Understanding Physical Models in Design Cognition: A Triangulation of Qualitative and Laboratory Studies

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Abstract – Designers use various kinds of physical models throughout their design process to enhance creativity. The existing literature provides conflicting guidelines about their implementation. The effects of physical models on design cognition remains largely unknown. Prior laboratory studies show that physical models supplement designers’ erroneous mental models and thereby lead to higher quality ideas. These prior studies fail to demonstrate any design fixation associated with the use of physical models. In contrast, a few prior observational studies on practicing designers show that the use of physical models causes design fixation. Based on these conflicting results, this study investigates the role of physical models in industry-sponsored projects and in the development of award-winning products through a qualitative research approach. This study explores two hypotheses: The Mental Models Hypothesis - physical models supplement designers’ mental models and the Fixation Hypothesis - physical models cause design fixation during the idea generation process. The data are coded qualitatively and then tested quantitatively. The results are triangulated with the results from the prior controlled study. The results provide support to the hypotheses. The differences observed between current and prior studies point to the potential role of the Sunk Cost Effect in engineering idea generation with physical models.

Index Terms – Design Fixation, Idea Generation, Mental Models, Physical Models

INTRODUCTION

Training engineers to be more innovative and creative is an important goal of design education. There is an increasing interest among the world’s top engineering schools in the inclusion of physical models in the design curriculum [1]. Physical models refer to prototypes of any scale created during the design to mimic aspects of the finished design [2]. These models range from fully functional to completely non-functional, aesthetic models [3]. The use of physical models in design education can enhance the acquisition of knowledge which prepares the designer to solve new open-ended problems [4]. Physical models are widely used in industry [5] and also in government agencies.

Although the use of physical models is highly encouraged, their effects on design cognition are largely unknown. The existing literature provides very limited insights. There are also conflicting guidelines which make their implementation further difficult. To ensure the effective use of physical models, their role in the cognition of a designer solving an open-ended real-world design problem needs to be clarified. The study presented in this paper further identifies the role of physical models in supplementing designers’ mental models and in causing design fixation.

BACKGROUND

The role played by physical models in the design process is not well understood and the existing design literature offers few insights. However, the Cognitive Psychology literature offers a few theories to explain the effects of physical models on design cognition.

Physical Models in Engineering Design

Physical models play a vital role in the design process. They help designers to externalize concepts and communicate them to other designers [6]. Physical models are important collaborative learning tools in design practice and they reduce the overall project cost and risk [1]. Tom Kelley of the product design firm IDEO strongly suggests the use of physical models in the design process [5]. Previous controlled studies have shown that physical models help to supplement designers’ incorrect mental models and lead them to more ideas satisfying all the problem requirements [7, 8]. A prior observational study also shows the importance of physical modeling in graduate students’ projects [9].

Existing literature also provides warnings about physical models. Building physical models requires a significant amount of resources. Christensen and Schunn in their observational study point out that physical models cause the suppression of distant-domain analogies leading to less innovative solutions [10]. Kiriyama and Yamamoto observe that physical models lead to design fixation in graduate design projects [9]. At the same time, a controlled study using a simple design problem shows no fixation [7, 8]. Considering these conflicting results, it is essential to understand physical models’ cognitive impacts and establish guidelines for implementation.

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Design Fixation

Designers fixating to the variations of their initial solutions and presented examples has been a major problem restricting designer creativity in engineering [11]. Literature in Psychology [11-13] and engineering design [14] has shown that designers are highly susceptible to fixation. There has been experimental evidence that both expert and novice designers fixate [14]. However, fixation in experts can be mitigated with relevant defixation materials whereas novices fail to take advantage of these materials [15]. The influence of physical models on design fixation is not well understood. The observational study by Kiriyama and Yamamoto [9] has shown that graduate design teams also fixate with physical models. Another observational study by Christensen and Schunn [10] showed that physical models restrict the number of between-domain analogies. At the same time, a prior controlled study fails to demonstrate design fixation with the use of physical models [7]. Hence, it is essential to identify the role of physical models in design fixation.

Mental Models and Naïve Physics

The areas of mental models and Naïve Physics deal with people’s perception about the physical world and show that very often these mental models are highly erroneous [16]. For example, people generally operate a home heat thermostat similar to a car’s accelerator due to their wrong mental models [17]. They think that the higher the setting, the faster the room heats. This has a large implication in the field of engineering design. Designers’ erroneous mental models can lead to infeasible solutions. A previous controlled study shows that physical models can supplement designers’ mental models and thereby lead to higher number of solutions satisfying all the requirements [7]. This study extends this result to real-world situations.

