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IDENTIFICATION OF DESIGN STRATEGIES AND THEIR EFFECTS ON PERFORMANCE OUTCOMES IN PAIR PARAMETER DESIGN TASKS

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ABSTRACT

Understanding design processes and behaviors are important for building more effective design outcomes. During design tasks, teams exhibit sequences of actions that form strategies. This paper investigates patterns of design actions to identify successful design strategies in paired parameter design tasks. The paper uses secondary data from a design experiment in which each pair completes a series of simplified cooperative parameter design tasks to minimize completion time. Analysis of 192 task observations uses principal component analysis to identify design strategies and regression analysis to evaluate their impacts on performance outcomes. Results show that the design strategy of short average action time, small average action size, and low action variation significantly decreases completion time. Discussion of results suggests smaller and more frequent actions provide more rapid feedback about each action to improve communication and understanding between pairs, leading to more efficient design processes. Results show that task order and the number of variables also significantly contribute to performance outcomes, which aligns with past literature. Results also show a negative relationship between lower English ability, experience level, and team performance outcomes. The discussion suggests that lower English ability can be a barrier to communication between pairs, and a lower experience level can decrease the ability to create effective strategies.

1 Introduction

In today's world, engineering design teams deal with complex problems. Design behaviors and strategies shape design outcomes, making design processes vital to achieving desired outcomes. During design processes, teams explore, communicate, and conduct decision-making processes that determine their actions and strategies. Understanding design behaviors and identifying strategies that lead to desired outcomes is important for creating more efficient design processes.

Designers exhibit different actions based on their experience level and the complexity level of the design tasks [1]. Within a narrowly-scoped design task, *micro strategies* are defined as sequences of actions that designers perform to reach the expected outcomes in a design process [1]. Identifying successful design strategies by grouping observed actions during a design task would help to inform future studies and industries to enhance their design processes.

Complex collaborative engineering designs, such as an aircraft design, consist of multiple interdependent subsystems. Any changes made in one subsystem would impact the other subsystems, and all subsystems needed to be in harmony for the entire design to work once integrated. For instance, in the case of an aircraft, if the wings and fuselage subsystems do not meet each other's requirements, the aircraft would not be able to function. Investigating the designer strategies in complex collaborative engineering design systems can lead to more efficient design processes.

Parameter design tasks are well-defined problems with controlled variables (parameters) [2]. Research using parameter design tasks can eliminate domain-specific complexities and focus on specific design parameters and designer behaviors. Using parameter design tasks as an experimental procedure gives the control of varying the technical complexity of tasks [3] and eliminates external complexities [2, 4]. These features of parameter design experiments provide a more concentrated way to investigate specific research purposes in design settings. This paper aims to understand the design process in complex collaborative design systems with an abstract-level collaborative design problem, eliminating domain-specific complexities.

This paper fills the literature gap by studying design processes in an abstract-level parameter design problem that enables the identification of design strategies, which can be applied to a wide range of design problems. Identifying design strategies in abstract design problems can bring interventions enhancing design processes that are not specific to any particular design problem or domain. The paper defines *design strategy* as a *similar set of actions designers follow that are generalizable over broad design problems* and investigates how groups of designer actions form strategies to understand better the design process and its effects on performance outcomes in paired parameter design tasks.

The analysis uses secondary data from a human parameter design experiment consisting of tasks with different levels of complexity, yielding a total of 192 tasks. The experiment consisted of 48 participants and 24 pair teams. The analysis first identifies observable design actions from the experimental log, runs a principal component analysis to identify design strategies exhibited during the experiment, and finally performs a regression model to evaluate the significance of design strategies on performance. Results show that the design strategy of short average action time, small average action size, and low action variation significantly increases the performance outcomes of pairs in the parameter design experiment. Results also show that the number of variables, task order, and some demographic factors significantly impact team performance outcomes in parameter design tasks.

2 Literature Review

2.1 Design Actions and Micro Strategies

Gero defines design as a goal-oriented, constrained, exploration, decision-making, and learning activity [5] with sequences of actions where designers perform micro strategies [1]. Micro strategies are self-sustaining actions focusing on the current state of the design process. Identifying similar actions observed in the design process and then following and grouping them will provide specific micro strategies that designers choose. Gero also notes that the designer's experience level and the complexity level of the task impact number of different micro strategies found in the design process [1]. From the stated definition, this paper focuses on the designer's decision-making and the strategy-building process by identifying designers' actions and grouping similar actions to differentiate some successful and unsuccessful strategies in paired parameter design tasks.

