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Linking Design Process to Customer Satisfaction Through Virtual Design of Experiments

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ABSTRACT

This paper focuses on better understanding how design processes affect design outcomes. Design process data were collected from journals kept as a part of mechanical engineering capstone design projects at Montana State University. Student processes were characterized by time coding journal entries using a 3x4 matrix of process variables. The data were modeled using a principal components artificial neural network, and the model used in a virtual designed experiment to obtain estimates for design process factors that significantly affect client satisfaction.

Results indicate that greater client satisfaction is achieved through: greater problem definition activity and idea generation at conceptual design levels, and problem definition and engineering analysis activities at the system design level. Whereas, detailed level design work and design refinement activities associate with lower client satisfaction. Some of these results support existing models of "good" design process, while others suggest modifications to adapt the models to novice designers.

INTRODUCTION

Design has traditionally been an important part of an engineer's training. It also plays an integral part in any organization with innovation as a core consideration. The past several decades have seen increasing emphasis being placed on design as the focus of engineering curricula. Large engineering companies and accreditation agencies alike have taken an aggressive stand as to what they need and expect from engineering graduates. Even so, design may still be one of the least understood fields in engineering education.

With continued growth in design theory and methodology research, numerous models have been proposed to describe the engineering design process or aspects thereof. However, few of these have been empirically or statistically validated and experimentally verified. Those developed from empirical data tend to suffer from dissimilarity to design in practice (e.g., studies limited to short-term problems of limited scope in a laboratory setting) or a very small sample size (one or two in many cases). Furthermore, few models explicitly consider student design processes relative to project outcomes. This study attempts to further our understanding of design processes by gathering data from actual projects (one in which the participants have real stakes) in large enough sample sizes to enable statistical modeling that directly links design process to outcome.

In academia, one of the principal objectives of capstone design courses is to incorporate a major design experience into the undergraduate curriculum. Because many students eventually work on design projects in industry, understanding their design processes would seem central to improving such courses, and more importantly the overall quality of work the engineers produce.

In this study, we analyzed data collected from 14 student mechanical engineering design projects, relating design process variables to customer satisfaction using statistical techniques. We wanted to better understand what process characteristics tend to be associated with good design outcomes. Specifically, we characterized the relationship between 12 design process variables (resources spent on problem definition, idea generation, engineering analysis and design refinement activities at the concept, system or detail design levels) and project outcomes as measured by client satisfaction. The key research questions addressed are:

1. What process variables are significantly associated with client satisfaction?

2. What is the magnitude of effect associated with the significant variables?

3. Which variables significantly increase or decrease the likelihood of success of the design project?

The next section provides a brief discussion of the methods presented in the design research literature to study and characterize design processes, and their applicability in addressing our research objectives. Then we describe our data collection and modeling methods, followed by results, discussion, and conclusions.

A LITERATURE REVIEW OF DESIGN PROCESS MODELS

A design process may be defined as the series of activities that take a design problem from an initial specification to a finished artifact that meets all the requirements of the specification [23]. In general, a design process can be broken down into a sequence of fundamental operations called tasks. A greater understanding and insight into these tasks and other factors, which can be correlated to success, enables us to closely represent the design process. As a result, the process of design has been studied by many researchers from different perspectives and using different techniques. Many authors use flowchart representations that shows discrete tasks (or task outputs) connected by transition arcs. Individual elements within the models identify tasks, procedures, or results important to the completion of the design. The overall structure of the representation provides a qualitative definition of the design process. A brief review of the models and techniques used to characterize design processes is presented in the following paragraphs (see also [19]).

Design research began in the 1960's, with so-called "first-generation" models used to attempt to find generic optimization routines that could be applied to any type of problem [4]. In 1969, Simon [36] suggested that satisficing might be a more appropriate approach, and over the next two decades, this idea appears in the "second-generation" models. During this time, two streams appear to develop in design research with engineering researchers favoring heavily sequential design models, and architectural design researchers experimenting with more cyclical models. The architectural models also tended to include cognitive processes, while engineering models attempted to define the stages the design process. "Third generation" models arrived after the 1980's, combining these two viewpoints [4]. Cross [11], Dym [16], Haik [20], Pahl & Bietz [29], Pugh [30], and Ullman [44] are some examples of hybrid "third generation" models.

What can be seen from the models is a trade-off between precision in task definition, and model stability with respect to sequence. Some of the earlier models (e.g., [14]) show very general steps like generate-conjecture-analyze, and simply say to repeat until done. Later models, like [44], have a detailed sequence prescribing the order in which a designer accomplishes everything from forming the design team to retiring the final product.

In addition to the above models, quantitative techniques have been proposed to model and analyze the sequence of design processes in complex design projects and handle the iterative sub-cycles that are commonly found in complex design projects. These techniques include Signal Flow Graphs [17, 21] and Design Structure Matrix [38, 42].

