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EVALUATING THE BOTTOM-UP METHOD FOR FUNCTIONAL DECOMPOSITION IN PRODUCT DISSECTION TASKS

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ABSTRACT

The purpose of this study is to continue to explore which function identification methods work best for specific design tasks. Prior literature describes the top-down and bottom-up approaches as equivalent methods for functional decomposition. Building on our prior work, this study tests the bottom-up method against the top-down and enumeration methods. We used a 3-factor within-subject study (n=136). While most of our diagram-oriented metrics were not statistically different, we found statistical support that: 1.) students reported that the dissection activity was more useful when using bottom-up, and 2.) that student engineers committed many more syntax errors when using the bottom-up method (by listing parts instead of functions). We believe that both these results are due to the increased focus on individual parts. We do not know if an increased attention to the parts would increase novelty or fixation, and recommend future studies to find out.

1 INTRODUCTION

Functional decomposition is an important process for supporting early design abstraction prior to concept generation and when dissecting or reverse engineering a product [1]. Our prior work began exploring functional decomposition in product dissection tasks, and found no difference between the energy-flow, top-down, and enumeration methods [2]. This paper seeks to test an additional method, bottom-up, which is noted to perform the same as top-down methods [1]. When viewing product dissection as a cognitive activity, we find that decomposition tasks are the same as the "divide and conquer" heuristic described in cognitive science [3]. Psychologists further describe two distinct cognitive sub-strategies for using divide and conquer: top-down and bottom-up [4], which appear to correspond to the functional decomposition methods of the same name. The top-down approach is largely driven by prior knowledge, whereas bottom-up is usually driven by what a person can sense. The mixing of these models and other problem solving strategies is called "opportunism", and closely mirrors descriptions of the enumeration approach [5]. Further, prior studies have found that the bottom-up problem solving strategy is generally used by novices, and top-down or opportunistic strategies are used by more experienced problem-solvers [4, 6]. Thus, we hypothesized that given the same conditions, that a novice engineering population would perform better with a bottom-up approach than an enumeration or top-down approach.

The results of this paper serve to define the tasks for which certain strategies work best. Functional decomposition is often used prior to concept generation [7], but is also applied to iterative design and reverse engineering, when a design already exists [1]. Many design theorists treat these tasks the same when applying functional decomposition methods [2], although we believe they represent different problem types [8]. Therefore, this study only evaluates methods for product dissection tasks. This paper discusses background information on the bottom-up method for functional decomposition, a study conducted to eval-

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uate differences between the bottom-up method and others, and discussion of results and interpretation. The paper concludes with recommendations for future work.

1.1 Definitions

Bottom-up is defined as a function identification method where an engineer determines functions for individual parts, groups these functions into meta-functions, and continues this process until defining the overall function. Top-down is defined as the reverse process, where an engineer determines the overall function, decomposes this into sub-functions, and continues until functions are defined on the part level. Energy-flow is defined as tracing material, information, and energy flows through a device, and mapping functions to changes in these flows. Enumeration is defined as writing out whatever functions come to mind, with no specific strategy for identifying them.

This paper regards design to be primarily an engineering activity which solves ill-structured problems [8], and reverse engineering to be a specific design task that represents a well-structured problem. Functions are defined as "the solution-neutral [or embodiment-neutral] detailed description of what are the intentions for the products" [9]. "Methods", as described in this paper, refer to strategies for identifying functions in a given functional decomposition task.

Except when discussing terms used by other authors, "functional analysis" is used to mean identifying functions where a design or concept already exists (i.e. well-defined problems), and "functional synthesis" means identifying functions for an original design where no prior design or concept exists (i.e. ill-structured problems.) "Functional decomposition" describes both synthesis and analysis simultaneously, and is defined as the general method of identifying functions (for new design, iterative design, reverse engineering, etc.).

2 BACKGROUND

Functional decomposition is an important design tool since design problems are largely ill-structured [10]. Engineers use decomposition methods to break an ill-structured problem into well-structured problems which helps them make sense of a difficult design problem [11]. Cognitive psychology can be employed to help describe engineering problems [8]. Cognitive science describes a number of problem-solving strategies, including divide and conquer [3], morphological analysis [12], and opportunistic problem solving (also known as Multi-attribute Utility Theory) [13]. The divide and conquer method is composed of two sub-strategies [4]. The first of these, top-down, is characterized by relying on prior abstract knowledge and using this to make sense of the given task. The second, bottom-up, relies on what is perceived by the senses to construct a total understanding. The opportunistic approach combines these and other strategies, borrowing what is necessary when it is necessary [4]. Experts tend to favor top-down approaches, whereas novices, bottom-up [4, 6]. This result from cognitive science seems to correspond with engineering studies of product dissection [5].

The four engineering function identification methods closely mirror cognitive problem solving strategies. Morphological analysis (not the ideation technique) considers every system element and every input and output in that system before using these to calculate a whole [12], and corresponds with the energy-flow approach used by many design authors. The bottom-up and top-down approaches [1] match the divide and conquer heuristic [3], as described above. Finally, the enumeration method lacks specific directions [7, 14], and is therefore opportunistic [15].