2.2 Parameter Design Problems

Parameter design tasks present a set of input variables (design parameters) to designers that influence a set of output variables [6]. Gero and Yu define parametric design as *a dynamic, rule-based process controlled by variations and parameters, in which multiple design solutions can be developed in parallel* [7]. Using parameter design tasks to study designer behaviors helps control external factors' effects, such as domain knowledge [4]. Using parameter design tasks supports the creation and organization of complex digital models [8]. Parameter tasks can have coupled and uncoupled characteristics. Uncoupled parameter design tasks include a one-to-one mapping between input and outputs whereas, where this condition is lacking, the parameter design tasks would be coupled [6].

One of the first parameter design experiments on human subjects are conducted by Hirschi and Frey [6]. They used a computer user interface and assigned participants tasks ranging from 2-input-2-output parameters to 5-input-5-output parameters. Later, Grogan and de Weck performed a human parameter design experiment by following the parameter design principles introduced by Hirschi and Frey [3]. They gave participants coupled and uncoupled parameter design tasks with varying technical and social complexity levels. Their results show that increasing technical complexity negatively impacts performance outcomes meaning that as the number of variables (parameters) increase in a task, the completion times increase with a power-law relationship. Their other significant conclusion was that as the team size grows, the completion times of design teams increase significantly due to increased social complexity.

Alelyani et al. later use secondary data from Grogan and de Weck [3] to investigate factors contributing to designers' behavior for parameter design tasks [4]. To quantify the relationship among design features, they identified three behavioral characteristics as the number of design actions, performance outcomes, and experienced error. Yu et al. conducted a human parameter design experiment where participants engaged with simulated design processes involving seawater reverse osmosis plants [2]. Their goal was to investigate the relationship between behavior and performance. Their findings showed that the best strategy was simulated annealing optimization algorithm for higher performance outcomes, and the worst strategy was pseudo random-search strategy with lower performance outcomes.

Later Avsar and Grogan adopt the parameter design problem experiment from Grogan and de Weck [3] to investigate the effects of Locus of Control (LOC) personality trait on performance outcomes [9] Their findings show statistically significant relationship between LOC and performance of pairs in parameter design tasks.

Wohr et al. build on the parameter design framework from Grogan and de Weck [10]. They conduct a human parameter design experiment to investigate the effect of the varying time interval between each integration and verification. Their findings show that varying the frequency of integration and verification significantly impacts performance outcomes. They show shorter time intervals between each integration, and verification improves designer performance outcomes by decreasing the completion times of tasks.

2.3 Teamwork and Design Process

Teamwork has been the subject of extensive study in various fields because of its wide usage and advantages. Teamwork can provide greater productivity and competitiveness [11], and literature shows that design teams can achieve higher quality than individuals in product development [12]. Teamwork brings a wider range of knowledge and expertise [13], enabling decomposition and allocation of design decisions and actions among team members to apply specialized knowledge [14]. However, interactions between design actors generate iteration loops and rework that may outweigh potential benefits [15].

By cooperation, teams can achieve better productivity and performance outcomes, but having distributed cognition and communication among different members makes the process challenging [16]. As team effectiveness impact outcomes in design settings and team effectiveness depend on various factors [17–19], this paper focuses on how design team processes affect design outcomes.

2.4 Literature Gap

Literature offers insights into various design behaviors and strategies utilized by design teams [20–26]. However, applying the findings to other contexts becomes challenging since each paper focuses on a specific research question and includes design tasks specific to a particular field. This paper aims to identify generalizable strategies that can be applied to various design problems and situations instead of recommending specific behaviors or strategies for selected design problems. Accordingly, the paper defines *design strategy* as a *similar set of actions designers follow that are generalizable over broad design problems*.

Literature shows that parameter design tasks provide a controlled environment to study design processes [3, 6–8]. Parameter design problems involve abstract design activities and eliminate domain-specific complexity, providing complete control over technical variables. As a result, they offer a suitable environment for investigating more broadly applicable design strategies. This paper aims to conduct an initial study toward identifying design strategies that can be applied to engineering design tasks across multiple domains. These strategies should be broadly applicable and not specific to any particular domain.

2.5 Research Objective

The objective of the paper is to fill the literature gap by studying design strategies in a parameter design problem to identify generalizable successful and unsuccessful strategies. Identifying and differentiating some successful and unsuccessful strategies that design teams use in parameter design tasks can help future studies and industries to bring interventions to design teams to direct them through using successful design strategies.