Design models differ widely across authors, particularly in the names of activities and in the level of detail to which tasks are defined. But the models consistently identify similar types of activities as central to design: problem identification and definition, ideation, evaluation and analysis, and iteration as quintessential examples. Furthermore, most models recognize that design projects transition through phases, or alternatively, that designers operate at different cognitive levels of abstraction over the course of a design project. Again, the phases or cognitive levels can differ widely and have different labels, but most models start with an early conceptual phase, conclude with a detail design phase, and connect the two with one or more intermediate phases.

In our review of design texts, we were unable to identify any models that had been empirically validated or that had explicitly correlated design process to outcome. Most authors seemed to be either expert designers writing from their work experience, or academics writing from their teaching experience [26]. In either case, the recommended models do not appear have not been based on rigorous research. Further, the models do not appear to be designed specifically for engineering students who can be accurately characterized as novice designers. Should a process that is well-suited to expert designers be recommended for novice designers?

Our intention, then, was to devise a study that would explicitly relate process to outcome and empirically validate a general design process model derived from the literature. This study makes at least two important contributions. First, we describe a novel approach to studying design processes using computer design of experiments. Such an approach allows the researcher to leverage powerful statistical techniques to elucidate patterns and relationships among variables in the data even without huge sample sizes. Second, we provide hard evidence that on one hand confirms conventional wisdom regarding "good" design processes, and on the other hand suggests alterations to conventional models that novice (a.k.a., student) designers might follow to achieve a more desirable end result. The next section describes our overall research design, including process and client satisfaction data collection and analysis methods.

RESEARCH METHOD

This study focuses on the capstone mechanical engineering design projects completed between Spring 2001 and Fall 2002 semesters at Montana State University. ME 404, the mechanical engineering capstone design course, is a four-credit one-semester course. Students are divided into teams of two to four, with a faculty member as advisor. The projects are industry sponsored so each team must interact with their client/sponsor to define their needs, devise a solution to meet those needs, and deliver a product (set of engineering drawings and specifications, written report, oral report, and in many cases a hardware prototype) by semester's end.

Data Collection: Process Variables

Researchers have used a number of techniques to collect data on design processes, including interviews [7, 23], retrospective and depositional methods [45], protocol analysis [3, 18], and direct observation [8]. However, for this study, a novel approach was needed to study design process *in-situ*, spread over 15 week time period (one semester), without a specified location or researcher intervention, while capturing exact details when and as they occur.

Design journals kept by individual students provide an alternative and novel approach to data collection that fit our desire to study actual student processes. This data collection technique overcomes many of the drawbacks of other research methods. Compared to interviews, retrospective, and depositional methods, the data is collected in real-time, but unlike observational approaches, our method does not require specially trained professionals. Like protocol analysis, the data can be readily quantified using a suitable coding scheme, but it requires little researcher intervention during data collection and therefore is a potentially more accurate representation of the actual design process. It is also more feasible to collect a relatively large sample size compared to videotaping or other approaches because the quantity of data captured, while still large, is more manageable.

As with any data collection method, disadvantages to the technique exist. Journals may offer an incomplete record of the design process. The student designers may be unaware of important information or may fail to capture critical details regarding the development of the design project. As an example, journals can be susceptible to "backfilling," the tendency for students to records events, not as they occur, but in retrospect. Backfilling can lead to journals that omit key details; for example, highlighting details viewed as important to the final results, but skipping over mistakes made and lessons learned along the way. Training and feedback during the project combined with a grade incentive can help designers overcome such shortcomings, but journal quality ultimately depends on the designer's commitment to keeping a good journal. Fortunately, multiple accounts from different members of the design team can serve to cover holes in individual records and to corroborate details of the record.

Students were asked to keep individual design journals (notebooks) to document their work over the semester as a part of this project [41]. Journals were periodically evaluated using a rubric to help encourage good record keeping, and students were given specific feedback on the expectations and quality of their journals. These journals constituted 15 % of the final course grade. At project completion, journals were collected and coded according to the scheme in Table 1, with times assigned according to the start and end times recorded.

Table 1: Coding Matrix

Design Activities			
	Concept (C)	**System (S)**	**Detail (D)**
Problem Definition (PD)	C/PD	S/PD	D/PD
Idea Generation (IG)	C/IG	S/IG	D/IG
Engineering Analysis (EA)	C/EA	S/EA	D/EA
Design Refinement (DR)	C/DR	S/DR	D/DR
Non-Design Activities			
Project Management	PM		
Report Writing	RW		
Presentation Preparation	PP		

Each design related activity received two codes. The first code designates one of three design levels. Concept-level design addresses a problem or sub-problem with preliminary ideas, strategies, and/or approaches. Common concept design activities are identifying customer needs, establishing the design specifications, and generating and selecting concepts. System-level design defines the needed subsystems, their configuration and their interfaces. Detail-level design activities focus on quantifying specific features required to realize a particular concept, for example defining part geometry, choosing materials, or assigning tolerances. From a practical standpoint, serious consideration of basic components (e.g., fasteners, shafts, or gears) were often coded "detail" if the problem scope was so narrow as to not lend much meaning with respect to the concept or system-level definitions.

