Design Space Exploration in Parametric Systems: Analyzing Effects of Goal Specificity and Method Specificity on Design Solutions

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ABSTRACT

In this paper, the effects of design-task specificity level on design space exploration are studied. An experiment was conducted to study the effects of goals and methods on design process and design solutions by 16 individual designers, who performed two design tasks under different combination of design goal and method specifications. Protocol analysis and outcome-based analysis were carried out. The results of the outcome-based analysis reveal that the *quality* of the design solutions can greatly be affected by goal specificity level of a design task, whereas in case of *quantity*, *novelty* and *designer's self satisfaction level*, the effects are insignificant. None of these metrics showed significant influence of method specificity levels of a design task. The process-based analysis on the other hand, reveals some interesting search behaviors in parametric systems, which are then used to explain the possible reasons for insignificance in quantitative data.

Author Keywords

Design space exploration, parametric systems, design outcomes

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms

Design, Experimentation, Theory, Performance, Measurement.

INTRODUCTION

Design is a goal-oriented process. It entails purposes and methods to achieve those purposes [2, 6, 10, 23]; together they define a boundary for design space exploration [27, 33]. Parametric systems, which recently have received wider attention across various design domains, have influenced design search behavior [36]. These systems provide designers with generative capabilities and model-making tools that can be used to explore alternatives and their variations through parametric changes [35]. In other words, they build models to explore solutions computationally while keeping the design logic consistent. In addition, through parametric dependencies, goals can become an integral part of the solution space.

In this study, we attempt to understand how design task specifications in parametric systems affect designers' solution search, and how they determine the outcome of the alternative solutions. Our major research question is to find if there exists any correlation between alternative solutions generated in parametric system and task specificity level in terms of goals and methods. This paper is part of a larger study that aims to understand design space exploration in parametric CAD systems when design goals and available parametric modeling methods are constrained; however, here the focus is mostly on design outcomes, and we measured the effects of design task specificity level on designer's satisfaction level; quantity, quality and novelty of design solutions produced.

We believe this topic needs further attention, for there are several approaches addressing the influence of task specifications on design, and they can be substantially different from each other. For example, while Shneiderman [25] suggests providing a semi-structured but orderly process to improve discovery and innovation in design processes, Akers [1] suggests that explorative-backtracking (which is but one strategy for design space exploration) happens only when there is a freedom to explore design alternatives, i.e., when the goal specificity is low. On the other hand Fricke [16, 17] claims that the more precise the problem statement given, the less time designers take in framing the problem hence they can produce a wider range of solution concepts. These approaches need to be tested further to determine how design task specifications affect design search patterns while developing alternative solutions and subsequently affect the design output.

We aim that the results from this study will contribute in (a) developing a descriptive model focusing on task specificity and method specificity effects on design exploration using parametric systems; (b) designing of effective user interfaces for design alternatives; and

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(c) helping designers to adapt or develop new use patterns in parametric systems when they are searching for alternatives.

LITERATURE BACKGROUND

The effects of task specificity on the effectiveness of the design exploration process in parametric systems can be measured by *process-based analysis* through protocol studies [2, 14, 30] or *outcome-based analysis* [18, 22, 25]. In this paper, however, a combination of both outcome-based and process-based evaluation was adapted. Both approaches are needed because (a) the value of a productive design generation phase is often evident in the quality of the solutions [19] that should assure finding a "*satisficing design*" [27, 28]; (b) discovery of activity patterns can be achieved by process analysis of design space exploration that can then be adopted to improve software interface design. Outcome-based analysis was mostly used for the verification of the hypotheses, while process-based analysis was used to see if there exist any patterns in design space exploration and to understand and explain why one hypothesis was verified and not others.

Design Outcome: What to Measure

We examined several design outcome evaluation metrics measuring creativity, innovation, flexibility, variety, novelty, feasibility, quality and quantity of alternatives produced. However, for objectivity and simplicity for this study we chose the metrics proposed by Shah et al. [24] which are widely accepted in various design domains [20]. The metrics measures effectiveness of design generation process and comprise of four properties: *quantity, quality, variety and novelty*. Out of these four metrics quality, novelty and quantity are applied in our study. Variety was also considered initially, but after the end of the study, we found out that most of the designers produced only one design solution for a given design task. This was not enough to measure variety. Instead, we asked participants to rate their satisfaction-level with the solutions they generated. This was considered important to measure, as it could reveal the designer's preference of specificity-level of goal and method as they search for design solutions.