This paper uses secondary data from a human parameter design experiment originally adopted from Grogan and de Weck's parameter design work to explore the effects of personality traits on team performance outcomes in design tasks [9]. The human experiment consists of cooperative paired parameter design tasks. The parameter design problem in the experiment represents an abstract level collaborative design problem without any domain-specific knowledge. During the design tasks, each designer in a pair can be thought of as representing a subsystem of a complex collaborative engineering design product.

This paper investigates the relationship between process variables and task outcomes, the experiment design process illustrated in Fig. 1. The analysis seeks to identify successful and unsuccessful design team design strategies by identifying action types and grouping them by principal component analysis (PCA) technique to differentiate strategies. For this purpose, the paper investigates the following hypothesis:

Teams follow different design strategies that affect their performance outcomes in parameter design tasks.

3 Methodology

This paper analyzes secondary data from a parameter design experiment that originally studied the effect of LOC on design behavior described in Ref. [9]. Secondary analysis further investigates how designer behaviors influence outcomes for cooperative pair design tasks irrespective of LOC. The design experiment uses the same parameter design features from the framework of Ref. [3] with an updated software platform[1]. The following sections review the methodology (design task, protocol, instruments, and data) of the source experiment.

3.1 Design Task

The underlying parameter design task defines a column vector of N scalar input variables $x = [x_1, \dots, x_N]^T$ with $x_i \in$

[1] Available from the authors under an open-source license at https://github.com/code-lab-org/collab-web

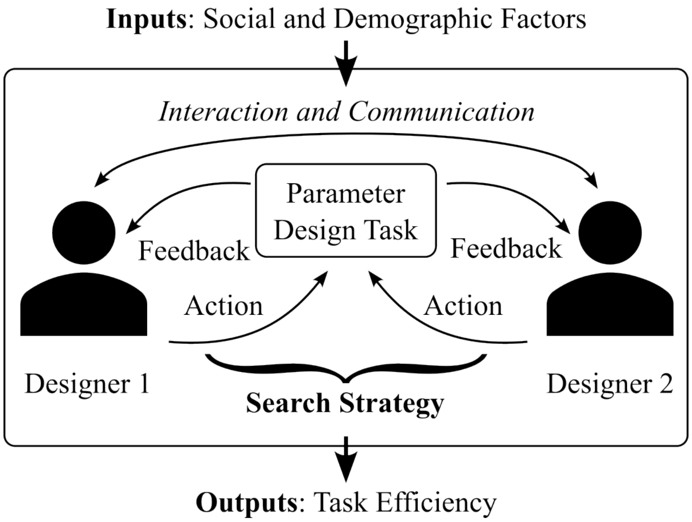

FIGURE 1: The design system consists of the parameter design task with two designers who iteratively make actions following a revealed design strategy. Inputs include social and demographic factors. Outputs measure performance via task efficiency.

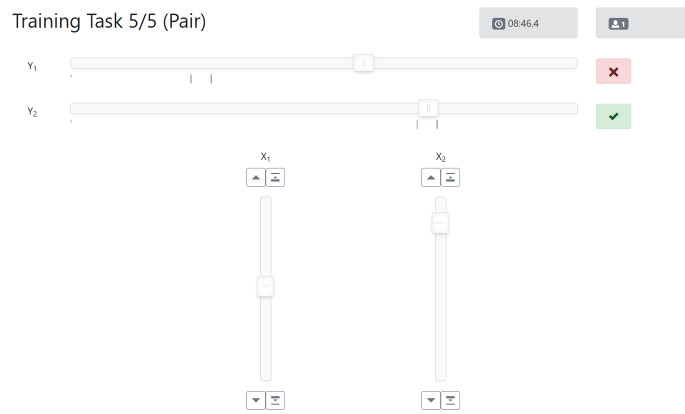

FIGURE 2: Example design task interface for a designer (#1) with two assigned input parameters (vertical sliders) and two assigned output requirements (horizontal sliders) with black bars marking target region boundaries. The outputs update in response to input changes by either designer. A timer counts down from a maximum duration allowed for each task.

$[-1,1]$ and a column vector of N scalar output variables $y = [y_1, \ldots, y_N]^T$. An $N \times N$ system matrix $M = [m_{ij}]$ relates inputs to outputs as a linear system of equations $y = Mx$ where element m_{ij} represents the sensitivity of output y_j on input x_i. Starting from an initial zero input vector ($x_i = 0 \; \forall \; i$), the task objective is to choose input variables x to achieve a target output vector $y^\star$ with a maximum allowable error $|y_i - y_i^\star| < 0.05$ in each output variable. The task duration measures the time required to meet all requirements.