The coding scheme also delineates four categories of design activity. Problem definition (PD) implies gathering and synthesizing information to better understand a problem or design idea through activities such as: stating a problem, identifying deliverables, and researching existing technologies. Activities in idea generation (IG) are those in which teams explore qualitatively different approaches to recognized problems, such as brainstorming activities, listing of alternatives, and recording “breakthrough” ideas. Engineering analysis (EA) involves formal and informal evaluation of existing design/idea(s), e.g., mathematical modeling and decision matrices. Finally, design refinement (DR) activities include modifying or adding detail to existing designs or ideas, deciding parameter values, drawing completed sketches of a design, and creating engineering drawings using computer-aided design (CAD) software.

The coding scheme also designates codes for non-design activities associated with project management and delivery so that every entry could be assigned a code. Project management (PM) covers planning and progress evaluation, including: scheduling, class meetings to discuss logistics and deadlines, identifying tasks, and reporting project status. The delivery category is for activities associated with interim and final report writing (RW) and final presentation preparation (PP). Even though these activities constitute as much as 50% of the total project time, a separate analysis found no statistically significant association between time spent on PM, PP, and RW activities and the design outcomes (client satisfaction and design quality, explained below). Thus, this study focuses only on the design activities described in the previous two paragraphs.

To give an idea of the kind of data captured in the student journals, a sample journal entry appears in Figure 1. The project from which this sample was taken was to design a “Tater Pig” machine that cores a raw potato and inserts a frozen sausage into the cored potato. The first line, “Group needs to…” was coded “PM” (project management) as it is a notation of a logistical nature and not directly related to the design problem at hand. The next block of text (11 lines) was coded “D/PD.” It is problem definition activity (PD) as the student is reasoning about the plunger functionality and constraints, and it occurs at a detailed design level (D) because the design is focused on one narrowly defined piece of the overall concept. The diagram immediately following was coded “D/IG.” It still concerns a component, so it’s at the detailed design level, but the diagram presents a new idea on the geometry of the plunger, i.e., idea generation (IG). The next sketch, however, illustrates the relationships between the cutter, the potato, the sausage, and the core. It was considered system-level design (S) since it appears to be visualizing the configuration and interaction among components. But, since a very similar idea appears earlier in the journal, this diagram was considered design refinement (DR) rather than idea generation. Thus the second sketch was coded “S/DR.” The notes below this sketch were coded “D/PD” (detail problem definition) and the sketch at the bottom as “D/IG” (detail idea generation) as the student asks some questions on the design’s constraints and then sketches a possible solution.