Number of Alternatives Generated

Classical literature on design confirms that generating alternative solutions is one of the most important stages of design [3, 4, 12]. According to Shah, Vargas-Hernandez and Smith [24] "quantity" can be defined as total number of *ideas* generated. It can also be understood as a measure of total number of global solutions [22], where global solutions refer to a set of one or more ideas generated against same design problem. The rationale for this measurement is that generating more ideas increases the chance of better ideas.

Novelty

Novelty is a measure of how unusual and unexpected an idea is when compared with other ideas [24]. Being a relative term it can be measured on different levels; against the whole world of ideas or a group of ideas generated with a design process. A solution may be considered novel on personal, societal or historical levels [24], each at different scales. This metric has also been studied by many other authors [3] for its significance and influence. Some authors related this measure of newness in ideas with innovation [25].

Quality

Quality as defined by Shah et al. [24] is the measure of the feasibility of an idea and how closely it meets design specifications. Measuring quality of a design is challenging. For objectivity and simplicity, some authors [22, 24] have tried to parse it to quantifiable attributes. When ideas are generated at a conceptual level, quality is largely related to the feasibility of an idea [22, 24].

Designer satisfaction level

Fundamentally, designer satisfaction with a solution is a chief measure of design outcomes [3, 8, 27, 28] – designers apply such evaluations routinely in their work. Satisfaction is inherently composite—it can be based on several variables such as complying with specifications and requirements, meeting cost constraints or any of the various "-ilities" (buildability, serviceability etc.). We chose to measure satisfaction as a single coarse Likert scale, accepting that this hides the actual composition of a designer's evaluation. The purpose of measuring satisfaction level is to probe the effects of goal specificity and method specificity level on designer's satisfaction with the generated solutions.

HYPOTHESIS

The objective of the study is to measure and explain the effects of task specifications on design process and design outcomes. The experimental hypotheses are as follows:

H1: There exist a relation between the *design task specificity level* (IV) and *number of alternatives* produced (DV) using a parametric CAD system by a sample designer group (MV) with advance or intermediate expertise levels in using the system.

H2: There exist a relation between the *design task specificity level* (IV) and the *quality* of designs produced (DV) using a parametric CAD system by a sample designer group (MV) with advanced or intermediate expertise levels in using the system.

H3: There exists a relation between the *design task specificity level* (IV) and the *novelty* of design alternatives (DV) produced using a parametric CAD system by a sample designer group (MV) with advance or intermediate expertise levels in using the system.

H4: There exists a relation between the *design task specificity level* (IV) and the *designer's satisfaction level* for design alternatives (DV) produced using a parametric CAD system by a sample designer group (MV) with advance or intermediate expertise levels in using the system.

RESEARCH METHODOLOGY

Research Design

In order to analyze the effects of goal specificity and method specificity on the design space exploration process using parametric design systems, a 2-by-2 task taxonomy proposed by Akers [1] was adapted with two specificity levels (high and low) of design goals and design methods. (Figure 1) The study tests each combination of goal and method and applies both outcome-based and process-based evaluations for analysis. Comparisons were made to identify similar patterns that might be observed among individuals.

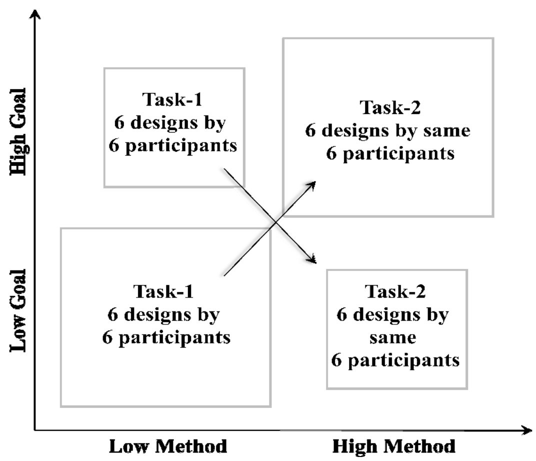

Figure 1 – Order of participants (Experimental group)

Sampling Design

The target population comprises designers with *SolidWorks* [29] experience. Upper-division undergraduate and graduate students of the School of Interactive Arts and Technology at Simon Fraser University were invited to participate in the experiment. The undergrad students had taken an advanced design course using *SolidWorks*. The graduate students had design backgrounds and were intermediate or advanced *SolidWorks* users.