We only found one design textbook that describes a bottom-up method for functional decomposition (the Subtract and Operate method [1]). In this process, a designer removes a random component from a device and sees what functions fail to operate. Repeating this method over several components, a designer may reconstruct the functional interactions between all the parts. This method is recommended for tasks where a concept or actual design already exist.

In this same text, Otto and Wood also describe a top-down method (the FAST method). To use this method, an engineer first identifies an overall function and then brainstorms a "spine" of primary functions. These primary functions may relate to an external, required function such as providing electricity. A string of secondary functions may be strung from any function along this spine. This method also distinguishes between one-time functions such as packaging, and functions which are concept dependent. These are drawn into a FAST diagram. In this study, we use the top-down method as described by Eckert [5] instead of the FAST method.

The engineering texts that do discuss the bottom-up method state or imply that top-down methods are equally effective to bottom-up methods [1, 16]. Otto and Wood state that top-down and bottom-up methods are inferior to the energy-flow method, since these first two are more subjective and may miss important details [1]. Schmekel and Sohlenius do not make any direct equivalence claims, but they implicitly treat the top-down and bottom-up methods as interchangeable [16]. We failed to find other mechanical engineering references to the bottom-up method or any empirical comparison between the bottom-up method and other function identification approaches.

3 METHODOLOGY

We found in our prior study that the literature on functional decomposition was inconsistently applied to a variety of engineering tasks [2]. Accordingly, we began testing various methods in different contexts to see which performed best. This study extends our prior work to include the bottom-up method. We hypothesized that the bottom-up method would perform best because it tends to be adopted by novices [4], and participants could manipulate parts and discover for the interactions for themselves (i.e. build their own schema [17]).

- Does the bottom-up method help students identify more functions or gain a greater understanding than other functional decomposition methods?

3.1 Design of Experiment

In order to answer our research question, we used a quantitative design of experiment, while also utilizing survey methods for understanding the students' thinking. The research question was converted into testable hypotheses. We decided to omit the energy-flow method because our prior results found that it was not different from the other methods, and because our qualitative observations suggested students struggled the most with this method. Consequently, we limited our study to top-down, bottom-up, and enumeration. Our hypotheses are:

- H0 - There is no difference between the bottom-up, top-down, and enumeration methods
- H1 - There is a difference between the bottom-up and top-down methods
- H2 - There is a difference between the bottom-up and enumeration methods
- H3 - There is a difference between the top-down and enumeration methods

The differences between these methods are measured using the following metrics: the total number of functions, number of unique functions, the efficiency of the diagram (unique functions / total functions), number of errors, error rate (errors / total functions), average and maximum geodesic distances, number of syntax errors, the ratio of errors to total functions, number of functions on each hierarchy level, the number of errors on each hierarchy level, the ratio of errors on each level divided by the number of functions on each level, and perceived usefulness of the method as measured on a 10 point scale. Since it is unknown which method would perform better than the others, a two-tailed test will be used. However, we expected the bottom-up method to perform better than other methods at generating more functions, identifying the greatest number of unique functions, having the fewest syntax errors, and proving the most effective as measured by students.

To test the hypotheses, a 3-level, within-subject design of experiment was used. This design is commonly used in human factors and product comparison studies [18], and has the advantage of multiplying the number of samples and reducing some types of sample bias and the effect of uncontrolled variables such as the time of day and self-selection bias [19]. One negative effect of this experiment design is that some effects are conflated; in this case, the product and time effects are conflated, meaning that we cannot distinguish between learning effects or fatigue effects and effects due to the specific product dissected.

FIGURE 1. A hair dryer, power drill, and NERF blaster

TABLE 1. Experimental Layout Over 4 Week Period; EN = Enumeration, TD = Top-Down, BU = Bottom-Up

	Hair Dryer	Power Drill	N/A	NERF
	Week 1	Week 2	Week 3	Week 4
Group A	EN	TD	N/A	BU
Group B	BU	EN	N/A	TD
Group C	TD	BU	N/A	EN

3.2 Procedure

Participants were in the course ME 297 (How Stuff Works) at Purdue University. They were asked to dissect three products (see fig. 1), over the course of four weeks, and use three methods for determining the functionality of those products (see tab. 1). All participants dissected a hair dryer on week one, a power drill on week 2, and a NERF blaster on week 4. Data was collected over a four week period in February and March 2013. All sessions were held on Thursdays and group A met at 9:30AM, group B at 11:30AM and group C at 1:30PM each week.

Each session began with instruction on how to create a function tree, characteristics of a function, the distinction between a function, behavior, and part, and instruction on how to use the decomposition method. Functions for this activity were defined as a verb followed by a phrase or noun. This instruction lasted approximately 10 minutes. Participants were then asked to physically dissect a product and determine its functionality using a top-down, bottom-up, or enumeration approach. After disassembly, students were asked to diagram a function tree describing the functions of the dissected product. Students also completed an initial survey to determine basic demographic information and a post-survey to evaluate the perceived usefulness of the activity and prior exposure to disassembling the product. After the function trees were submitted, the products were reassembled and participants were shown how the product works and relevant engineering equations relating to certain aspects of each product. Participants were given surveys before and after the session, and open interviews were held with a few students after sessions.

