We designed the time-based coding scheme for this purpose.

The 11-point assessment scale

In order to meaningfully compare pre-workshop students, post-workshop students, and experts, it was important to develop a metric that accurately measured how close each participant came to the correct solution. However, most of the participants—including experts—made significant progress on the problem but failed to fully complete the gearbox problem in such a short amount of time (5 minutes), so we needed a more nuanced way of measuring progress than percentage of participants who completed the puzzle. Through an iterative coding process we created an 11-point time-agnostic scale for this purpose.

Coding videos with this metric occurred as follows. While watching the video, if the participant performed an action that matched one of the codes, we assigned a 1 to that code. If the participant's action matched a code partially, we assigned a 0.5 to that code. No time information was recorded (hence time-agnostic); that is, at the end of the video, two participants who carried out the same actions in different orders would receive the same score. At the end of the video, we summed up the scores across codes and assigned this to the participant. A score of 0 meant the participant made no progress on the problem, while a score of 11 meant the participant completely solved the problem. The higher the score, the closer to finishing successfully.

The time-based coding scheme

Since the 11-point assessment scale did not capture any temporal information, we designed a second time-based video coding scheme to categorize the different types of actions participants carried out while attempting to solve the gearbox problem. This coding scheme allowed us to analyze how sequences of actions differed between groups. The final coding scheme contained 14 codes that belonged to 4 categories: planning, evaluation, context, and action. The coding scheme complements the 11-point assessment scale and was designed so that it could be translated into other coding schemes used in similar analyses (Tschan, 2002; Worsley & Blikstein, 2013).

This time-based coding scheme went through a number of iterations. Initially, we coded the exact state of the gearbox as participants worked on the problem. Each code consisted of a set of pieces with an optional sub-code indicating if any pieces were added or taken away in that moment. A major flaw of this coding scheme was the inability to distinguish between a correctly-assembled set of parts and an incorrectly-assembled set of parts. Ultimately, this coding scheme proved to be too noisy for any useful analysis. The next iteration of our coding scheme treated the participants' actions in a more general way. Instead of hundreds of possible codes, we narrowed down the meaningful actions to 9 codes: exploring, looking, rotating, plastic connection, magnetic connection (correct), magnetic connection (incorrect), meshing gears, disassembling, and placing an axle in a hole or bracket.

Finally, in order to make our coding scheme cross-compatible with other coding schemes of interest (Tschan, 2002; Worsley & Blikstein, 2013), we added new codes and further refined the existing ones. The final coding scheme contained 14 codes in 4 categories. We designed custom software to streamline the process of coding the videos. Each time the participant carried out an action, the appropriate code was entered and linked to the video using a timestamp (Figure 2). After coding a participant's video, we were left with a full sequence of the participant's actions during the problem. In other words, we transformed video of the participants' actions into a time-stamped sequence of codes.

Figure 2: an example of a sequence of actions at different time points coded with the Time-Based Coding Scheme. From left to right: **axle**, **rot**(ate), **plas**(tic connection), **mesh**(ing gears), **axle**, **mag**(netic connection).

Results

Hypotheses 1 (novices' improvement from pre to post) and 2 (experts vs novices)

For hypotheses 1 and 2, we used the 11-Point Assessment Scale described in the coding section to assign each participant a score between 0 (no progress) and 11 (finished solution) on the Gearbox task (1a). We first visually explored our dataset using boxplots (Fig. 3, left side). Half of the novices completed the gearbox task before the workshop, and the other half completed it afterwards. All experts completed the task. The descriptive statistics are as follows: for the novices on the pre-test, N = 9, mean = 2.5, SD = 2, for the novices on the post-test, N = 8, mean = 3.69, SD = 1.85, and for the experts N = 18, mean = 6.97, SD = 2.45. The boxplots also revealed that there was an outlier among the novices in the pre-test. One student scored a 7 while the second best student scored a 3. This particular participant had worked in the lab full-time as an assistant for 3 months preceding the workshop and was excluded from the following analyses. To test our first hypothesis (whether our novices improved from pre to post-test), we used an ANOVA to compare the novices' performance before and after the workshop. We found that a significant improvement from pre to post: $F(1,14) = 5.17, p < 0.05$, Cohen's $d = 1.14$. To test our second hypothesis (whether experts performed better than novices), we grouped pre- and post-tests for novices and used an ANOVA to compare them to the experts. We found that experts did significantly better at the gearbox task than novices: $F(1,34) = 27.00, p < 0.001$, Cohen's $d = 1.82$.