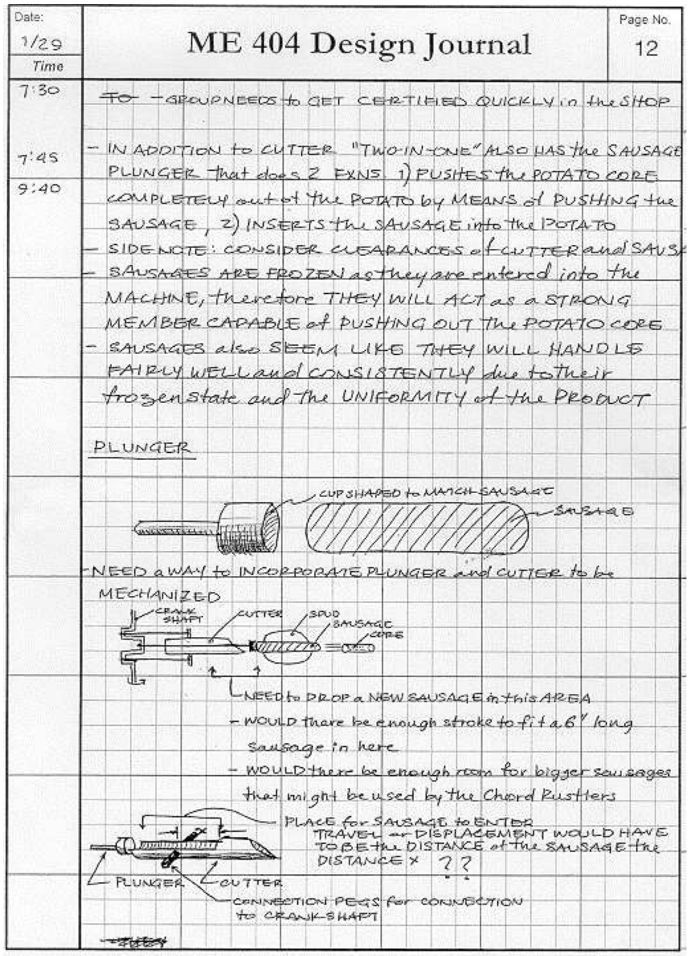


Figure 1: Sample Journal Entry

The process of journal coding proceeded in two stages. First, research assistants familiarized themselves with the projects by reading the final written reports, then coded data and captured times by walking through team members' journals in lock step, considering all the members' entries for a given day before moving to the next day. Simple rules were devised for allocating time, and resolving discrepancies among the different journal accounts. The principal investigator then reviewed the coding as a crosscheck on accuracy and consistency. The disagreements were resolved through discussion and the process continued until mutual agreement was reached. The time data on the various process variables was then entered into a database, and aggregated for the project by combining individual journal data (see [40] for more journal coding details).

The sample size for this study is 14 design projects (47 journals total). The 12 design level-activity pairs (four activity categories across three design levels) served as the independent variables in the model described in later sections. Thus each project in the sample was characterized by a percent allocation of total design time across these 12 variables.

Data Collection: Client Satisfaction Data

It seems fair to define a "good" design process as one that leads to a good outcome. Thus to determine the goodness of a design process we need a way to measure the goodness of the end product. For this study we developed two outcomes measures, a client satisfaction score and a design quality index for the final designed product. Consequently, two separate instruments, the Client Satisfaction Questionnaire (CSQ) and the Design Quality Rubric, were developed, validated and deployed for measuring client satisfaction and design quality quantitatively. In this paper, we report the methods and results associated with client satisfaction.

The CSQ was developed based in part on previously developed surveys [5, 6, 25, 34], which were adapted and expanded to more closely align with our objectives. The final questionnaire was composed of 20 questions. A five-point Likert scale is used for recording the responses.

The survey was validated prior to implementation using content and face validation techniques. Analytical hierarchy process [31] was used to determine weights for the metrics and the questions in each metric. The respondents were faxed a copy of the survey, then a research assistant walked them through the questions by telephone and filled in the responses by hand. Next the survey data was analyzed for statistical reliability using the Cronbach's alpha coefficient [33]. The test found that only the quality and overall metrics displayed adequate internal consistency and inter-metric consistency. As a result, the satisfaction index was obtained by the summing the weighted average of only these two metrics. Table 2 displays the measures and Cronbach's alpha statistics associated with these two metrics. The final satisfaction scores were on a scale of 2-10 with 10 being the highest (each metric being on a 1-5 scale, and the two summed).

Table 2: Client Satisfaction Metrics

Metric	No. Of Measures	Measures	Cronbach's α
Quality	2	The percentage of the design objectives the client thought the team achieved The closeness of the final outcome to client's initial expectations.	0.78
Overall	4	Design's feasibility in its application and fabrication Client's opinion on implementing the design Client's opinion on students' knowledge of math, science and engineering in developing solutions Overall satisfaction with the design outcome	0.70

A complete description of the techniques used to code the responses, missing values analysis, descriptive question analysis, and other issues on these instruments can be obtained from [22] or [39].

Data Analysis Approach

The small sample size and high dimensionality of the data in this study pose significant challenges. To address these concerns, we built a model out of the data currently available (so-called happenstance data) and then constructed a metamodel to study the process under desired conditions and deduce conclusions about cause and effect relationships within the system [32]. If the model is reliable, it should imitate the actual design process and we can use it to generate responses in a virtual design of experiments (VDOE).

We modeled the happenstance data using a principal component neural network, a special class of neural networks designed for data with high dimensionality [13, 43]. This hybrid architecture reduces the dimensionality of the data to help compensate for the small sample size, and allowed us to predict the output in terms of the original variables. A neural network model was constructed using the percent of time spent at each design level/activity combination (see Table 1) as inputs, and client satisfaction score as the target variable. A subset of the sample (11 exemplars) was used to train the network, and the remaining samples were used to cross-validate. To model the design data, several different network architectures were constructed and trained using Neurosolutions software [27] with the best network chosen using the mean squared errors (MSE) of the training and cross validation sets as the judging criteria.

To determine the relationships among the design process variables and the outcome measure, we analyzed a 2^{12-4} fractional factorial experiment design with client satisfaction as the response variable. The data for each run in the design grid was simulated via the artificial neural network model. For more information on neural networks and their use in statistical analysis refer to [35, 37, or 46].

Due to the deterministic nature of the neural network model, classical notions of experimental unit, blocking, replication and randomization were irrelevant in the experimental design. The final factorial was a resolution V design with 299 runs. Data transformation, model fitting, analysis of variance (ANOVA), model reduction and model adequacy checking were all performed in Design Expert software to obtain the response curves for various factors and factor interactions. Responses were predicted under various process settings within the range of the data utilized to construct the model. Results of the analysis are reported in the next section.