The experiment ran over a three weeks period, yielding a sample size of 16, sufficient for ANOVA. Out of these 16 participants, 12 were assigned to the treatment group and 4 to a control group.

Pre-experimental Survey

Although we invited students who had *SolidWorks* experience before by successfully completing an upper-division course, a pre-experiment survey was conducted to ensure that the sample population had a suitable background. It was designed to confirm that all participants had a design background and intermediate or advanced level *Solidworks* experience. A questionnaire was used to prescreen the participants based on their self-reported confidence level in using *SolidWorks*. The questions included whether they had any design experience if so, how much and in what field. In addition, they were asked to rate their experience in various parametric software on a 5-level Likert scale where '1' represented "Novice" and '5' represented "Expert". We used the above information largely to interpret outliers in the collected data. Only one participant showed inconsistency with the expertise level chosen. This participant attempted to use online help in the beginning of the experiment. We eliminated this participant's data from the evaluation.

The pilot experiment

Before starting the experiment, we performed a pilot test using similar design problems and the same media we gave to all participants. We found the average time used to design all possible solutions under both conditions was about 50 minutes and the number of alternatives produced, on average, was 2.5. Using this as a guideline, we then came up with the maximum time expected for the experiment to be 60 minutes.

Experimental Design

Confounding Variables

It is necessary to identify the confounding variables that possibly could affect the design space exploration process. In this section, we discuss these variables one by one and how we attempted to control them.

Human Factor

Designer's personality, for example, mood, motivation and experience with the related design problems and expertise in parametric design tools, are some of the variables that influence the designer's search for alternatives. Three strategies were adopted to control this confound. In addition to the pre-experiment survey, a $30 gift card honorarium was offered to all participants as well as the possibility of winning a $30, $50 or $100 gift card for the best overall designs. This was chosen to increase the motivation level of participants. Furthermore, each designer was asked to perform two design tasks randomly under two different goal and method specificity levels.

Type of the Design problem

Each participant completed two design tasks. In order to reduce learning effects, we constructed two different design problems with similar design typology and complexity: a bus stop and a beach changing room. Although these design tasks are slightly different with respect to detailed requirements, e.g. one structure requires privacy for use, while other demands visibility for upcoming bus; they are highly similar structurally, as they both are temporary-use structures and comprise similar architectural elements.

Environment variables

In order to reduce the effects of tools and design environment, all designers were asked to use the same parametric design software (*SolidWorks*) and each session was conducted in the same location, seating and computers and with controlled ambient light and temperature. The time of day could not have been controlled and was set to be convenient for the participants.

Grouping of Participants

Participants were grouped to perform tasks in one of the combinations of the three factors: design problem (bus stop or changing room), goal specificity level (High or Low) and method specificity level (High or Low). Participants were grouped into two groups: a first-group with 12 participants for experimental analysis and a second-group with four participants as a control group. This allowed us to test the plausibility of alternative explanations that could account for the study results. The major reason to use a control group was to detect and measure any effects of design task order. Participants in the control group were assigned the same goal and method specifications under both conditions; the only changing condition was type of design task (bus stop or changing room).

Participants were randomly assigned to either of the groups. The distribution of the participants along with the randomization of design conditions, under which they were analyzed, is shown in Table 1 and Table 2.

Order of Participants

In case of goal specificity level, out of the 12 participants, 6 were randomly assigned low goal design tasks for their first session and high goal for their second session. Whereas, remaining six were given high goal deign task for the first session. In method specifications, all 12 participants were assigned low methods for their first session. The reason was that before high method specificity design task, the participants were taught parametric design patterns to use during their exploration for alternatives. (Figure 1)

No. of participants (Experimental Group)	Task 1			Task 2		
	Goal	**Method**	**Design Problem**	**Goal**	**Method**	**Design Problem**
3	Low	Low	Bus Stop	High	High	Changing Room
3	Low	Low	Changing Room	High	High	Bus Stop
3	High	Low	Bus Stop	Low	High	Changing Room
3	High	Low	Changing Room	Low	High	Bus Stop
12						