Prior Controlled Studies [7, 8, 18]

To evaluate the effects of physical models on design cognition, Viswanathan and Linsey [7] hypothesized that physical models supplement designers’ erroneous mental models and also cause design fixation. They evaluated these hypotheses through a controlled laboratory experiment. They asked senior undergraduate engineering students to generate as many ideas as possible to a simple design problem of securely binding papers together. They distributed the participants across four experimental conditions: Sketching Only, Building, Building & Testing and Constrained Sketching. In each condition, the participants generated ideas to solve the design problem using the medium of representation specified by the title of the respective condition. In the Constrained Sketching condition, the participants were presented with the materials that they would later build their models from and then asked to only sketch their ideas. This condition was designed to evaluate the effects of implicit constraints associated with the building process on the design cognition.

The data showed a significantly higher percentage of functional ideas in the Building and Building & Testing conditions compared to the Sketching Only condition. This showed that being able to build physical models of their ideas supplemented designers’ mental models and led them to more functional ideas. At the same time, the data gave no support to the hypothesis that physical models cause design fixation.

The study presented in this paper replicates these results in a more realistic design situation. Data from graduate design teams solving industry-sponsored design projects and case studies of award-winning products are used for the present study. These data are analyzed and results are interpreted to evaluate the two hypotheses:

Mental Models Hypothesis: Physical models supplement designers’ mental models.

Fixation Hypothesis: The Sunk Cost Effect during the building of physical models leads to design fixation. Design fixation is not inherent to physical representations but instead due to the Sunk Cost Effect.

METHOD

To evaluate the hypotheses in real world design situations, a qualitative approach is used. In realistic settings, the effects of physical models on designers’ mental models and design fixation do not have independent effects on the outcome. In controlled laboratory settings, these effects can be separated using relevant conditions. However, in a qualitative setting, it is difficult to find metrics which can capture these effects independently. Hence two metrics are developed to infer these effects and the hypotheses are evaluated by measuring these metrics simultaneously. The two metrics used in this study are: (1) Fraction of changes during the modeling stage which result in improvements to the ideas (2) Frequency of changes to the features that are being tested. Table 1 provides the relation between the outcomes of these metrics and the hypotheses being investigated in this study. For example, consider case 1 in the table. In this case, the changes made to the ideas cause improvement in a significantly higher number of cases and the tested features change more frequently than those not tested. Results in case 1 indicate that physical models supplement designers’ mental models and lead to design fixation. Similarly, if most changes result in improvements and the frequencies of both tested and not tested changes are similar, design fixation is absent and designers’ mental models are supplemented. Only these two cases are of interest in light of the presented hypotheses and the results from the prior studies [7, 8]. Cases 2 and 4 are indistinguishable using the current metrics, but they are not of interest.

There are two data sources used for this study; data from industry-sponsored projects and data reported in books about the development of award winning novel products. More details about these data sources and the procedure followed are given in the sections below.
Industry-Sponsored Projects Data

These data are collected from graduate design teams generating concepts for their design projects as a part of the Advanced Product Design course taught by one of the authors at Texas A&M University. This course covers the basic product design procedure with a focus on creativity. The students in this course are divided into various teams of 1 to 4 people. Each team is assigned a project. Majority of the projects are sponsored by industry. The details of the problems are not reported in this paper. The teams do all parts of preliminary design including customer needs collection, creating technical specifications, functional modeling, concept generation and down-selection of concepts. Towards the end of the semester, the design teams are required to build proof-of-concept models for their concepts. The teams are required to submit a final report to the instructor which covers all the details about their designs. The data are collected from the teams using specially designed templates and their final reports. The teams are asked to report all the changes they make to their ideas in the proof-of-concept stage. Majority of the proof-of-concept models are physical models and the rest are a few virtual models done in SolidWorks 3-D modeling package.

The data reported in this paper are collected over two semesters. For the first semester, the data is collected mainly from the reports of the teams. Specially designed templates are provided to each team which requires reporting of the features they measure, the associated physical principles, the methods they use for testing, any changes they make during the building and alternative changes they can think of, if any. The templates are designed to enable direct reporting of the changes during the building process by the students. These teams failed to fill the templates provided to them correctly. Hence most of the data are collected directly from the final reports of the teams. These templates are revised based on the feedback from the first semester and reused in the second semester. The revised templates also collect the same data as the first one, but the questions are re-arranged to make them clearer to students. The templates filled by the teams show that there is a difference in the quality of the data obtained from both templates. For the teams from the second semester, the data from the templates are used. However, for teams that fail to include any relevant data in the templates, the data are collected from their final reports. A portion of the second template version filled with a change during the development of OJex Manual Citrus Juicer (This is an award-winning product as explained in the next paragraph) is shown in Figure 1. Since the quality of template used varies across the two semesters, it can bias the data. However, any missing data is added from the final reports of the teams to bridge this gap. There are a total of five design teams in the first semester and seven in the second. The data from two teams in the second semester are not considered for analysis because they do not use any physical or virtual modeling.