RESULTS

Table 3 reports the means and standard deviations of the process and outcomes data used in the modeling. The values for the process variables are expressed as percent of total design time; for example, teams in the sample spent an average of 13.14% of their total design effort (as reported in the journals) on concept level problem definition activity. The number of hours varies considerably across the design process variables with the most amount of time spent on design refinement work. A correlation analysis of the 12 variables found only 2 pairs of variables out of a possible 72 were significantly correlated at a 1% significance level.

Table 3: Summary Statistics

	Mean (% of Time)	Standard Deviation
Process Data		
C/PD	13.14	9.28
S/PD	2.16	3.27
D/PD	8.68	6.10
C/IG	4.41	2.45
S/IG	2.83	1.90
D/IG	2.78	2.87
C/EA	2.94	3.82
S/EA	0.80	0.75
D/EA	24.44	16.72
C/DR	1.39	2.55
S/DR	3.54	3.48
D/DR	32.93	16.90
Outcome Data		
CSQ	8.14	1.42

Table 4 presents the architecture summary of the neural network model constructed. The principal components network reduced the original 12 variables to six independent components explaining 99 % of the variation in the data. The best performing network (based on the judging criteria) contains a single hidden layer with 3 hidden neurons. From the learning results, it was observed that the established network architecture had a good "memory," and the trained matrices of weights and bias reflected the hidden functional relationship well. Thus the model can serve as a reasonable surrogate to reality. Finally, because the testing and validation errors (MSE) were small and the R-Sq values low, the models developed can be considered reliable for the prediction of the response scores under any combination of the process parameters as long as they are within the range investigated and close to the same level of resolution.

Table 4: Network Architecture

Parameter	Client Satisfaction Model
Number of input Variables	12
Number of Principal Components	6
Number of hidden layer	1
Number of hidden neurons	3
Training set	11
Testing Set / Cross Validation	3
Learning Rate	1.75
Momentum	0.7
Step Size	0.1
Number of iterations	1000
MSE (Training Set)	< 0.01
MSE (Cross Validation Set)	< 0.11

Next, Table 5 presents the analysis of variance (ANOVA) results for the satisfaction experimental design results. The insignificant factors are not included at $p \leq 0.05$. The large values of the F-ratios and the small p-values suggest that the terms significantly affect the response. Within interactions, the individual variables follow the same trend as their primary effects, save that some variables insignificant as primary effects appear significant in interactions (specifically D/PD and D/EA).

Table 5: ANOVA Results of the Satisfaction Experimental Design Results

Source	Sum of Squares	*df*	Mean Square	F Value	Prob > F
Model	206.81	25	8.27	36.32	< 0.001
C/PD	67.32	1	67.32	295.54	< 0.001
S/PD	19.48	1	19.48	85.51	< 0.001
C/IG	9.66	1	9.66	42.43	< 0.001
S/IG	2.04	1	2.04	8.95	0.003
D/IG	6.71	1	6.71	29.48	< 0.001
C/EA	4.50	1	4.50	19.74	< 0.001
S/EA	6.53	1	6.53	28.69	< 0.001
C/DR	21.87	1	21.87	96.01	< 0.001
S/DR	3.46	1	3.46	15.20	< 0.001
D/DR	15.78	1	15.78	69.27	< 0.001

Table 6 presents an estimate of the relative importance of the significant factors in the VDOE model. The slopes of each variable versus the response variable were taken from the response plots of the ANOVA, then divided by the absolute value of the smallest magnitude slope among significant variables (i.e., D/DR). These relative slopes estimate the relative impacts the independent variables have on the response variable.

While statistical association does not necessarily imply causality, it appears that the strongest positive effect observed in the virtual experiment is that of system level engineering analysis. Its effect is 21 times stronger than detail level design refinement. Concept level problem definition and idea generation activities, and system level problem definition activities also appear to have significantly positive effects. On the negative side, concept level design refinement activity appears as the variable with highest negative impact, followed by concept level engineering analysis. All detail level work has either a negative or insignificant impact on customer satisfaction. System level idea generation is insignificant.

Table 6: Relative Factor Slope Scaling

* Insignificant at $p \leq 0.05$

Factor	Relative Slope Estimate
Conceptual Problem Definition (C/PD)	8.20
Conceptual Idea Generation (C/IG)	8.16
Conceptual Engineering Analysis (C/EA)	- 4.09
Conceptual Design Refinement (C/DR)	-11.83
System Problem Definition (S/PD)	9.46
System Idea Generation (S/IG)	*
System Engineering Analysis (S/EA)	21.06
System Design Refinement (S/DR)	- 4.13
Detailed Problem Definition (D/PD)	*
Detailed Idea Generation (D/IG)	- 7.71
Detailed Engineering Analysis (D/EA)	- 6.06
Detailed Design Refinement (D/DR)	- 1.00

DISCUSSION

Table 7 displays the general trends in the relationships of individual process variables to client satisfaction as determined by the virtual experimental design. The plus and minus signs represent statistically significant positive and negative effects ($p \leq 0.05$) of the independent variables on the response variable. A single plus or single minus indicates a significant factor on the same order of magnitude as detail level design refinement (D/DR), the significant variable with the weakest effect. Double plus or double negative indicates an order of magnitude greater impact than D/DR as reported in Table 6. Blanks denote the insignificant factors.