Table 1 - Distribution of participants in experimental group

No. of participants (Control Group)	Task 1			Task 2		
	Goal	**Method**	**Design Problem**	**Goal**	**Method**	**Design Problem**
1	Low	Low	Bus Stop	Low	Low	Changing Room
1	High	High	Changing Room	High	High	Bus Stop
1	Low	High	Changing Room	Low	High	Bus Stop
1	High	Low	Bus Stop	High	Low	Changing Room
4						

Table 2 – Distribution of participants in control group

Goal and Method Specificity

The goals were assigned mostly on the basis of design requirements. A low-goal design task in our study refers to design problem with minimum design specifications. An example for low and high goal specificity level for changing room is shown (Table 3).

Whereas, in case of method specificity level, at the low level participants were given no constraint on the method they use and at the high level they were introduced to three parametric design patterns [36]: *ClearNames* refers to a series of clear and meaningful names to identify objects and features throughout the model. *Jig* suggests users build abstract frameworks that can later be embedded with more details while maintaining the base structure intact. Lastly, *Increment* structures parametric changes to occur in the model through explicit sequences of related values and functions. An example of how low and high method specified design tasks were given to the participants is shown in Table 3.

Outcome-based Evaluation

Number of Alternatives Generated

In this paper we use the term "number of alternatives" to represent the quantity of design outcomes. During the design of the study, the authors unanimously decided that this would be the total number of solutions indicated by a designer as an "alternative solution". Otherwise, interpretation of the solutions during encoding as 'alternative' could introduce bias without using any metrics. So far, we haven't seen a metric presented in the literature.

Low Goal-Low Method	Propose two person free standing changing room for Vancouver beaches
Low Goal-High Method	Propose a two person free standing changing room for Vancouver beaches. When designing try to use the Increment, Jig and ClearNames design patterns.
High Goal-Low Method	Propose a two person free standing changing room for Vancouver beaches. Make sure your design is between 1.50 – 2.00m long, 1.20 – 1.50m wide and 2.30 – 2.50m tall. The design should also include a wind proof roof, provide privacy to the user while maintaining proper natural ventilation, and be securely and easily fixed to the underlying surface.
High Goal-High Method	Propose a two person free standing changing room for Vancouver beaches. Make sure your design is between 1.50 – 2.00m long, 1.20 – 1.50m wide and 2.30 – 2.50 tall. The design should also include a wind proof roof, provide privacy to the user while maintaining proper natural ventilation, and be securely and easily fixed to the underlying surface. When designing try to use the Increment, Jig and ClearNames design patterns.

Table 3 - Description of design tasks with respect to levels of "Goal" and "Method" specifications

m	**Attributes (*f, weights*)**	***S* = 1**	***S* = 3**	***S* = 5**
1	Type of structure (0.15)	Solid Wall and Roof	Column and beam	Others
2	Geometry (0.15)	Square or rectangular	Deformed square or rectangle	Others
3	Added purpose (0.1)	No purpose	One purpose	2+
4	Privacy(0.1)	Door / full coverage	Partial coverage / zigzag Entrance	Others
5	Fixable to base surface (0.1)	Weight / bolts	Cables	Others
6	Light (0.1)	Artificial light	Natural light	Others
7	Natural ventilation(0.1)	Artificial	Upper and lower windows / Louvers	Others
8	Roof drainage (0.1)	Flat roof for snow and rain drainage	Slanted or curved roof	Others
9	Materials (0.1)	Steel / Concrete / Wood / Glass	Cloth / Plastic / Rubber /	Others

Table 4 – List of attributes and weights for calculating "Novelty" score for beach changing room

Novelty

Two methods were adopted for calculating novelty scores for each design. First one is the *a priori* method proposed by Shah et al. [24]. It is used where a universe of ideas for comparison is subjectively defined for each function or attribute, and at each stage [24]. It is given preference over *post facto* approach, as in *a priori* method attributes are defined before analyzing any data to avoid bias. Please note that, in this study, all designs were analyzed only at a conceptual level, befitting the time constraints on the experiment. To do the analysis, the design problem was first decomposed into a set of key functions or characteristics, and a weight was given to each function prior to data collection (Table 4). Each function was then described in terms of how novelty for that function can be fulfilled in any design solution. It was again decided prior to data collection that what would be considered novel and a weight was assigned accordingly (Table 4).