In order to ensure consistency, each participant received paper copies of all instructions, examples, and definitions mentioned above. Participants were also provided with a list of function verbs. The function verb list was taken from the pruned function list by Caldwell et al. [20] though the hierarchy of the verbs was not retained. Participants were also given a packet explaining how to perform the method for the experimental session.

Qualitative data from the study consisted of casual observations made by the authors and other test administrators. Observations were recorded immediately after testing periods. No formal protocol was used to complete the observations. Only field notes and debriefing notes were recorded. These observations were made at the length of the study.

3.3 Population

Participants were selected based on their participation in a product dissection class at Purdue (ME 297) in Spring 2013, and thus is a convenience sample. This sample is distinct from that taken in our prior work [2]. Students in the class are not taught any method to analyze functions, nor taught what a function is. Participants were told that the activity would help them prepare for the final project in the class.

Each session consisted of varying numbers of participants due to how scheduling for the class was conducted. Group (section) A had 18 participants; group B had 17; and group C had 18. Over all groups, 10 students identified as freshmen, 28 as sophomores, 10 as juniors, and 5 as seniors. Slightly more than half of the participants (26 out of 51) identified as being in mechanical engineering. Other majors were generally engineering, and included aerospace, electrical, computer, materials science, biomedical and agricultural engineering, with five students not reporting. Most of these categories only had two to three students. More than half (40) participants reported not having learned functional decomposition before, many of which had already taken a required course that covers functional decomposition. This corresponds with findings in other studies that students often forget methods taught early in their education [21].

3.4 Independent Variable - Abstraction Method

The independent variables used are:

- Bottom-Up, manipulate each part and define a function for it. Combine these functions into groups. Continue until all functions are grouped under a single function.
- Top-Down - Start with the highest level of abstraction (the whole machine) and determine overall function. Break down into sub-systems and determine functions of each of these systems. Iteratively become more detailed for each level. Write these functions into a tree.
- Enumeration - Write down relevant functions as they seem appropriate in whatever order they come to mind. Organize these into a tree.

3.5 Dependent Variables

We used the same dependent variables we had used in our prior work [2]. These build on metrics used in other functional decomposition studies, as seen in table 2. The dependent variables we use include:

TABLE 2. Metrics used in prior research on functional decomposition

Name of Metric	Metric Type
Unique functions [2]	Refined count (M5)
Conformance metric [22]	Raw count (M1)
Exact/approximate scoring [20]	Raw count (M1)
Unit of information [23]	Raw count (M1)
# spoken functions [9]	Raw count (M1)
# levels of abstraction [9]	Qualitative
# levels of hierarchy [9]	Tree depth (M2)
# func. on a hierarchy level [9]	Branch width (M3)
Completeness of func. analysis [9]	Raw count (M1)
Rubric (Energy-Flow only) [24]	Error count (M4)
# parts exposed [25]	Raw count (M1)
# same features [25]	Raw count (M1)

- Functions (Func., M1) - the total number of phrases in a diagram and gives an very rough idea of how detailed the student investigated the device
- Number of unique functions (Unq. Fn., M5) - the number of non-redundant phrases in a diagram. This helps measure how broadly the student understood the device.
- Tree efficiency (Eff., M5) - the ratio of unique functions to total functions. This shows how redundant a tree is.
- Maximum Geodesic Distance (Max GD, M2) - the largest of all the shortest paths in the diagram. It serves to detect diagram errors and tree size (level depth) when compared with the average geodesic distance.
- Average Geodesic Distance (Avg GD, M2) - the average of the shortest paths between nodes in the diagram. When compared with max GD, it can help distinguish a tree that is both "tall" and "bushy" from a tree that is simply "tall". This helps detect diagram errors, such as when a portion of the tree is used as a flow-chart rather than a hierarchy.
- Number of syntax errors (Errors, M4) - the number of phrases not written as a verb-phrase or left blank. This approximates how many phrases are actually functions, and helps measure how well a method aides functional thinking.
- Error ratio (Err Rate) - the ratio of errors to total functions. This normalizes the syntax error for each participant.
- Number of functions on a hierarchy level (Fn. Lvl X, M3) - the number of phrases on each hierarchy level. This tells us how detailed and deep the tree goes.
- Error ratio on each hierarchy level (Err. Lvl X) - the ratio of

errors on each level to functions on each level. This indicates if certain levels are used more often for non-function entries.
- Perceived usefulness of activity (Survey) - student responses of how useful each method was on a scale of 1 to 10 (high).

3.6 Covariates

- Class level - freshman, sophomore, junior, or senior.
- Learned functional decomposition before - yes / no.
- Frequency of disassembly outside of class - never / rarely, sometimes, often.
- Prior experience with disassembling a hair dryer, power drill or NERF gun - yes / no.

We chose these covariates on the basis of perceived relevance to the study. We are not aware of functional decomposition studies that have used these covariates, however similar studies have. Class level can affect performance in specific design tasks [26], and prior experience is well known to affect performance [27]. It is not known if any of these factors directly influence performance in functional decomposition.