Table 7: Graphic Display of VDOE Results

	PD	IG	EA	DR
C	+	+	–	– –
S	+		+ +	–
D		–	–	–

Several trends can be identified from Table 7:

1. Problem definition (PD) at the higher abstraction levels appears positively related to client satisfaction.

2. Client satisfaction improves with greater effort in idea generation (IG) at concept level, but not at the system or detail design levels.

3. Greater time spent on design refinement (DR) activities across all design levels is negatively associated with client satisfaction.

4. Greater time spent at the detail (D) design level appears comparatively non-value added to client satisfaction.

5. Time spent on problem definition and engineering analysis activities at the system (S) design level leads to better client satisfaction.

We develop these themes in more depth in the following subsections, then conclude the discussion with study limitations.

Problem Definition and Project Scoping

Time spent on problem definition (PD) activity at the higher abstraction levels seems to have a strong positive effect on client satisfaction. Many PD activities can also be classified as information gathering, while others are sense-making activities on the collected information. Conceptual level problem definition includes activities like an internet or library search on existing design solutions, interacting with client to clarify the problem space, researching basic design mechanisms or analysis methods, and examining existing designs. Similarly, system level problem definition (as seen in design journals) includes activities like exploring requirements for the various subsystems, identifying the constraints on interfacing mechanisms, and understanding the final assembly sequence for the design. However the effect of similar activities at the detail abstraction level is insignificant.

Since problem definition activities at higher abstraction levels seem to have a positive impact on client satisfaction, it follows that student designers should perhaps focus more on activities that help define the problem scope and system architecture issues related to concepts under consideration. Time spent defining problems and gathering information at detailed levels (e.g., how do I decide the number of weldments needed?) seems to add little to client satisfaction. These results concur with Adams and Atman's [1] comparison of university freshmen and senior design processes. They found that problem scoping cycles tended to be positively associated with performance – both in terms of design quality and of efficiency of design process.

Idea Generation

Perhaps the most counter-intuitive result concerns the effect of idea generation (IG) in the sample. Even though it is a generally accepted precept that good designs result from processes that consider multiple alternative solutions, our results are mixed across design levels. Time spent on idea generation (IG) at the concept design level is positively related to the client satisfaction, while idea generation at the detail design level shows a negative association with client satisfaction. Idea generation at the system design level was insignificant. One might expect idea generation at all levels to associate with higher client satisfaction, but this was not the case with this study.

A possible explanation for this may lie in client expectations coming into the project. Many clients hope for a useable design, but expect to have to put quite a bit more effort into the designs to make them feasible. Clients in this sample seemed to be quite satisfied if they got a few new ideas from the project, and have some confidence that these ideas will work. Thus, idea generation at higher levels of abstraction is value-added, but idea generation at detailed levels would likely be completely redone, so is comparatively non-value-added. This might also explain why problem definition activities at concept and system design levels are significantly positive, whereas problem definition activities at detailed levels are not significant.

Iteration and Design Refinement

Table 7 shows that the effect of design refinement (DR) activity is consistently negative across all design levels. Design refinement activities are those that modify existing ideas and design solutions and/or that add the finishing details on designs (e.g., specifying tolerances or fasteners). Most CAD work, prototyping work, and design changes based on test or analysis results are considered DR. Design refinement constitutes about 40% of total design time devoted to the average student project.

The negative association of design refinement activity seems consistent with Newstetter and McCracken's [28] observation of a typical student design pattern they term "design shutdown." They observe a tendency among student designers to focus on one design they "like" and try to make it work. Student designers effectively "shutdown" the design from any new ideas that could potentially be tested or evaluated in parallel. This often leads to a design that does not conform to a certain design constraint and so the student designers tweak the design to make it conform to specifications. But doing so leads to other changes needed to accommodate the first alterations, and a vicious cycle can ensue. Our study may be capturing this phenomenon in the form of the large amounts of effort devoted to design refinement activities (especially at the detail design level), suggesting that those teams which lock into flawed designs and spend large amounts of effort trying to make them work achieved lower client satisfaction scores.