Overall novelty for each idea was then computed from the formula [24];

$$Novelty = \sum_{j=1}^{m} f_j \sum_{k=1}^{n} S_{jk} P_k$$

Where, m is the total number of functions/attributes, f is the weight assigned to each function with respect to its importance. S is the sub novelty score for each function, P is the weight assigned to each stage, and n is the total number of stages analyzed. As in our study only one stage (conceptual level) was used so, P was ignored.

In our second method, a jury of three design professionals was asked to grade each design for novelty in their ideas on the conceptual level. All three professionals were selected on the basis of their educational background in architecture and expertise in design education. All of them have minimum seven years of education and two to four years of professional design experience. They were asked to rate each design for novelty by comparing it within the group. It was considered important to compare the designs with each other to see which specificity level of goal and method helps in producing more novel outputs.

Quality

Quality is a construct requiring a carefully designed analysis technique. As when we talk about measuring "how close a design comes to meet the design specifications" [24] both explicit and implicit design requirements must be considered. Explicit requirements occur directly in the design problem. Implicit requirements may be just as firm, but are taken as givens. For example, if a person is asked to design a chair, then it is an implicit requirement that a chair will have a base to bear load and will provide a place to sit. Keeping this in mind, while using Shah's [24] measuring formula for quality, various implicit attributes were selected as shown in the Table 5. Weights were given to each attribute such that if one attribute is satisfied fully, it was given a maximum score of 5 and was then multiplied by its weight. Adding all together gives a total score for quality.

m	Attributes	Weight (f)	Max. Score(S)	Stage (k)
1	Privacy	0.14	5	1
2	Size	0.14	5	1
3	Wind proof roof	0.14	5	1
4	Securely fixed to surface or other structure	0.14	5	1
5	Light	0.14	5	1
6	Natural ventilation	0.14	5	1
7	Roof drainage	0.14	5	1
	SUM OF WEIGHTS	**1**		

Table 5 – List of attributes and weights for calculating "Quality" score for beach changing room

To avoid inter-rater bias, three researchers together calculated the scores for quality for each design, according to the set rules discussed above, and weights specified in the table. Again, like novelty, each design was analyzed for quality at a single conceptual stage. In case of a designer presenting two or more alternatives as a solution, an average score was calculated. The final score was calculated by the formula as stated by Shah et al. [24];

$$Quality = \sum_{j=1}^{m} f_j \sum_{k=1}^{n} S_{jk} P_k \Bigg/ n * \sum_{j=1}^{m} f_j$$

Where, m is the total number of attributes/functions, n is the total number of stages (which is 1 in our case, conceptual stage). S is the score for each attribute against each design and f is the weight of that attribute. P is the weight for stage k.

Designer satisfaction level

Designers were asked for their self satisfaction with the proposed design solutions under each condition. They were asked to rate their satisfaction level on a 5 level Likert scale where 1 represented least satisfaction level and 5 represented highly satisfactory design solution.

Process based evaluation

Data collection

To record the design process, each participant's computer screen was videotaped during the experiment. These videos provided authors with insight into designers' intentions through a chain of iterated actions, along with the design completion time. In addition to these videos, designers were asked to save screen shots whenever they believe they have accomplished a sub-goal task during their design process. The sub-goal could either be a designer's self specified goal or a goal explicitly stated inside a design problem. Such moments in a process were named *design states.*

A post-experiment survey asked participants their satisfaction level with the design outcomes, as well as their preference for specificity level of design goals and methods.

Data encoding

After the successful collection of screen captures, videos and *SolidWorks* files; data was reviewed, encoded by three encoders and was transformed into design trees. It was noticed that some of the participants did not save screen shots to depict design states. According to the post experimental survey, they forgot to do so, while searching for design solutions. So a new strategy was adopted to define design states. Various signals were decided by the authors to call for a design state, which included: saving a file, prolonged interface actions (zooming/rotating) and opening a new file or part. According to these signals, design trees were prepared, analyzed and compared for significant patterns.

RESULTS

Outcome-Based Analysis

The data collected was analyzed using a factorial design ANOVA with two between-subjects factors (Goal and Method specificity levels). Each of the dependent variable mentioned was analyzed individually. In this section, the results from the analysis are discussed one by one.