Coupled task instances with $m_{ij} \neq 0 \; \forall \; i, j$ are generated as follows to achieve certain invariant conditions. First, generate M as the orthonormal basis of a random $N \times N$ matrix with elements sampled from a uniform (0,1) distribution. Next, generate a candidate $y^\star$ as the orthonormal basis of a random $N \times 1$ column vector with elements sampled from a uniform (-1,1) distribution. Compute the task solution as $x^\star = M^T y^\star$ and, if any solution variables are close to the initial design point with $x_i = 0$ ($\exists \; i : |x_i^\star - x_i| \leq 0.2$), generate a new target (repeat as necessary). Resulting tasks preserve distance in input and output spaces irrespective of N, i.e. $||x^\star|| = ||y^\star|| = 1$, to control for distance scales in larger design problems.

The design tasks are adapted to multi-actor design problems by assigning control over input variables and visibility over output variables to n individual design actors. A binary control matrix $n \times N$ control matrix $C = [c_{ij}]$ assigns designer i to have control of input variable j. A binary $n \times N$ visibility matrix $V = [v_{ij}]$ assigns designer i to have visibility of output variable j. Each input and output variable is assigned to only one designer.

Designers interact with design tasks in a graphical, rather than numerical, format. The browser-based user interface in Fig. 2 illustrates the user interface from the perspective of one design actor. Vertical sliders ranging between -1 and 1 represent controlled input variables and horizontal sliders with target regions between black bars display output variables and target requirements. Quantitative information is hidden to prevent mathematical solutions. Designers are limited to visual feedback on their own interface and face-to-face communication with teammates. Designers modify inputs by dragging the slider thumb up and down (using the touch-pad or touchscreen) and inputs only update once released. Designers may also use arrow keys on the vertical sliders to change the input by 0.1 or 0.01 units.

Designers attempt to finish each task as quickly as possible. A timer visible in the interface counts down from a maximum duration allowed for each task. Individual tasks require the designer to meet the target region of all horizontal sliders, changing the signal icon from a red cross to green check mark. Pair tasks require both partners to meet the target region of all horizontal sliders at the same time. Completed tasks award points to all participating designers based on the relative efficiency (one point per second remaining). Cumulative points earned throughout an experiment determine rankings for monetary incentives.

3.2 Experiment Protocol

The source experiment follows a between-subjects design with replication at group and task units to study the effect of LOC on design processes. The experiment controls group factors pairing LOC types (I: internal or E: external) in design pairs as I-I, I-E, or E-E. Each pair works on a sequence of design tasks of varying size to yield multiple observations of process and outcome variables. The protocol was approved by the Institutional Review Board at Stevens Institute of Technology (#2019-025).

The study includes two distinct cohorts, each consisting of four replications of each group factor (I-I, I-E, and E-E) across six sessions (total: 24 pairs). The cohorts were separated in time by several months and followed slightly different task sequences described below; however, both cohorts used the same experiment rooms, computers, instructions, and overall procedures. Participants were recruited from adult on-campus student populations via email and flyers.

All sessions were conducted in university classrooms using a standard room layout with assigned seats. Paired participants sit face-to-face with each team at a separate table. Tables are arranged such that each computer display is only visible to the seated individual. Pairs may communicate face-to-face but not share any computer displays. Each session evaluates two pairs in parallel, both working on equivalent tasks and scheduled based on mutual availability. The two teams in each session may not communicate with each other.

Sessions consist of five training tasks and ten experimental tasks described in Table 1. Training tasks introduce the task objectives and computer interface and take about 20 minutes to complete. The remaining ten experimental tasks take about 40 minutes to complete. Sessions in Cohort 1 include both individual and pair tasks administered in fixed order, of which this paper only considers the six pair tasks. Sessions in Cohort 2 include ten pair tasks administered in randomized order subject to the constraint that tasks with four variables must take place in the second half of the experiment.

To incentivize efficiency, participants earn 1 point per second a task is finished ahead of the maximum time and 0 points for an incomplete task. At the end of a session, participants are ranked based on total accumulated score and privately paid in gift cards ranging from minimum of \$8 to maximum of \$15 based on their successive ranks. Aggregated scores are only released at the end of a session to limit strategic behavior including end-of-session boundary effects.