4 QUANTITATIVE RESULTS

Since a within-subject experimental design was used (n = 136, 23 samples not used), we ran a univariate ANOVA in SAS with the participant code and the device/week factor set as blocking factors. We only considered main effects due to the experimental structure.

4.1 Validation of ANOVA Assumptions

ANOVA-family analyses require that the data must be normal, satisfy the homogeneity of variance criteria, and that dependent variables are independent of one another [28]. The dependent variables were tested for normality by comparing their histograms to a normal curve. A few variables are skew right, including the functions on levels 5 through 7 and the number of errors on every level. These variables are not considered to be important unless several of them are found to be significant since they would be biased toward finding a significant difference [28]. Non-parametric tests would be used in the case of several being significant. All the dependent variables met the variance criteria (alpha = 0.05). The variables are tested separately to satisfy the independence criteria.

4.2 ANOVA Results

A significance of 0.05 is used to determine significance, and each dependent variable was tested separately. Following the ANOVA, we used Tukey's least means method of multiple comparisons to determine how the independent variables and covariates were grouped.

The ANOVA showed a statistically significant ($p < 0.05$) or near-significant ($0.1 > p > 0.05$) difference between the methods for the student perception of usefulness of each method ($F = 3.06$, $p = 0.0522$), the number of syntax errors ($p = 0.0025$) and the error ratio ($F = 6.45$, $p = 0.0261$), and the error rate on the top level of the tree hierarchy ($F = 9.49$, $p = 0.0002$).

TABLE 3. Differences between top-down and bottom-up methods: Post-hoc significant (< 0.05) and near-significant (< 0.10) differences in mean using Tukey comparisons and the Tukey-Kramer adjusted p.

Effect	Est.	t Value	Adj P
Errors	-1.827	-2.74	0.0202
Err Rate	-0.1685	-2.13	0.0899
Err Lvl 1	-0.3278	-3.82	0.0009

TABLE 4. Differences between enumeration and bottom-up methods: Post-hoc significant (< 0.05) and near-significant (< 0.10) differences in mean using Tukey comparisons and the Tukey-Kramer adjusted p.

Effect	Est.	t Value	Adj P
Errors	-2.3107	-3.39	0.0031
Err Rate	-0.2095	-2.6	0.0299
Err Lvl 1	-0.3331	-3.77	0.001
Err Lvl 3	-0.1425	-2.14	0.0885
Survey	-0.8537	-2.3	0.0614

The Tukey comparisons (see table 3) show that the bottom-up method is significantly different from other methods. When we examine the averages for each of these variables (see table 2), we see that bottom-up scored the worst on the number of errors and the error rate, as well the rate of errors on each level of the tree hierarchy. The perceived usefulness results, however, showed that students rated the activity as more useful when they used the bottom-up method compared to enumeration and possibly top-down. The number of functions on level 6 are greater for the top-down method than for the enumeration and possibly the bottom-up method, but other levels were not significant.

The device-used / week-tested covariate tested significant for several graph related metrics including the number of functions, tree efficiency, maximum and average geodesic distance, and the number of functions on several levels of the tree hierarchy (see table 4). In each case, the averages for these metrics decrease with time (figure 3); however, it is not certain if this is due to learning effects or the device used. Since there is a clear pattern, we assume learning effects.

The average function tree had 11.42 functions, 8.24 of them which were unique. The average tree efficiency was 66.9%. The average geodesic distance was 2.4 and the maximum was 4.7. The average tree had 2.6 syntax errors, meaning the average tree had an error rate of 28.3%. The average number of functions on each level, starting at 2 and going to 7, was 3.1, 4.2, 1.2, 0.3,

	Survey	Errors	Err Rate	Fn. Lvl 6	Avg Errors on Tree Level Lvl 1	Lvl 2	Lvl 3	Lvl 4
TD	6.52	2.86	25.1%	0.31	13.3%	30.2%	19.1%	25.7%
EN	6.36	2.47	19.0%	0.06	15.9%	22.8%	13.5%	20.3%
BU	7.17	4.42	39.7%	0.13	46.5%	37.8%	26.9%	35.9%

EF = Energy-Flow; TD = Top-Down; EN = Enumeration; BU = Bottom-Up

FIGURE 2. Average values for significant variables by method, darker values higher. See section 3.5 for definitions of variables.

	Avg Func.	Eff.	Max GD	Avg GD	Avg Functions on Tree Level Lvl 1	Lvl 2	Lvl 3	Lvl 4	Lvl 5
HD	14.46	0.68	5.75	2.82	0.98	4.46	2.10	0.65	13.0%
PD	11.92	0.75	5.00	2.54	0.88	3.92	1.35	0.33	26.3%
NG	11.67	0.91	4.91	2.53	0.83	3.46	1.00	0.28	22.0%

HD = Hair Dryer; PD = Power Drill; NG = NERF Gun

FIGURE 3. Average values for significant variables by device/time, darker values higher. See section 3.5 for definitions of variables.

0.1, and 0.1. Most errors were committed on the top levels with 1 error on average in the second and third levels. The average reported perceived usefulness of the activity was 6.7 out of 10.