Quality

This analysis revealed a significant main effect for goal specificity level, $F(1, 20) = 6.16$; $p = 0.022$. The sample means are displayed in Figure 2. Tukey's HSD test showed that participants in the high-goal specificity condition scored significantly higher on quality than participants in the low goal specificity condition ($p < 0.05$).The main effect for method specificity level was not significant, $F(1, 20) = 0.79$; $p = 0.38$. The interaction between goal and method specificity level was also not significant, $F(1, 20) = 0.08$; $p = 0.77$.

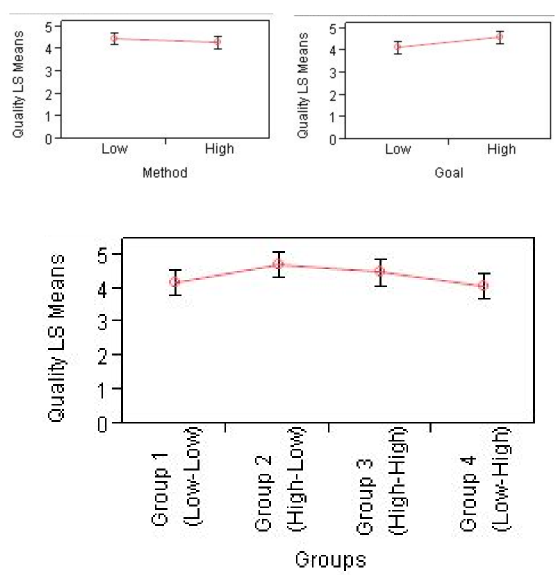

Figure 2 – Comparison of "Quality" score between groups

The results were also compared among four groups made according to each combination of goal and method. The line graph in Figure 2 shows that participants score highest under high-goal and low-method specification design task compared to all other groups. In the figure, *High-Low* means high-goal and low-method respectively.

Quality Score by Professionals

To our surprise, the quality scores given by professionals were insignificant for both goal specificity and method specificity, $F\ (1, 20) = 0.09$; $p = 0.766$, and $F(1,20) = 0.09$; $p = 0.766$ respectively. Figure 3, shows the distribution of quality grades assigned by professionals, across groups.

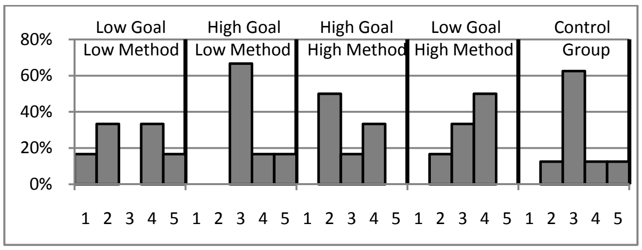

Figure 3 – Normalized distribution of *Quality* scores by professionals in each group on a Likert scale of 1 to 5

Novelty

This analysis did not reveal any significant main effect. Neither for goal specificity level, $F(1, 20) = 1.42$; $p = 0.25$, nor for method specificity level, $F(1, 20) = 1.46$; $p = 0.24$. The interaction between goal and method specificity level was also not significant, $F(1, 20) = 1.88$; $p = 0.18$.

Again the results were compared among four groups made according to each combination of goals and methods. The line graph in Figure 4, shows that mean novelty scores under low-goals high-methods is higher compared to all other groups, where group 4(Low-High) scores highest; *Low-High* means low-goal and high-method respectively.

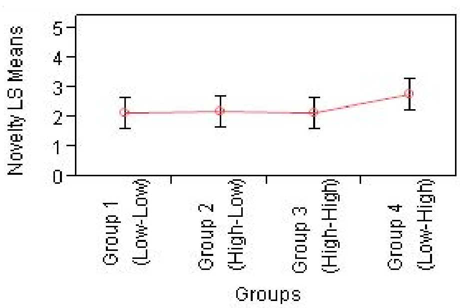

Figure 4 – comparison of "Novelty" score between groups

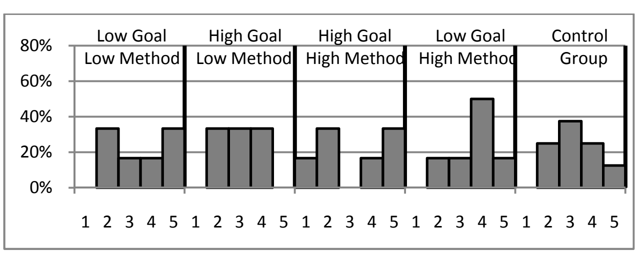

Figure 5 – Normalized distribution of *Novelty* scores by professionals in each group on a Likert scale of 1 to 5