3.3 Experiment Instruments

Prior to working on tasks, participants complete a demographics survey with six items including age (years), gender (male, female, or other), post-secondary education (years), professional work experience (years), native language, and English proficiency. English proficiency is measured on a scale with four levels: Fluent/Native, High (TOEFL $>$ 95 or IELTS $>$ 7), Medium-High (TOEFL 85-94 or IELTS 6.5-7), Medium-Low (TOEFL 60-84 or IELTS 6), or Low (TOEFL $<$ 60 or IELTS $<$ 6). Analysis assigns numerical values from 0 to 4 scale to English language ability (0: Low; 4: Fluent/Native).

During a design task, an automated log records all design actions (i.e., input slider movements) as time-stamped events. Post-processing computes the time to complete each task (task efficiency) as the the timestamp difference of the first and last design action. Each design task requires the input sliders to move a total of 1.0 units from the initial state to reach the target solution, regardless of problem size N; however, design strategies may produce different patterns of size, timing, and sequence of design actions.

3.4 Experiment Data

A total of 48 subjects (20 women and 28 men) participated in the experiment. Subjects ranged from 21 to 40 years of age. All participants either previously completed or were in their last year of STEM undergraduate studies, and more than half were currently pursuing a graduate engineering degree. 39 participants listed one of 19 different languages other than English as their native language. 21 subjects claimed to be fluent English speakers, 19 reported TOEFL scores above 95 (IELTS $>$ 7.0), 6 between 85-94 (IELTS 6.5–7.0) and 2 between 60-84 (IELTS 6.0) prior to starting their studies.

The experimental design yields observations from 192 design tasks ($12 \times 6 = 72$ from Cohort 1 and $12 \times 10 = 120$ from Cohort 2) summarized in Table 2 by task size and mean task completion times. Approximately 17% (32/192) of the tasks were not solved in the given maximum time limit and were assigned the maximum completion time in Table 1 as a conservative assumption for subsequent analysis.

4 Analysis and Results

To address the hypothesis that differential design strategies affect performance outcomes in parameter design tasks, the analysis first performs principal components analysis (PCA) to reduce the dimensionality of input and process features. Finally, regression analysis investigates whether input and process components have a significant effect on task performance.

4.1 Input Factor Dimensionality Reduction

The initial set of input factors for each pair of designers includes: mean English ability (measured on 0–4 scale), number of females per pair (0–2), mean age (years), mean post-secondary education (years), and mean professional work experience (years). To reduce the dimensionality of the demographic input factors, PCA identifies orthogonal vectors of input factors.

The analysis uses `sklearn` (version 0.24.1) function `PCA` with `RobustScaler` and a 90% variance threshold to determine the number of components. The radar plot in Fig. 3 visualizes the resulting three input principal components (IPCs). Distinguishing characteristics include:

TABLE 1: Training and experimental design tasks for Cohort 1 and Cohort 2

Training Tasks (Fixed Order)				Cohort 1 Tasks (Fixed Order)				Cohort 2 Tasks (Random Order‡)			
Type	Size	Repl.	Time (s)	Type	Size	Repl.	Time (s)	Type	Size	Repl.	Time (s)
Individual	1	1	90	Individual	2	2	120	Pair	2	4	180
Individual	2	1	120	Individual	3	2	240	Pair	3	4	360
Pair	2†	1	270	Pair	2	3	180	Pair	4	2	720
Pair	2	1	270	Pair	3	3	360				
Pair	3	1	540								

†: uses an identity coupling matrix M to simplify training, ‡: size 4 tasks cannot appear within first five tasks

TABLE 2: Summary of mean design completion time by task size

Task Size (N)	Mean Completion Time (s) ($\overline{T}$)	Standard Error Completion Time (s) $s_{\overline{T}}$
2	64.3	5.36
3	184.6	13.40
4	454.9	52.87
All	165.7	12.68

1. IPC1: Elder pairs with higher levels of education and work experience.
2. IPC2: Pairs with lower English ability and work experience.
3. IPC3: Younger pairs with lower education experience.