Some metrics were not analyzed due to low sample size. For example the error rate and number of functions on specific levels of hierarchy were not evaluated for levels 5-7. These were omitted since the number of samples were too small to do an appropriate analysis. Very few function trees extended beyond level 4, with especially few having levels as deep as 6 or 7.

4.3 Reanalysis Including Data from Prior Study

To be certain that our values were accurate, we also reanalyzed the data including the data from our prior study [2]. We used the same ANOVA approach and Tukey analysis, and the metrics met the assumptions in the same way as described above. Although energy-flow and bottom-up were not consistent between the two studies, it allowed us to make tentative comparisons between the two.

Except for a few unimportant differences, all the same variables were significant as in the first analysis. While the majority of the results are not presented here due to repetition, it is interesting to note that despite including energy-flow, the bottom-up method still shows the same differences. Students are more likely to rate the activity as useful when using bottom-up, but are also much more prone to syntax errors. See figure 4 for more details.

5 DISCUSSION OF QUANTITATIVE RESULTS

While diagram-oriented metrics (e.g. unique functions, functions, max. geodesic distance) are virtually the same for the bottom-up and other methods, other measures are not. A near-significant ANOVA result for the survey results suggests that students who use bottom-up are more likely to report a better experience with the dissection activity, suggesting that they prefer that method over others, or that it makes sense to them [4]. However, students who used bottom-up committed significantly more syntax errors than when using other methods. In general, and qualitatively, these syntax errors were due to using part names rather than explicit functions. As mentioned before, the syntax errors and error ratio are slightly skew right, but the p-values are consistent for both analyses and are rather low, suggesting to us that these are truly significant, and not simply biased.

We believe that these data mean that when student engineers use bottom-up, they focus far more on parts and less on functionality. For example, figure 5 shows a diagram made by a student using the bottom-up method (digitized in NodeXL). While this particular student had a low syntax error rate (0%), all the functions are clearly written with a particular part in mind. On the other hand, figure 6 shows an example made using the enumeration method (where the student had used the bottom-up method the week before). In this example, the functions are clearly less oriented toward parts, and describe systems or particular types of outcomes rather than particular actions accomplished on a part level. The difference is subtle but important.

We should point out that an increase in errors does not necessarily mean that the students did not gain an understanding of how the device works. The students using bottom-up identified just as many unique functions as other students. For example, they may have also simply skipped the step to convert all of the parts into functions.

However, in a practical sense, while students may understand the design as well as using other methods, the increased focus on parts may serve to fixate students, or fail to help them abstract the actual functions of the device. The purpose of functional analysis is to determine its functionality independent of form [5], and not simply to make a part hierarchy. This the function represents a more abstract concept that simply listing the part name and its physical connectedness, discovering functions represents deeper learning [27]. This would suggest that function

	Survey	Errors	Err Rate	Fn. Lvl 3	Avg Errors on Tree Level			
					Lvl 1	Lvl 2	Lvl 3	Lvl 4
EF	6.05	2.00	17.6%	4.08	16.7%	14.6%	12.6%	19.4%
TD	6.46	2.76	21.9%	5.63	14.5%	26.2%	16.9%	22.3%
EN	6.59	2.14	16.1%	5.25	16.2%	17.4%	12.8%	14.0%
BU	7.17	4.42	39.7%	5.75	46.5%	37.8%	26.9%	35.9%

EF = Energy-Flow; TD = Top-Down; EN = Enumeration; BU = Bottom-Up

FIGURE 4. Average values for significant variables by method using data from this and prior study [2]. Darker values higher. See section 3.5 for definitions of variables

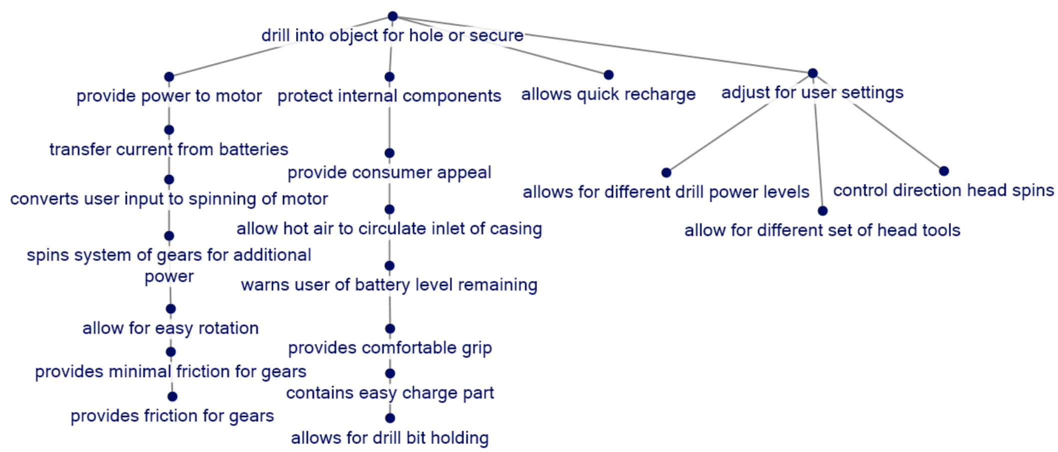

FIGURE 5. An example of a function tree created by a student for the power drill using the bottom-up method