Novelty Score by Professionals

The novelty scores given by professionals like quality scores were insignificant as well, for both goal specificity and method specificity, $F\ (1, 20) = 0.08$; $p = 0.77$, and $F(1,20) = 0.21$; $p = 0.65$ respectively. (Figure 5)

Number of Alternatives

This analysis did not reveal any significant main effect either. Neither for goal specificity level, $F\ (1, 20) = 0.33$; $p = 0.57$, nor for method specificity level, $F(1, 20) = 0.58$; $p = 0.45$. The interaction between goal and method specificity level was also not significant, $F\ (1, 20) = 0.0366$; $p = 0.85$.

Results when compared among groups show that the mean value for number of alternatives is highest for the group performing low-goal and low-method design task (Figure 6) but is neither significant nor large.

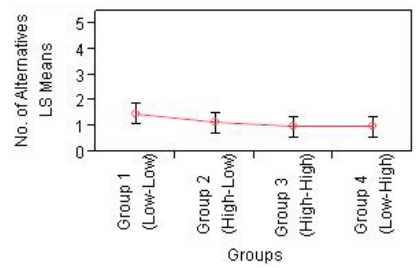

Figure 6 – Comparison of "No. of Alternatives" between groups

Designer's Satisfaction Level

The results for satisfaction level are non-significant again (Figure 7), but it was observed that the mean value for the satisfaction level was higher when the design task given to designers was set with high goals and low method specifications.

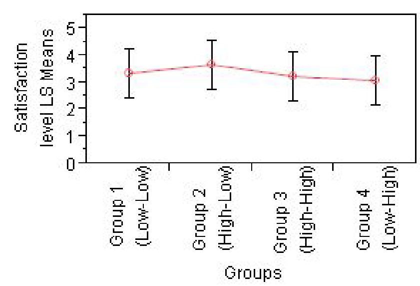

Figure 7 – Comparison of "Satisfaction level" between groups

Process Based Analysis

Except for the quality of design solutions, the results from the quantitative analysis of design outcomes were mostly insignificant, therefore, it was considered necessary to give an alternative explanation through process-based analysis. We structured our analysis using the classical literature on design problem solving [27, 28] and designer's search behavior/pattern [10, 12, 23].

Design Goals

We observed that Akin's [2, 3] act of "redefining design problems", persists even more strongly in parametric design patterns. As designers move ahead in design space, they keep on redefining goals and constraints even though the problem could have been considered well-defined [30]. Designers exercise this freedom of changing goals and constraints, as the understanding of the problem develops and the definition of the solution proceeds [14]. This pattern in design is consistent with 'opportunistic' strategy. The same pattern was observed among all participants, which could be the possible reason behind the significance of quality scores against goal specificity in this experiment.

It was observed that in parametric systems, most of the designers first set a rough framework of ideas with ill-defined problem goals and constraints, and as they proceed, they take the liberty of going back at any stage for alterations. Such backtracking events were sometimes observed to be explorative, and sometimes to refine details (if designer had already reached a satisfactory design solution). In both cases, designers were observed to be defining goals and sub-goals repetitively.

According to design literature on designer's behavior, it is the evaluation of the solution that is important, not the analysis of the problem [14]. This strategy was observed in many design processes, when designers reached a certain design state where they took some time to think either to proceed or to go back and make alterations. It was observed that instead of going through design goals or requirements one by one in an orderly strategic manner, designers preferred making decisions depending upon the current scenario after analyzing the partial solution.

An evidence of co-evolution of solution and problem [10] was also observed when designers develop intermediate solutions to help understand the problem formulation. They move back and forth in problem space and solution space with intermediate partial structuring of sometimes problem and sometimes solution [12].