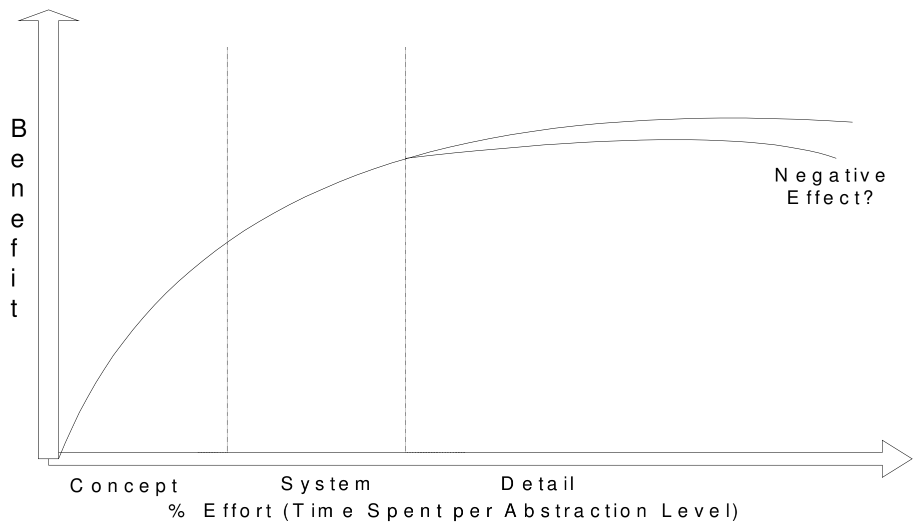
Although design is generally viewed as an iterative task, there are different types of iteration that can be beneficial or detrimental to the design outcome. For example, Costa and Sobek [9] classify design iterations as rework, design or behavioral. The authors conclude that design teams should try to eliminate rework iterations, perform design iterations without skipping abstraction levels, and do behavioral iterations in parallel. We suspect that much of the DR activity seen in student design processes is rework iteration. If that is the case, then one would expect more effort on such activities to be associated with poor outcomes. Exploring this supposition is the topic of ongoing work.

Detailed Design Work

A fourth observation concerns the negative effects and insignificance of the detail design work across all the design activities. This result is consistent with authors on design who agree that the early stages in the design process are the most important. This result is particularly striking considering that student teams spend an average of 70 % of their total design time on detail design level work. One of the possible reasons for this could be that those design teams who skimp on the conceptual and system level design must compensate for it with additional detail level design work, and the trade is not one-for-one.

This discussion further suggests that there are diminishing returns associated with the different levels of design abstraction. As illustrated in Figure 2, the incremental benefit of effort spent at higher levels of abstraction is comparatively greater than the incremental benefit of detailed design work. It follows that more effort during the conceptual and system level stages results in better design quality and customer satisfaction. A second curve on the plot in Figure 2 illustrates the possibility that too much effort in detailed work may actually produce a negative effect.

Figure 2: Effort vs. Benefit by Design Level



System Design Work

Finally, Table 7 reveals another perhaps surprising trend. Even though the student design teams in our sample spent little time in system-level work as opposed to concept or detail work (about 9% of design time on average; see Table 3), system-level activity has the only "++" marks in the table. This suggests that system-level design is a high-leverage activity, and yet many design teams do little of it. Conceptual ideas are difficult to evaluate. But by fleshing out the system-level design, the design team can get a much better estimate of performance of an idea without spending the many hours it takes to detail a design. Adjustments at the system level are fairly easy to make, while adjustments at the detailed level (e.g., in a detailed CAD drawing or prototype) are comparatively time consuming to make. So it seems that effort levied at the system-level issues can prevent time-consuming adjustments later in the design process.

These results are consistent with Ahmed, Wallace and Blessing's [2] study of the basic differences among the design patterns of novice versus more experienced designers. They found that the novice design pattern was to generate ideas, implement them, and then evaluate. Experienced designers tend to add a fourth step, "preliminary evaluation", between generate ideas and implementation. Ahmed, et al.'s [2] preliminary evaluation is similar to our definition of system-level design. Similarly, Newstetter and McCracken [28] found that student designers tend to jump from conceptual to detail-level work, skipping intermediate-level work. Ignoring this step leads to a higher probability that the design will have to be revised, thereby leading to a trial and error pattern. Combining this pattern with the negative trend of design refinement noted above suggests that perhaps excess of design refinement activities are a result of overlooking the system level work or skipping the "preliminary evaluation" step.

These observations are particularly striking given that many of the design models in design textbooks overlook this step. Those that include system-level work spend little time on it. And there are few tools available today to aid designers in system-level work. System-level design, then, appears to hold high potential for increasing the productivity of designing engineers.

Limitations & Future Continuations

Like most, this study is not without limitations. The sample size used to draw the conclusions may well be the biggest detractor of this study. Small sample sizes can produce inaccurate or misleading results. However, the data used are aggregate measures and potentially possess strong explanatory power. For example, the 14 projects in the sample represent 47 student journals, over 4,000 pages of documentation, and some 8,600 person-hours of effort. Since journal data were aggregated to the project level, each data point represents dozens if not hundreds of person-hours. So the data are fairly robust, diminishing the drawback of a small (in statistical terms) sample size.