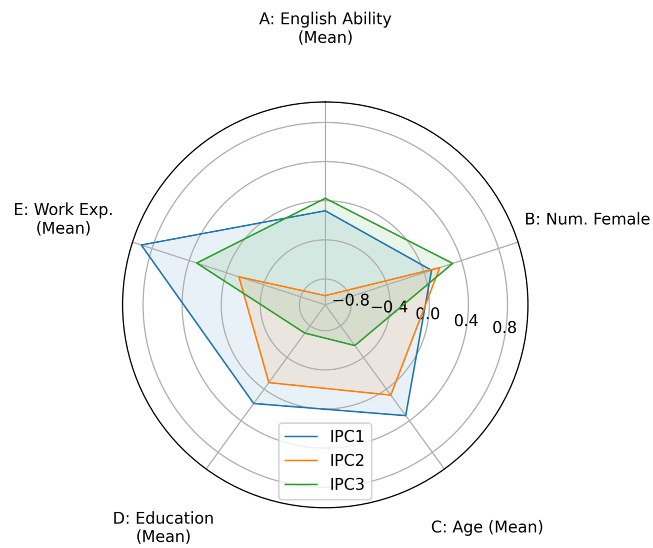

FIGURE 3: Principal components of input (demographic) features. IPC1 shows elder pairs with higher education and work experience. IPC2 shows pairs with lower English ability and work experience. IPC3 shows younger pairs with lower education.

4.2 Process Factor Dimensionality Reduction

Post-processing of the experimental log computes nine candidate process-oriented metrics in five categories:

1. Action size (mean, standard deviation, skew): distance traveled by the input slider for a single action. User interface buttons permit action sizes of 0.1 and 0.01 and moving the slider thumb permits arbitrary action sizes.
2. Action time (mean, standard deviation, skew): elapsed time between successive actions.
3. Input delta (mean): indicator variable for input slider changes between successive actions. A value of 1.0 indicates a different slider for each successive input and a value of 0.0 indicates all actions target the same slider.
4. Designer delta (mean): indicator variable for input controller (designer) changes between successive actions. A value of 1.0 indicates alternating actions among designers and a value of 0.0 indicates sequential actions from one designer.
5. Designer share (max): indicator variable for the input controller (designer) for each action. A value of 0.5 indicates equal numbers of actions among both designers and a value of 1.0 indicates actions by only one designer.

To study interrelationships among process factors, correlation analysis first investigates multicolinearity. Figure 4 shows the resulting correlation matrix, confirming multicolinearity.

Next, a similar PCA technique to the input factors is applied to reduce the dimensionality of the nine process factors. A 90% variance threshold again determines the number of components. The radar plot in Fig. 5 visualizes the resulting three process prin-

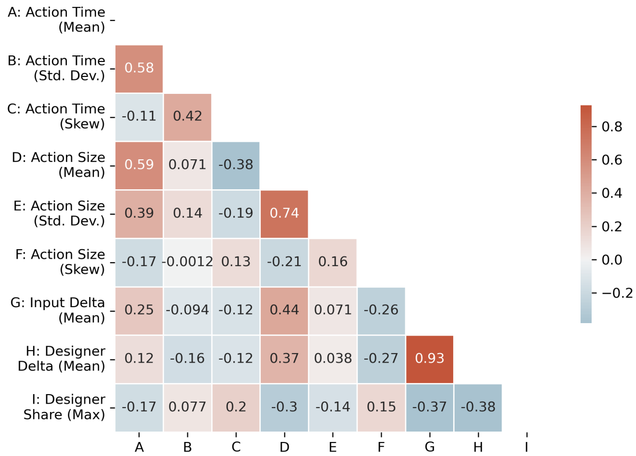

FIGURE 4: Correlation matrix for nine identified design process features confirming the presence of significant multicolinearity.

TABLE 3: Summary of principal components for observed process variables for tasks of variable size

Task Size (N)	Mean PPC1	Mean PPC2	Mean PPC3
2	-0.58	0.17	0.03
3	-0.41	-0.13	-0.05
4	3.47	-0.12	0.08

cipal components (PPCs). Distinguishing characteristics include:

1. PPC1: High variation in time between actions and large action size skew (few actions much larger than average).
2. PPC2: Long average action time, large average action size and variation, and frequent switching between inputs and designers.
3. PPC3: Short average action time, small average action size and variation.

Table 3 shows mean principal component values for each task size.

4.3 Analysis

The research question investigates the effect of the process variables (designer behavior) on task completion time while controlling for differences in inputs (demographics) and task structure. Analysis proposes a linear model with similar transformations for completion time ($\ln T$), task size (N^2), task order ($\ln O$), and input/process variable principal components.