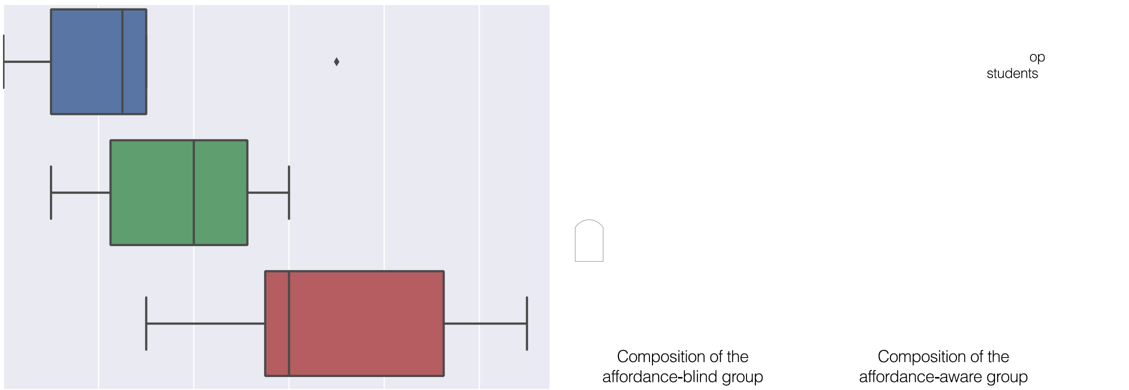


Figure 3. Left: Boxplot of the novices' scores on the 11-point scale for the pre and post-test compared to experts' scores on the gearbox task. Right: Composition of the novice and expert groups found by clustering on problem-solving sequences.

Hypothesis 3: novices' similarity to experts after the workshop

Since one of the goals of the study was to see if novices became more like experts after taking part in a long-term workshop in the FabLab, we needed a way to capture the similarity between any two problem-solving sequences. We used two different techniques to test this hypothesis: first, we translated sequences into an existing coding scheme (Tschan, 2002) to estimate how many "ideal cycles of cognition" (described below) novices and experts went through. Second, we used computational techniques to compute a similarity score between all participants and used an unsupervised clustering algorithm to separate participants into groups based on their problem-solving sequences. The main idea behind both analyses is to see whether novices at the post-test start to display more "expert-like" behaviors.

Ideal cycles of cognition

Tschan (2002) found that individuals and groups of students performed better on a problem-solving task when they completed a higher number of "ideal cycles of cognition". An ideal cycle is composed of three steps: planning, acting, and evaluating. We collapsed the 14 codes of the time-based coding scheme as follows: planning (fdis, look, org), acting (axle, axlex, dis, disx, mag, magx, plas) and evaluating (mesh, meshc, rot, test). This distinction is obviously not ideal, because the planning and evaluating phases overlap. But as a preliminary result, we found a trend similar to the left plot of Figure 2 (see boxplots on Fig. 5).

An ANOVA revealed a significant difference between novices and experts: $F(1,34) = 14.45, p < 0.001$, Cohen's I = 1.43 (novices mean=1.07, SD=0.77; experts mean=2.81, SD=1.55). For novices, there was a trend in the same direction (although non-significant): $F(1,14) = 3.10, p = 0.10$, Cohen's $d = 0.99$ (pre-test mean=0.75, SD=0.83; post-test mean=1.43, SD=0.49).

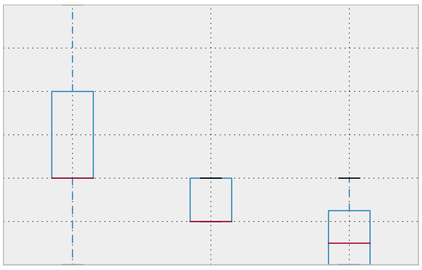


Figure 5. boxplots showing the number of ideal cycles of cognition for novices and experts.