Second, the results apply only to the range of the data in the sample. For example, that detail level design refinement is negatively associated with client satisfaction does not mean that student design teams should avoid these activities and drive this number to zero because zero is not within the range of the data in the sample. Rather, this result simply means that student design teams should strive to structure their design projects in such a way as to minimize the amount of time and effort required in these activities. In any case, the conclusions cannot be extrapolated beyond the range of the sample data.

Next, use of questionnaires in measuring satisfaction may include bias despite careful measures to avoid it. Furthermore, the data collected in this study (both process and outcome) is to some extent subjective. It can also be argued that the data collected from design journals can be inaccurate, incomplete or biased. We addressed these limitations through a rigorous cross-checking procedure of the journal coding, statistical validation of questionnaire metrics, and using neural networks which are designed specially for noisy data. Still, more studies should be conducted to substantiate these findings.

Another limitation of this study is the number of variables not considered, such as team dynamics, team diversity, advisor effects, team experience, and project-related characteristics (e.g., whether a prototype was required, whether it was a "clean sheet" project or not). Some may see this as a limitation as these could have provided more insight into the results. But in some ways it actually strengthens the study: we get significant results without accounting for all of these other sources of variability! The effects of process, therefore, must be fairly strong.

Lastly, the chronological order of the occurrence of the process variables was not considered. It is possible that the timing of the various activities is just as important as whether they occur or not and in what amounts. Thus future work will seek to identify the significance of the sequence of the various design process variables.

CONCLUSION

This study attempted to gain insight into what design process variables affect outcomes in student engineering projects. We collected data from 14 projects (representing some 60 students total) and modeled the data using an artificial neural network with a client satisfaction score as the target variable. Then by performing a virtual design of experiments, and using the artificial neural network models to predict the magnitude of the response variable, we were able to obtain estimates of the relative impacts of the 12 design process variables used. In other words, we could answer which process variables positively or negatively impacted project outcomes, and the relative magnitude of those effects. Thus one contribution of this work is demonstrating the viability of virtual designed experiments (also called computer design of experiments) as a methodology appropriate for design research.

A second contribution lies in providing substantive evidence in support of or against design processes commonly advocated in design textbooks. Specifically, they support general admonition that problem definition is important to client satisfaction, and that idea generation, at least at the more conceptual levels, also has a positive impact. The results also support those design process models that include intermediate design levels.

On the flip side, students are not expert designers, and our results point towards modifications to the more common process models to make them more applicable to novices. Numerous studies have found significant differences between novice and expert designers across varied fields of study [1, 2, 12, 24, 28]. For example, research suggests that designers rely heavily on their memories and experiences [10]. But how do the novice designers rely on experience that they do not yet have? Such research begs an important question: how can one design process model be well suited for both novice and expert designers?

Our study suggests that design process models can be modified in several key aspects to produce better design outcomes for engineering students and other inexperienced designers. First, problem definition and information gathering activities should receive greater prominence than an obligatory mention and exhortation that “it’s important” for good design. Further, our results suggest that novice designers should not necessarily be encouraged to “try to come up with some ideas,” advice commonly heard from advisors. Rather, they should be encouraged to research existing solutions to similar problems. In doing so, and trying to improve them, the novice engineer begins to build that experience base that will enable him/her to become an expert designer. The idea generation will come naturally, and be more substantive.

Second, our results strongly suggest that students should be encouraged to delay jumping to detailed design until sufficient system-level problem definition and analysis work has been done. This could be another way to avoid ideation without substance [28]—require students to flesh out and evaluate any idea at the system level before considering it a bona-fide alternative. Additionally, the students' ability to define an alternative at the system level may be a good test as to whether sufficient problem definition work has been done. The challenge here is that system-level design tools are still rare.

Third, evaluating student design teams based on whether they followed a given process or not may not be the wisest course of action. We simply do not yet have a large research base from which to determine what design processes are best for students (although we think this study is a start in that direction) since the extant processes purported in the literature have not been empirically validated. It may be better, in the near-term, to include at least some assessment of the "goodness" of the students' end products in the final evaluation.

Of course, these results are not conclusive (sample consists of 14 projects from one discipline at one institution), but they begin to lay the groundwork for additional studies to substantiate the design process models advocated in the literature, something that heretofore has not be done using statistical analysis. Studies to further substantiate the well-accepted models should continue. In addition, research into how design/engineering expertise is acquired would be highly beneficial. As previously mentioned, the timing and sequence of design process steps is another possible avenue of investigation. New representations and tools for system-level design and analysis are needed. In short, a good deal of work is still lies ahead before we fully understand how to help our students become the best designers they can be.

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