Award-winning Products Data

The case studies of award-winning products are used as a data source [20, 21]. Ten products are selected for analysis. Most of these products are honored by the Industrial Design Excellence (IDEA) award by Business Week magazine. The criteria for the selection of the products are that the developers use physical or virtual modeling as a tool for their design and they report the changes they make during the modeling stage. Figure 2 shows the various physical modeling stages of OJex Manual Citrus Juicer, which is one of the ten products being considered. The other products that we use are: BMW StreetCarver, Cachet Chair, Clip ‘n’ Stay, Watercone, Watergate, Bottle Stopper/Opener, Scorpio 270, Overflowing bath and Snowboard boot.

Procedure

A qualitative approach is used to code the data and the obtained metrics are analyzed using statistical methods to evaluate the hypotheses. The qualitative coding process that we use in this study is based on previous studies in design [22, 23] and qualitative procedure used in Psychology [24]. In this study, one of the authors determines the coding categories required to evaluate the hypotheses, based on the metrics presented in Table 1. Table 2 shows the categories that we use for this study. Then the author goes through all the available data including the project reports, templates and case studies and notes down all the information related to the changes during the physical or virtual modeling process. Then these data are organized into the various predetermined categories. The data in each category are counted to form the metrics. These metrics are analyzed using a chi-square test.

<table>
<thead>
<tr>
<th>Case</th>
<th>Design Fixation is present</th>
<th>Mental Models are supplemented</th>
<th>Did Changes Improve the Idea?</th>
<th>Comparison of Frequency of changes in features evaluated by the physical model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Tested &gt; Not Tested</td>
</tr>
<tr>
<td>2</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Tested = Not Tested</td>
</tr>
<tr>
<td>3</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Tested = Not Tested</td>
</tr>
<tr>
<td>4</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Tested = Not Tested</td>
</tr>
</tbody>
</table>
If designers deliberately test a feature with the intention of verifying or improving it, it is considered as intentional testing. At the same time, in many cases, tests using physical models for few selected features provide information regarding the possible or required improvements in the other associated features. The designers make changes to these features. Such tests are termed as unintentional tests.

Among the categories shown in Table 2, cases where designers realize the infeasibility of the idea during physical modeling are excluded from analysis. In such cases, designers do not attempt to make changes and instead interpret that the ideas cannot be made functional. Four such cases are identified in the industry-sponsored projects data. These cases are difficult to interpret with the present metrics and are left for future work.

To illustrate the procedure, consider the example of a design change reported during the development of breadboard model of OJex Manual Citrus Juicer shown in Figure 1. The test reported is designed to evaluate the mechanism operation and it results in a change which improves the idea, as reported by the developers. This change is considered as a change resulting from an intentional test and one that improves the idea. In a similar manner, other changes in the development of this product are considered. To ensure reliability of this procedure, an independent judge repeated the coding procedure. This second judge is a graduate student in design and is given about 90% of the total data. An inter-rater agreement of 0.98 (Pearson’s correlation) is obtained, which is satisfactory.

\section*{RESULTS AND DISCUSSIONS}

The qualitatively coded data are counted to convert them into quantitative measures and then analyzed to address the hypotheses. The results show that most of the changes made while building physical models lead to the improvements in the ideas and the features tested change more frequently than those not tested. In reference to Table 1, this supports both of the hypotheses presented. It demonstrates that physical models support designers’ mental models, meanwhile leading to fixation. The full results are detailed below.

It is likely that there is a reporting bias in the books and probably a hindsight bias also. The books likely report successful changes quite frequently, but very rarely report unsuccessful ones. Hindsight bias probably also causes the award winning product cases to present what they learned during testing as intentional instead of accidental. Since the initial industry-sponsored data was captured before testing, the unintentional tests can be identified.

As shown in Figure 3, it is observed that majority of the changes that designers make after making physical models of their ideas result in an improvement in the respective idea. In case of industry-sponsored projects, very small fraction of changes do not result in an improvement. In case of award-winning products, this fraction is further less, but this can be due to the reporting bias. The states of the idea before and after each change are carefully considered to determine whether the change results in an improvement or not. A chi-square test demonstrates that in significantly higher number of cases the changes not including those resulting from unintentional ones result in improvements in ideas ($\chi^2=3.60$, p=0.06). This significance goes up as the changes from unintentional tests are included ($\chi^2=13.50$, p < 0.001).

The data show that in majority of the cases, the features tested change very frequently and the features not tested remain the same, as depicted by Figure 4. A chi-square test shows that this is statistically significant without including unintentional tests ($\chi^2=10.89$, p=0.001) and with including the unintentional tests also ($\chi^2=20.57$, p=0.001). Again, the award-winning product cases may be biased since they report even unexpected changes as results of intentional tests. Furthermore, Figure 1 is used to show that in award-winning product design cases also this trend is true.