Clustering on raw actions

By clustering participants according to their entire set of actions on the gearbox problem, we were able to identify two groups of participants. One group contained 13 participants, composed of all of the pre-workshop high-school students, 62.5% of the post-workshop high-school students, and 6% of the experts. The other group contained 19 participants, composed of zero pre-workshop high-school students, 37.5% of the post-workshops students, and 94% of the experts (Fig. 3, right side).

We used the R package TraMineR for clustering participants on their raw actions (Gabadinho, Ritschard, Mueller, & Studer, 2011). By computing the edit distance between all pairs of sequences using TraMineR's optimal matching algorithm, we were able to construct a symmetric distance matrix that captured the similarity between all pairs of participants. That is, for all pairs of participants, we computed a single index that captured the similarity of their problem-solving trajectories. Finally, we used agglomerative hierarchical clustering (Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2016) to separate out the two groups of participants who were most similar to each other.

Based on the compositions of these groups, we labeled the first group affordance-aware and the second group affordance-blind. We chose these labels based on the most prevalent actions within each group. The participants in the affordance-aware group carried out a higher proportion of axle-related actions, gear-meshing actions, correct magnetic connections, and rotations (Figure 4). In comparison, the affordance-blind group carried out a higher proportion of incorrect magnetic connections and incorrect plastic connections (Figure 4). More importantly, the affordance-blind group carried out almost zero axle, gear, or rotation actions. The affordance-blind group seemed unable to perceive the important affordances of the pieces, while the affordance-aware group took these into account when solving the gearbox problem.

The only sub-group split between the two clusters were the post-workshop high-school students. Our interpretation for this split is simple: the workshop had a positive effect. After participating in the workshop, nearly half of the students were more similar in their problem-solving behavior to experts than to pre-workshop high-school students. To validate the integrity of the two clusters, we compared each cluster's scores on the time-agnostic 11-point assessment scale using a two-tailed t-test. Not only was there a strongly-significant difference between the affordance-blind group (mean=2.35, sd=1.20) and the expert-like group (mean=6.89, sd=2.00) (t(28.23)=7.89, p < 0.001), but the difference in means was even-larger than the previous tested difference (effect size of previous test is d=1.97, while effect size of current test is d=2.65) (Figure 4).