Preliminary analysis constructs an ordinary least square regression model to investigate effects of all demographics factors

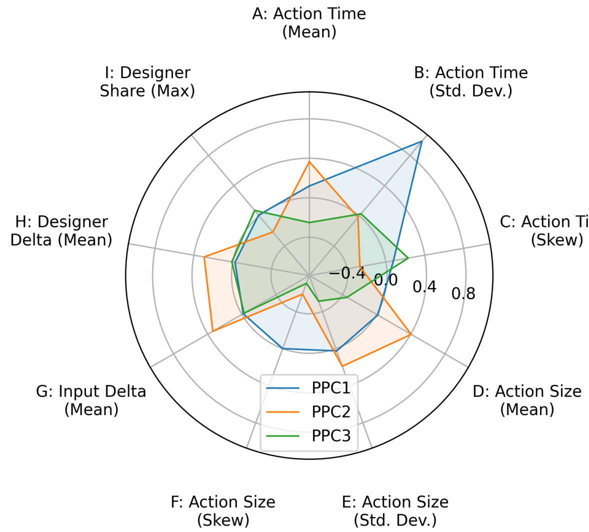

FIGURE 5: Principal components of process variables. PPC1 shows high variation in time between actions and large action skew. PPC2 shows long average action time, large average size/variation, and frequent switching. PPC3 shows short average time, and small average size/variation.

(IPC1, IPC2, and IPC3), all process variables (PPC1, PPC2, and PPC3), task order, task size on completion times. Summary results finds IPC2 (p-value=0.048), PPC3 (p-value=$6.41 \cdot 10^{-9}$), task order (p-value=$1.72 \cdot 10^{-5}$) and task size (p-value=$3.58 \cdot 10^{-27}$) as statistically significant variables affecting task completion times of pairs. Model results show other variables do not have a statistically significant effect on completion times (IPC1 p-value=0.366, IPC3 p-value=0.329, PPC1 p-value=0.353, and PPC2 p-value=0.154). Subsequent analysis eliminates ineffective factors and only considers statistically significant factors.

Equation (1) presents the resulting linear model with principal component factors as drivers of task completion time.

$$\ln(T) = B_0 + B_1 N^2 + B_2 \ln(O) + B_3 IPC2 + B_4 PPC3 \quad (1)$$

Analysis of the Eq. 1 model runs both ordinary least squares regression and mixed effects models finding that ordinary least squares regression yields substantially similar results to a mixed effects model with easier interpretation. Table 4 shows ordinary least squares regression model results using `statsmodels` (version 0.12.2) function `ols`. Visualization of model residuals via a quartile-quartile plot verifies normality assumptions. Results indicate expression of PPC3 behaviors significantly decrease task completion time (p-value=$3.19 \cdot 10^{-9}$), presence of IPC2 demographics significantly increase completion times (p-value=0.046) and both task size (p-value=$5.72 \cdot 10^{-30}$) and task

TABLE 4: Regression of the effect of process variables on time

Factor	Coefficient	Std. Err.	t-stat.	p-value
Intercept	3.8276	0.171	22.379	$8.87 \cdot 10^{-55}$
$\ln(O)$	-0.3830	0.085	-4.482	$1.29 \cdot 10^{-5}$
N^2	0.1821	0.013	13.678	$5.72 \cdot 10^{-30}$
$IPC2$	0.0870	0.043	2.008	0.046
$PPC3$	-0.2919	0.047	-6.219	$3.19 \cdot 10^{-9}$

order (p-value=$1.29 \cdot 10^{-5}$) are statistically significant factors for task completion times.

4.4 Summary of Analysis Results

Post-processing of event logs produces five types of process variables during the paired parameter design experiment: 1) action size as the distance traveled by the input slider, 2) action time as the elapsed time between successive actions, 3) input delta as the indicator variable for input slider changes between successive actions, 4) designer delta as the indicator variable for input controller (designer) changes between successive actions, and 5) designer share as the indicator variable for input controller (designer) changes between successive actions. PCA combines co-observed process variables into three types of design strategies identified as PPC1: High variation in time between actions and large action size skew (few actions much larger than average), PPC2: Long average action time, large average action size and variation, frequent switching between inputs and designers, and PPC3: Short average action time, small average action size and variation. Analysis of the effects of these design strategies on performance outcomes of pairs in the parameter design experiment finds that only the PPC3 factor is significant.

5 Discussion

The hypothesis investigates the effects of design strategies on team performance outcomes in paired parameter design tasks. Results show that variation in performance outcomes can be traced to differential designer actions. Analysis indicates that the PPC3 strategy, which describes consistent small and fast actions, has a statistically significant effect on task completion times. Teams exhibiting the PPC3 strategy have significantly lower completion times than teams following other strategies, leading them to more successful outcomes. In contrast, the PPC2 strategy, with relatively large and slow actions and frequent switching between inputs and designers, and the PPC1 strategy, with high variation in action time, have no significant effect on task completion time.