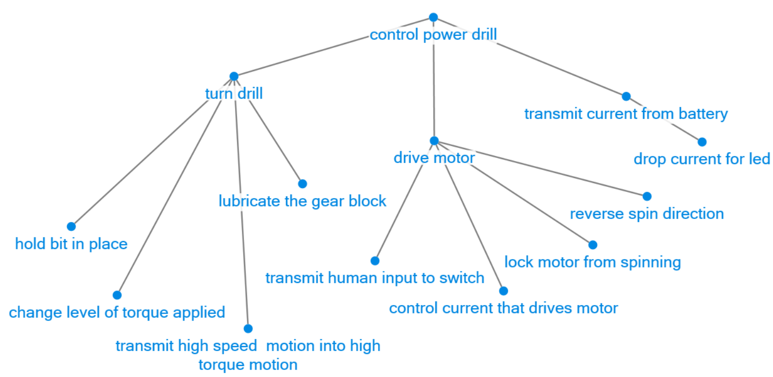

FIGURE 6. An example of a function tree created by a student for the power drill using enumeration (with prior exposure to bottom-up)

trees might be preferable to part trees. Further, in a design context, the lack of a functional understanding could lead to reduced creativity and increased fixation when generating concepts [29].

On the other hand, some recent studies by Toh and Miller have found that when students dissect products and only create a bill of materials (BOM), they are more creative than if they diagram the layout of all the parts. They hypothesize that since the BOM did not show interactions between the parts, the students did not retain those connections when improving the designs later [30]. It is therefore possible that an increased focus on parts independent of their relationships is desirable, and therefore should be promoted. However, our study did not explore this aspect of functional decomposition.

Regardless of whether an increased focus on parts is desirable or not, we cannot conclude that top-down and bottom-up are equivalent methods. The two almost certainly represent different

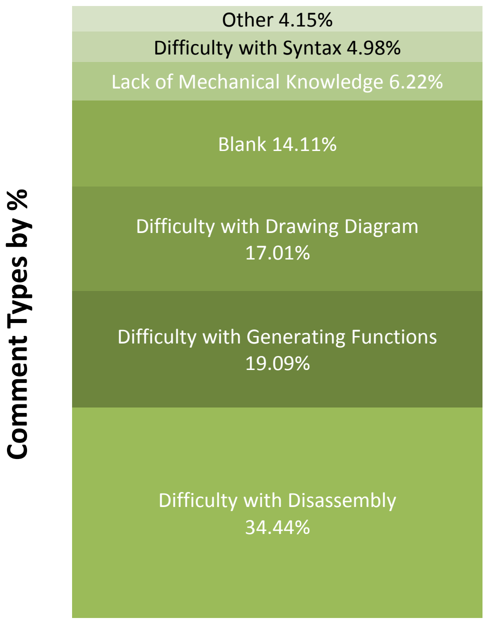

FIGURE 7. Aggregated comments by percentage over all sessions

modes of cognition, in accordance with descriptions in cognitive science [3, 4]. Students who use bottom-up are more prone to identify parts than when using top-down, and are much more likely than when using enumeration or energy-flow. This is also observed on the top level function when using bottom-up. We consider the differences between the number of functions on various levels of the tree to be inconclusive, although more data may show some differences. Thus, we reject the null hypothesis, but do not accept all the alternate hypotheses.

- H0 (Rejected) - There is no difference between the bottom-up, top-down, and enumeration methods
- H1 (Accepted) - There is a difference between the bottom-up and top-down methods
- H2 (Accepted) - There is a difference between the bottom-up and enumeration methods
- H3 (Rejected) - There is a difference between the top-down and enumeration methods

6 QUALITATIVE RESULTS AND DISCUSSION

The qualitative data from this study was already reported jointly with our prior study [2], but it is reviewed in brief. In each session, participants were asked, ”What was the hardest part of the dissection activity?”. The participant responses were qualitatively categorized by content and compiled into categories describing the nature of the comment, as seen in figure 7.

After disassembly, the students seemed to struggle most with generating functions and drawing the diagrams. Other aspects such as not having enough mechanical knowledge or difficulty adhering to the syntax were not mentioned frequently, but qualitatively, we noted that these were issues too. Perhaps these are secondary tasks, and they are less represented because the more important tasks were difficult for many students. We also noted that many students did not see a direct benefit of functional decomposition. This may be due to lack of experience with it, or poor educational experiences with it.

6.1 Qualitative Evaluation of Function Trees

The function trees that were submitted often lacked certain types of functions. One of these types were parts that do not have an effect on the operation of a device, including aesthetic parts, redundant systems, redundant support structures, etc [1]. For example, on the NERF gun trees, we observed that very few identified functions filled by parts such as the clip on the top (for attachments) or the orange tip which fills a legal function (for identifying the gun as a toy). We also noticed only one participant described the loop on the power cord for hanging up the hair dryer. The omission of these parts is likely due to the perceived relevance of these parts and their functions. The loop on the hair dryer is non-essential to the operation of the hair dryer, and not perceived as relevant.