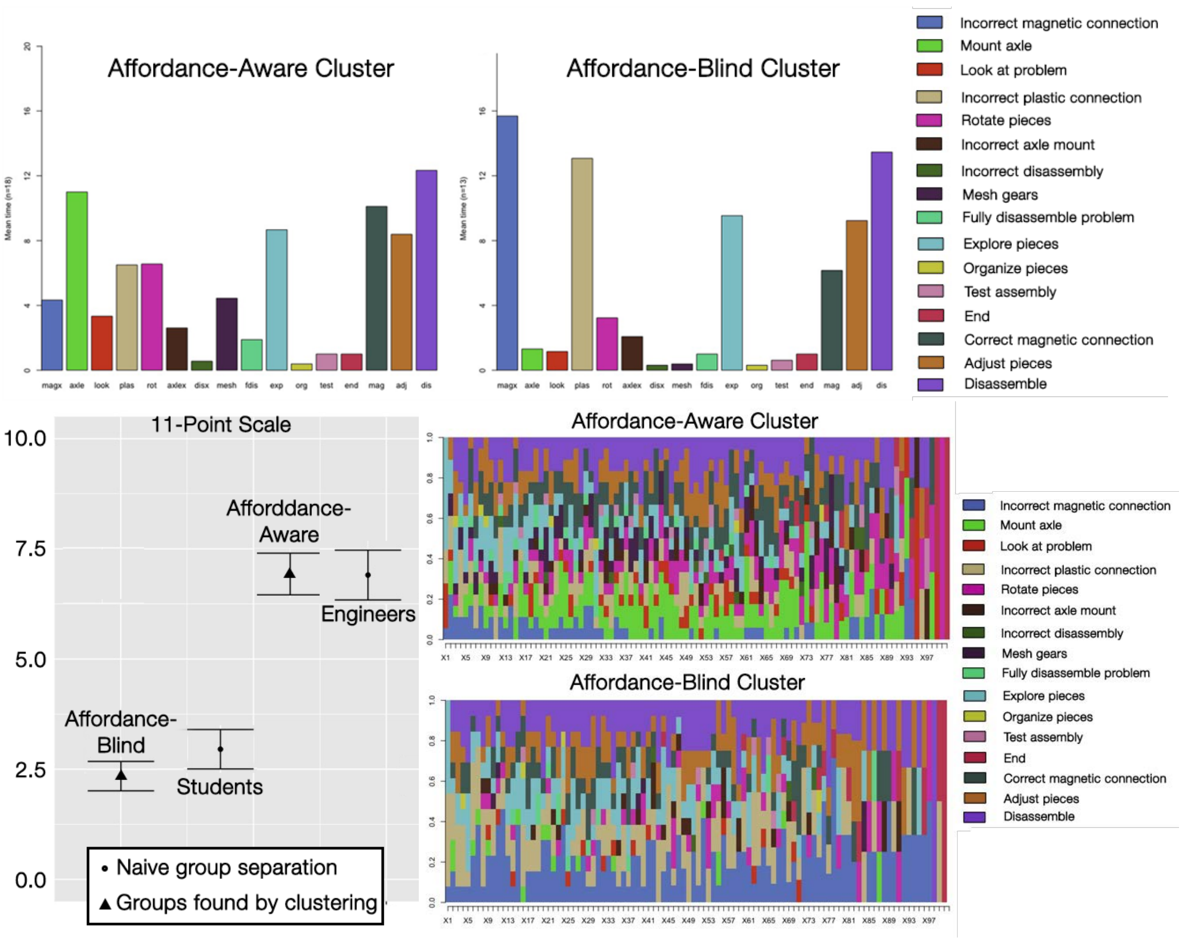


Figure 4. Top: Frequency of actions by cluster. Bottom: Proportion of actions at each time step for each cluster. Note the higher proportion of axle-related actions (green), meshing gears (dark purple), and rotation (fushia) in the Affordance-Aware cluster, and the higher proportion of incorrect magnetic connections (sky blue) and incorrect plastic connections (beige) in the Affordance-blind group.

Discussion

The motivation for this work was to develop a new methodology for capturing students' learning in makerspaces. We have designed a new kind of task-based assessment where students had to rebuild a gear system, fix everyday devices, and debug a microcontroller. These tasks were designed to assess skills that participants learned during the workshop, such as constructing a 3D object from 2D parts, building an input-output system, and understanding that complex systems are made of small interconnected parts.

For our preliminary analyses, we have focused on the first task of this assessment (the gearbox). We developed an extensive coding scheme to estimate students' performance and found that participants significantly improved from pre- to post-test. This suggests that the workshop had a positive effect on their ability to reason about and assemble complex mechanisms. Additionally, we asked experts (graduate students in mechanical engineering) to complete the same tasks and found that novices became more like experts in their perception of the salient features of the problem and in their problem-solving approach. This finding suggests that novices' improvement actually reflects one (or several) skills that experts have gained through many hours of studying and interacting with mechanical systems. It makes us more confident that we are capturing an important aspect of what constitutes an engineer.

These results are promising, but they are also preliminary: we have only analyzed one task out of six. The main reason for this narrow focus is that the coding schemes took a significant amount of time to develop and apply. Next, we plan to analyze the 5 other tasks and attempt to replicate the findings of this paper. Another limitation of this work is the fact that by limiting our analysis to a single task we were forced to use between subject analyses, which considerably reduced our statistical power. Finally, we acknowledge that our tasks only capture a small portion of what constitutes an expert. The job of mechanical engineers is vastly more complex than rebuilding gear systems and fixing everyday devices.