The results indicate that faster and more consistent design actions significantly reduce task completion times in this experiment. This finding can be attributed to the cooperative nature of the tasks. In cooperative tasks, each action of one designer affects the outcomes of their pair. Accordingly, pairs not only need to understand specific actions that will lead them to success but also the actions required for their partner to succeed, requiring high levels of communication and understanding. Small and fast actions indicate more frequent communication between designers and faster feedback to understand how one's action impacts the other's outcome. Accordingly, small and frequent actions would help inform better next steps, leading to more consistent actions and more successful strategies. Contrary, having larger-sized actions with longer action times (an anti-PPC3 strategy) would lead to unexpected errors, less understanding of the impact of specific actions, and less frequent communication between the designers.

The analysis also shows that task order and the number of variables in a task significantly affect the completion times of pairs aligning with the findings in the literature [3]. Results suggest that the designer pairs' completion times decrease as the task order increases. The learning effect can explain this finding. Later in a task sequence, designers leverage their experience and understanding of tasks, leading to better performance outcomes. The analysis also shows a significant and exponential relationship between the number of variables in a task and designer completion times. This paper supports the findings of Grogan and de Weck, suggesting that an increase in the number of variables in a task increases the technical complexity level of a task leading to lower performance outcomes [3].

Results also show that participants with less working experience and lower English ability showed lower performance outcomes. In general, it is expected to observe better performance outcomes from more experienced designers. Even though this was a parameter design experiment with no specific domain knowledge requirement, more experienced designers might be able to understand the tasks faster to build more effective strategies due to their higher experience level. Moreover, designers' English ability might create a communication barrier between a pair, resulting in lower performance outcomes. The paper also needs to note that although the negative effects of lower English ability and lower experience level were observed in the experiment, no statistically significant result indicates older participants with higher education and work experience showed higher performance outcomes.

5.1 Limitations

Results from this paper are subject to several limitations. First, it uses secondary data from an experiment on the effect of the LOC personality trait on team performance outcomes in parameter design tasks [9]. No experimental control was exerted over the identified input or process principal components.

The experiment uses a highly simplified parameter design task representative of cooperative design only at an abstract level. Although using a parameter design framework helps understand the design process, it also greatly simplifies the design tasks by neglecting factors such as domain knowledge and creativity. The parameter design task should be considered a component of design, for example, searching over a tradespace of alternatives rather than a holistic representation of end-to-end design.

Constraints on session duration limited the number of pair tasks to keep the total experiment time less than one hour and retain participant attention. Additionally, experimental resources only allowed for twelve sessions, limiting the amount of data collected. Finally, experimental tasks consider interactions between two participants at a time, take place over a short time period (minutes), have a small number of design variables without any domain-specific design context, and incentivize behavior using a financial reward tied to relative ranking in a design session. These limitations indicate results of this experiment might show variations with a larger team size or with the application of domain-specific design tasks.

6 Conclusion

Identifying successful design strategies for design teams is important for creating more efficient design processes and achieving more successful design outcomes. This paper analyzes secondary data from a pair parameter design task experiment to find specific groups of actions that build a strategy leading design teams to have higher performance outcomes. Results show that principal component analysis can help identify specific design strategies on a design task by combining observed action groups during design processes.

The paper also illustrates that design strategies with more frequent and smaller actions in pair parameter design tasks lead to more successful outcomes. The discussion explains that this strategy might be successful because it leads to more frequent communication and understanding of the actions of a pair. Findings also align with literature that there is a negative relationship between number of variables in a task and performance outcomes whereas a positive relationship between task order and performance outcomes in parameter design tasks [3]. Results of this paper also show that demographic factors of English ability and experience level are important in the performance of design teams. The discussion explains that these factors might impact designers' communication levels. Also, more experienced designers might be able to develop better strategies even if the tasks are not domain specific.

Summary conclusions provide evidence that designer teams exhibit diverse design strategies, affecting performance outcomes in paired parameter design tasks. The paper suggests that more frequent and faster designer actions can allow faster feedback, communication, and understanding between pairs, leading to better performance outcomes in a parameter design problem. Future studies can bring interventions before the parameter design tasks to help designers exhibit preferred design strategies. Future studies should also investigate how successful design strategies for design teams would show variations in domain-specific tasks.

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