Design Methods

According to literature on design search, designers are reasonably efficient whenever they adopt systematic and logical approaches, while designers produce mediocre or poor design solutions when they act unsystematically [16, 17]. But according to our analysis, the reason for no correlation in methods is not that there was no systematic approach in their process, instead parametric systems allowed backtracking at and to any stage of the design process to make changes. We found that none of the designers followed a strategic methodology in terms of sequencing such actions. One thing which was quite evident in all design processes was introducing parametric dependencies through equations and smart dimensions as a way of recording design constructs or intent while proceeding towards a satisfactory solution. Designers were able to backtrack at any moment of design process and add such dependencies. This opportunity has given designers a freedom not to adopt any strategic plan of actions. This may partially explain some of the lack of significance in the quantitative data.

Satisfaction level

Designers satisfice rather than optimize [28]. The criteria by which a designer decides that a design is satisfactory are complex, including explicit, implicit, external and internal. In the study, designers who were unable to accomplish their pre-conceived goals rated their work at a low level of satisfaction, even though their solution was considered "better" by the evaluators compared to solutions by other designers or by the same designer.

Number of Alternatives

It was observed that due to the use of parametric systems, the final solution proposed by most of the designers was a single solution, yet there is an evidence of variations and alternatives at the process level. During the experiment all designers tried alternatives by using one of the following strategies: by changing parameters, by improving details in an already built model-part through backtracking or by saving instances of already built parts through design tables (a feature - provided inside *SolidWorks* for creating alternative solutions for a model part).

Although the quantitative analysis shows no significance in terms of number of alternatives saved by designers, there is a clear evidence of alternative solutions tried during the process. These alternatives were part of the design process but were not saved, and hence no record for them was seen in the final design solutions.

DISCUSSION

The reasons behind the insignificance of quantitative data has already been discussed and explained in process-based analysis, still there is a need to discuss some issues which might have affected the results and hence the insignificance. One of the major issues could be the fact that all designers were asked to perform two design tasks in the time span of two hours (max.), this limited time frame plus the fatigue might have influenced the results for the second task.

Secondly in the high-method design task, designers were asked to use three parametric design patterns, in their design process. But most of the designers, while searching for solutions, either forgot to incorporate those patterns or they chose not to use them, considering them less important with respect to the design solution they had in their minds. This variability in use of patterns can be the major reason behind non-significance in method specificity level. In retrospect, we likely asked subjects to apply patterns too early in the process. Woodbury [36] points out that patterns are most appropriate when model-making requires a divide-and-conquer strategy, that is when models become complex. The relative simplicity of the models produced may simply have not been amenable to patterns.

Goal	Method	No. of Observations	Mean (Quality)	Mean (Novelty)	Mean (Satisfaction level)	Mean (No_ of Alternatives)
Low	Low	6	4.21	2.16	3.33	**1.50**
Low	High	6	4.10	**2.82**	3.08	1.00
High	Low	6	**4.72**	2.21	**3.67**	1.17
High	High	6	4.50	2.17	3.25	1.00
Control Group		8	4.45	2.5	2.625	1.00

Table 6 – Overall results comparing the mean values of each dependant variable against both "Goal" and "Method"

CONCLUSION

The outcome-based analysis of an experiment with designers exposed to different design goal and method specificity levels allowed us to measure the effects of these design task specificities on the design process and ultimately the design solutions generated. These effects were measured by an outcome-based analysis technique, and the alternative explanation for those effects was made through process-based evaluation.

Although most of the quantitative results were insignificant in order to make a claim, still depending upon the differences in mean values (Table 6) and descriptive explanation of results from protocol analysis, a thought should be given to what level of goal and method specificity should be provided to designers, to gather what sort of design outcomes, while exploring design space in parametric systems. Here are some speculative thoughts.

- When quantity of the solutions is sought, then designer might be given low specifications for both design goals and design methods.
- When more feasible and quality-wise better output is sought, then designers might be triggered with high goals and low method specifications.
- When higher novelty in design solutions is sought, then design task with low goal but high method specifications might be formed.
- When higher satisfaction level is sought, then a design task might be formulated with low goal specificity and high method specificity level.

Besides these conclusions, there is a need for further analysis of data, and perhaps running the experiment one more time with more participants in all task specificities; and with reduced confounding variables, such as, fatigue and individual expertise level in using parametric design patterns. Furthermore, as this study analyzed design outcomes only on conceptual level, further investigation should include analysis at embodiment and detail levels.

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