Even with those limitations, we consider our contribution to be a significant advance in capturing learning in makerspaces. Previous work was mostly limited to qualitative accounts of students' experiences in those spaces or traditional pen and paper questionnaires. We designed semi-authentic engineering tasks, and found preliminary evidence that participating in a maker workshop had a positive impact on participants. Not only did they improve from pre to post, but they also became more similar to mechanical engineers in their actions.

While this approach can be viewed as a new type of assessment, we also view it as a way to gain a more nuanced understanding of the types of cognitive change that are fostered in maker spaces (and potentially other unstructured learning environments). In its current form, our approach provides a starting point for other types of task-based assessments and analyses. We are currently working on a more general framework that provides guidelines for the design of additional tasks and coding schemes. Finally, it is worth mentioning that we also collected all of students' gestures and body postures using a Kinect sensor. Future work includes the analysis of this dataset to extract indicators of expertise that would act as a proxy for the coding schemes we developed in this paper. In the long run, our hope is to automatically collect and process task-independent measures of students' performance using sensors and machine learning algorithms.

Conclusion

Makerspaces are inherently messy learning environments. In them, students learn a variety of skills: they come up with original project ideas; they address problems in their communities; they learn to overcome failure; they learn to communicate and collaborate with their peers; and finally, they learn to think like engineers. These skills are central to many current (and upcoming) career paths, but it can be difficult to teach them in formal learning environments. Furthermore, it has proven difficult to capture these changes using traditional methods. This paper introduces a new method for capturing these changes though a combination of task-based assessments and qualitative/computational analysis techniques. Using this method, we found that students who took part in a maker workshop became more like engineers in their ability to reason about and solve complex problems. More specifically, the students learned to recognize the functional affordances of complex mechanisms—that wheels are for rotating and gears are for meshing. This shift in perspective is an important, empowering educational outcome, and provides new motivation for studying the educational impact of fostering a maker mindset in youth.

References

Blikstein, P. (2013). Digital fabrication and "making" in education: The democratization of invention. *FabLabs: Of Machines, Makers and Inventors*, 1–21.

Blikstein, P., & Krannich, D. (2013). The makers' movement and FabLabs in education: experiences, technologies, and research. In *Proceedings of the 12th international conference on interaction design and children* (pp. 613–616). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2485884

Dougherty, D. (2013). The maker mindset. *Design, Make, Play: Growing the next Generation of STEM Innovators*, 7–11.

Fields, D. A., Searle, K. A., Kafai, Y. B., & Min, H. S. (2012). Debuggems to Assess Student Learning in e-Textiles (Abstract Only). In *Proceedings of the 43rd ACM Technical Symposium on Computer Science Education* (pp. 699–699). New York, NY, USA: ACM. https://doi.org/10.1145/2157136.2157367

Gabadinho, A., Ritschard, G., Mueller, N. S., & Studer, M. (2011). Analyzing and Visualizing State Sequences in R with TraMineR. *Journal of Statistical Software*, *40*(4), 1–37.

Halverson, E. R., & Sheridan, K. M. (2014). The Maker Movement in Education. *Harvard Educational Review*, *84*(4), 495–504.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., & Hornik, K. (2016). *Cluster: Cluster Analysis Basics and Extensions.*

Martin, L. (2015). The Promise of the Maker Movement for Education. *Journal of Pre-College Engineering Education Research (J-PEER)*, *5*(1). https://doi.org/10.7771/2157-9288.1099

Papert, S. (1980). *Mindstorms: children, computers, and powerful ideas*. New York: Basic Books.

Peppler, K., & Bender, S. (2013). Maker movement spreads innovation one project at a time. *Phi Delta Kappan*, *95*(3), 22–27.

Piaget, J. (1973). To understand is to invent: The future of education. Retrieved http://philpapers.org/rec/PIATUI

Tschan, F. (2002). Ideal Cycles of Communication (or Cognitions) in Triads, Dyads, and Individuals. *Small Group Research*, *33*(6), 615–643. https://doi.org/10.1177/1046496402238618

Worsley, M., & Blikstein, P. (2013). Towards the development of multimodal action based assessment. In *Proceedings of the third international conference on learning analytics and knowledge* (pp. 94–101). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2460315