We further observed that function trees frequently omitted deeply buried parts such as the torque limiter in the NERF gun. The torque limiter was shown to the students, but few students recorded their related functions. We suppose that the amount of effort to individually retrieve certain parts also influences the depth of effort reflected on the function tree.

7 IMPLICATIONS

Our results show that the bottom-up approach is cognitively different from other approaches, where students who use it are more likely to commit syntax errors, but also more likely to perceive the method as useful. We believe this means that the method pushes them to focus on the parts more than the functions. If this is true, this would confirm that the bottom-up method may be a good link to combine function activities with part identification activities, if followed with more detailed functional decomposition methods, such as energy-flow [1].

Because the students reported the activity to be more useful when using bottom-up, we can presume this means that they felt that they learned more. While the other variables, such as the number of unique functions, do not support the idea that the students identified more functions, the act of examining parts may have served to develop a mental model of how the device works [17], which our metrics may have missed. If the students have a better mental model, this might explain why students rated bottom-up as more useful.

If this is true, we need to explore the bottom-up method from learning theory and cognitive science perspectives. Since design can be viewed as a particular type of learning activity [8], we can similarly view functional analysis as a type of activity somewhere between well-defined (since there is an existing product and the parameters are well set) and ill-structured (since nearly any reasonable tree is correct). These types of problems require more abstract thinking than for other problems [10].

Bloom's theory and constructivism are both helpful for explaining the optimal pattern for abstracting. Bloom's theory [31], and related theories such as Skill Theory [32] suggest that there are various stages of learning, starting at concrete facts and moving toward deeper learning or abstraction. By starting at the individual parts, rather than the abstract, overall function, the bottom-up approach may take advantage of the natural learning process. Furthermore, contructivism asserts that each learner must develop his or her own schema and mental model of what he or she is learning through experiential learning tasks [17, 33]. The bottom-up approach would aid in this building of a mental model by explicitly encouraging students to manipulate individual parts and observe the responses.

If these are the active learning mechanisms behind the bottom-up approach, we would expect students to report more success with a method like bottom-up. If this is true, the bottom-up method may be a good initial activity for learners who do not have much mechanical knowledge, or for designers who are unfamiliar with the product. After a bottom-up approach is used, then a more sophisticated approach could be used, such as energy-flow, if needed [1].

8 CONCLUSIONS

The results of this study suggest that there is a cognitive difference between the bottom-up method for functional decomposition and other methods, confirming prior work in cognitive psychology [4]. Novice engineers who use the bottom up are significantly more likely to make syntax errors, which are usually equivalent with listing parts or behaviors instead of functions. However, students who use the bottom-up approach also report finding product dissection activities more useful. This result differs from prior descriptions of these methods [1]

These results may be directly due to an increased focus on parts, which may either fixate novice engineers on a few embodiments [29], or may help them consider new ideas by seeing abstract connections [25]. We suspect the second case is true, and we hypothesize that the bottom-up approach may be more successful at helping engineers use natural learning patterns to understand an existing design more thoroughly. If this is true, the bottom-up method may be especially well-suited to designers who are unfamiliar with a particular design. Therefore, the increased number of errors may not be bad, and may simply represent a different mode of cognition.

There are some limitations to this study. There was an observable learning effect throughout the study, and that may have influenced some of the data. Additionally, the combined analyses with our data from this study and our prior studies may have obscured some of the results regarding the number of functions on each tree level, which could be useful information if one method tends toward "leafier" trees. We also did not follow the FAST method of product tear-down [1], which may have yielded different results than what we found.

The scope of this study is also limited. No professional level engineers were tested, and thus the results of this study are only informative of novice designers. Some of the engineers in the study were in fields where functional decomposition is not widely used, which may have also biased the study. Finally, given the fact that the participants represent a convenience sample, there may be an undetected bias in the results.

Further research should determine whether the bottom-up method and its increased focus on parts is beneficial or inhibitive. Studies should also be conducted to validate the results of this study and other functional decomposition methods. We are of the opinion that each of the methods are useful for particular purposes and tasks, and future research should explore which tasks are best suited for which situations. Additionally, insights from psychology should be incorporated into this work to enrich our understanding of how functional decomposition affects thinking in the design process. Two potential factors include learning styles and personality.

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REFERENCES

[1] Otto, K., and Wood, K., 2001. *Product Design: Techniques in Reverse Engineering and New Product Development*. Prentice Hall.
[2] Booth, J. W., Reid, T. N., and Ramani, K., 2013. "Understanding abstraction in design: A comparison of three functional analysis methods in product dissection". In Proceedings of ASME IDETC.
[3] Wang, Y., and Chiew, V., 2010. "On the cognitive process of human problem solving". *Cognitive Systems Research,* ***11***(1), Mar, pp. 81–92.
[4] Hayes-Roth, B., and Hayes-Roth, F., 1979. "A cognitive model of planning". *Cognitive Science,* ***3***, pp. 275–310.
[5] Eckert, C., Ruckpaul, A., Alink, T., and Albers, A., 2012. "Variations in functional decomposition for an exisiting product: Experimental results". *AIEDAM,* ***26***, pp. 107–128.
[6] Sweller, J., 1988. "Cognitive load during problem solving: Effects on learning". *Cognitive Science,* ***12***, pp. 257–285.
[7] Dym, C. L., and Little, P., 2000. *Engineering Design: A Project-Based Introduction*. John Wiley & Sons.
[8] Jonassen, D. H., 2000. "Toward a design theory of problem solving". *Educational Technology: Research and Development,* ***48***(4), pp. 63–85.