Comparing the above mentioned results with the cases presented in Table 1, the data show trends similar to Case 1. In significantly higher number of cases the changes during physical modeling result in improvements in the ideas. The frequency of changes resulting from tests is significantly higher than that of those not resulting from tests. According to Case 1, these results indicate that physical models supplement designers’ mental models and also cause fixation. The data agree with the hypotheses.

\section*{Intentional and Unintentional Testing of Features}

The data demonstrates that many of the feature changes result from unintentional testing. Figure 5 shows the fraction of the two kinds of tests observed in the industry-sponsored project data. The award-winning product data report all the tests as intentional, likely due to hindsight bias. Very importantly and unlike currently available virtual models, physical models are capable of providing useful insights about the possible improvements in their designs even when the features are not intentionally tested.

\begin{table}[h]
\begin{center}
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline
Proof-of-concept & Purpose of the proof-of-concept & Features tested & Test used & Was it scaled? & Did the test give satisfactory results? & Any modifications made to the idea? & Did the change improve the idea? & Limitations observed, if any \\
name & & & & & & & & \\
\hline
Breadboard model & Check the operation of the mechanism & Operation of the full scale wooden model & No & Yes & Yes & Mechanism modified & Yes & None \\
\hline
\end{tabular}
\end{center}
\caption{A sample of the revised template. The data filled in is for OJex Manual Citrus Juicer}
\end{table
Triangulation with the Controlled Study

As described above, the data show that building physical models of ideas during the design process leads to more changes, which results in idea improvements. The data also show that tested features change much more frequently than the features which are not tested. Comparing these results with the theory presented in Table 1, it can be interpreted that physical models supplement designers’ erroneous mental models and also cause design fixation. This supports both of hypotheses presented in this study.

To clarify the role of physical models in design cognition, these results can be triangulated with those from the previous controlled studies [7, 8, 18]. The results from the controlled studies show that physical models supplement designers’ erroneous mental models. This result is replicated in this qualitative study too. At the same time, the controlled studies fail to show the fixation caused by the building process. However, the data from the current study shows that designers fixate to their initial ideas. The controlled studies use a very simple design problem and we attribute the absence of fixation in the controlled studies to Sunk Cost Effect [25, 26]. Once significant amount of money, effort or time is invested in a course of action, it is unlikely that the designer will choose a completely new course. For both the current and prior studies, Sunk Cost Effect explains the findings. In the previous controlled studies, the sunk cost is low as the design problem is very simple, hence designers do not fixate. In the current study, all the design problems are complicated and have comparatively larger sunk costs. Hence, the building process leads to fixation in these cases. The prior follow-up study by Viswanathan and Linsey [18] shows that Sunk Cost Effect is a factor in determining the presence of fixation in design problem solving.

CONCLUSIONS

The evidence obtained from this study provides strong support to the results from the previous controlled study. The data shows while building physical models, designers often make changes in their ideas. These changes result in the improvement of their ideas in significantly higher number of cases. In significantly higher number of cases, these changes are resulting from intentional or unintentional tests. These results demonstrate that physical models supplement designers’ erroneous mental models and help them to improve their final designs. Due to erroneous mental models, designers tend to generate infeasible
solutions during idea generation, whereas the use of physical models helps them to come up with more feasible solutions. At the same time, they cause designers to fixate to their initial solutions. This restricts their solution space, thereby restricting the novelty and variety of their ideas. The difference in results of this study with the prior controlled study provides a good argument for the presence of the Sunk Cost Effect in design problem solving with physical representations. In the controlled study, a very simple design problem is used which has a lower Sunk Cost and hence the participants do not fixate. In the cases considered their initial solutions. This restricts their solution space, whereas the use of physical models helps them to come up with more feasible solutions during idea generation, whereas the use of physical models helps them to come up with more feasible solutions. At the same time, they cause designers to fixate to their initial solutions. This restricts their solution space, thereby restricting the novelty and variety of their ideas. The difference in results of this study with the prior controlled study provides a good argument for the presence of the Sunk Cost Effect in design problem solving with physical representations. In the controlled study, a very simple design problem is used which has a lower Sunk Cost and hence the participants do not fixate. In the cases considered for this study, the problems are more complicated and the associated sunk costs are higher, hence they lead to fixation. As design and engineering schools show increasing interest towards the implementation of physical models in their curricula, it is essential to clarify their role in design problem solving. Guidelines need to be developed regarding when in the design process physical models can be introduced to provide maximum benefit to the designer. This study also needs to be extended to other available data sources like the NASA public data base with more complex products.

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