[9] Eckert, C., Alink, T., Ruckpaul, A., and Albers, A., 2011. "Different notions of function: results from an experiment on the analysis of an existing product". *J Eng Design, **22***(11-12), pp. 811–837.
[10] Goel, V., and Pirolli, P., 1992. "The structure of design problems spaces". *Cog. Sci., **16***, pp. 395–429.
[11] Ho, C.-H., 2001. "Some phenomena of problem decomposition strategy for design thinking: differences between novices and experts". *Design Studies, **22***(1), pp. 27 – 45.
[12] Ritchey, T., 1998. "General morphological analysis: A general method for non-quantified modelling". In EURO Conference on Operational Analysis.
[13] Morera, O. F., and Budescu, D. V., 1998. "A psychometric analysis of the "divide and conquer" principle in multicriteria decision making". *Organizational Behavior and Human Decision Processes, **75***(3), pp. 187–206.
[14] Magrab, E. B., 1997. *Integrated Product and Process Design and Development: The Product Realization process*. CRC Press.
[15] French, M. J., 2002. *Engineering Design Synthesis*. Springer, ch. 2: Insight, design principles and systematic invention, pp. 19–34.
[16] Schmekel, H., and Sohlenius, G., 1989. "Functional models and design solutions".
[17] Piaget, J., 1980. *Language and Learning*. Harvard University Press, Cambridge, MA, ch. The psychogenesis of knowledge and its epistemological significance, p. 23.
[18] Proctor, R. W., and Zandt, T. V., 2008. *Human Factors in Simple and Complex Systems*, 2nd. ed. CRC Press.
[19] Seltman, H. J., 2009. Experimental design and analysis. Tech. rep., Department of Statistics at Carnegie Mellon (Online Only), November 1.
[20] Caldwell, B. W., Thomas, J. E., Sen, C., Mocko, G. M., and Summers, J. D., 2012. "The effects of language and pruning on function structure interpretability". *ASME J Mech Design, **134***, pp. 1–11.
[21] Lee, Y. S., Gero, J., and Williams, C. B., 2012. "Exploring the effect of design education on the design cognition of two engineering majors". In Proceedings of ASME IDETC.
[22] Caldwell, B. W., Ramachandran, R., and Mocko, G. M., 2012. "Assessing the use of function models and interaction models through concept sketching". In Proceedings of ASME IDETC.
[23] Curtis, S. K., Harston, S. P., and Mattson, C. A., 2012. "Characterizing the effects of learning when reverse engineering multiple samples of the same product". *ASME J Mech Design, **135***.
[24] Nagel, R. L., Bohm, M., and Linsey, J., 2013. "An investigation into the effectiveness of an algorithmic approach to teaching functional modeling". In Proceedings of ASME IDETC.
[25] Toh, C., Miller, S., , and Kremer, G. E. O., 2012. "The impact of product dissection activities on the novelty of design outcomes". In Proceedings of ASME IDETC.
[26] Atman, C., Kilgore, D., and McKenna, A., 2008. "Characterizing design learning through the use of language - a mixed-methods study of engineering designers". *J Eng Edu, **97***(3), pp. 309–326.
[27] Bransford, J. D., Brown, A. L., and Cocking, R. R., eds., 2000. *How People Learn: Brain, Mind, Experience, and School*. National Academy Press.
[28] Keselman, H. J., Huberty, C. J., Lix, L. M., Olejnik, S., Cribbie, R. A., Donahue, B., Kowalchuk, R. K., Lowman, L. L., Petoskey, M. D., Keselman, J. C., and Levin, J. R., 1998. "Statistical practices of educational researchers: An analysis of their ANOVA, manova and ancova analyses". *Review of Educational Research, **68***(3), Fall, pp. 350–386.
[29] Jansson, D. G., and Smith, S. M., 1991. "Design fixation". *Des. Stud., **12***(1), pp. 3 – 11.
[30] Toh, C., Miller, S., , and Kremer, G., 2012. "Mitigating design fixation effects in engineering design through product dissection activities". In 5th International Conference on Design Computing and Cognition.
[31] Bloom, B. S., 1965. *A Taxonomy of Educational Objectives Handbook I : Cognitive Domain*, 2nd ed. McKay, New York.
[32] Fischer, K. W., and Lamborn, S. D., 1989. *Transition Mechanisms in Child Development: The Longitudinal Perspective*. Press Syndicate of the University of Cambridge, ch. Chapter 2: Mechanisms of variation in developmental levels: Cognitive and emotional transitions during adolescence, pp. 33–67.
[33] Gillett, E., 1998. "Relativism and the social-constructivist paradigm". *Philosophy, Psychiatry, & Psychology, **5***(1), pp. 37–48.