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# SEQUENTIAL DESIGN DECISION MAKING UNDER THE INFLUENCE OF COMPETITION: A PROTOCOL ANALYSIS

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## ABSTRACT

In this study, we focus on crowdsourcing contests for engineering design problems where contestants search for design alternatives. Our stakeholder is a designer of such a contest who requires support to make decisions, such as whether to share opponent-specific information with the contestants. There is a significant gap in our understanding of how sharing opponent-specific information influences a contestant's information acquisition decision such as whether to stop searching for design alternatives. Such decisions in turn affect the outcomes of a design contest. To address this gap, the objective of this study is *to investigate how participants' decision to stop searching for a design solution is influenced by the knowledge about their opponent's past performance.* The objective is achieved by conducting a protocol study where participants are interviewed at the end of a behavioral experiment. In the experiment, participants compete against opponents with strong (or poor) performance records. We find that individuals make decisions to stop acquiring information based on various thresholds such as a target design quality, the number of resources they want to spend, and the amount of design objective improvement they seek in sequential search. The threshold values for such stopping criteria are influenced by the contestant's perception about the competitiveness of their opponent. Such insights can enable contest designers to make decisions about sharing opponent-specific information with participants, such as the resources utilized by the opponent towards purposefully improving the outcomes of an engineering design contest.

**Keywords:** Design Search, Design Contests, Decision-Making, Stopping Strategy, Information Acquisition

## 1 Introduction

Product design plays a crucial role in improving competitiveness through (incremental or radical) innovations [1]. Conversely, competition is inadvertently an influencing factor for product design innovations. For example, innovations at companies such as Apple and Samsung are influenced by the past products of their competitors.

In the context of product design under competition, we focus on crowdsourcing contests for engineering design. Unlike product design competition between firms, crowdsourcing contests are designed by their organizers to purposefully achieve a design outcome. Consider the design competitions organized by NASA and Airbus on a crowdsourcing platform such as GrabCAD [2]. Such competitions are intended for receiving high quality innovative solutions from diverse participants that do not necessarily work for the organizations.

To design crowdsourcing contests, contest designers (organizers) need to make several decisions such as what and how much information to share with the contestants [3]. Examples of various types of information include knowledge about the organizers of the contest, the historical winners of the contest, the prize of the contest, and the players in the contest [4]. Knowledge about such types of information heavily influences the strategic decisions of the contestants [5]. In engineering design contests, the contestants are designers whose behaviors such as design decision-making influence the quality of design solutions they generate. The quality of the design solutions in turn determines the success of an engineering design crowdsourcing contest. Thus, the organizers need to understand how the decisions to design a crowdsourcing contest influences the outcomes of such a contest (e.g., the quality of solutions).

We focus on a contest designer's decision to share historical information about the contest with the contestants. In crowdsourcing contests for engineering design, a lot of information about past design contests already exists. In our previous study [6], we analyzed publicly available data on GrabCAD [2]. The GrabCAD data included information about past contests such as the winning solutions, the associated winners, and the overall participants [6]. A visit to other crowdsourcing platforms such as Innocentive [7] and Ennomotive [8] also established that the past contests' information is readily available. Availability of such information educates the participants about the history of such contests which influences their behavior [9].

There is extensive literature on information sharing in contests within behavioral economics [3, 10–13]. However, research in behavioral economics does not address the nuances of engineering design scenarios. For example, designers in engineering design processes typically search the design space. They search by iterating through several design solutions before making artifact decisions. Each of these iterations involves information acquisition decisions such as whether to search for more solutions or not. Such decisions allow the designers to explore the design space and update their state of knowledge about them. Sharing opponent-specific information influences a designer's information acquisition decisions. For example, a contestant may search for a better design solution if they are aware that their opponent has a history of generating high quality design solutions. Thus, there lies a need to understand how sharing opponent-specific information influences designer behaviors in an engineering design process. Through this understanding, stakeholders can predict the influence of such information on designer behaviors and outcomes. Such predictions can help, for example, the designers of a crowdsourcing initiative to make decisions about how much and what information to provide while designing such contests.

In this study, we investigate *how participants' decision to stop the information acquisition activities of a design process is influenced by the knowledge about their opponent*. The objective is achieved by conducting a protocol study. We interview participants at the end of a behavioral experiment. The experiment was a part of our previous study [14] where participants were provided with information about their opponent and their design decisions were analyzed. In [14], we presented a model that quantifies how opponent-specific information would influence participant behaviors in a strategic sequential information acquisition and decision making (s-SIADM) activity. In this study, we analyze the interviews to investigate how and when participants account for opponent-specific information in their s-SIADM process.

The remainder of this paper is organized as follows. In Section 2, we summarize the s-SIADM process and the behavioral experiment conducted as a part of our previous study [14]. In Section 3, we describe the details of the protocol study including the interview questions, the data collection and analysis technique. In Section 4, we report our observations from the interview analysis. In Section 5, we elaborate on the future work by discussing an approach to model the observations towards descriptive modeling of participant behaviors.

## 2 Strategic Design Search

In this section, we summarize a class of design problems we term as Sequential Information Acquisition and Decision Making (SIADM) problems. The SIADM problems in context of a crowdsourcing contest results in strategic decision making behaviors termed as s-SIADM activities of the designers. Then, we discuss the details of the behavioral experiment based on which the participants were interviewed.

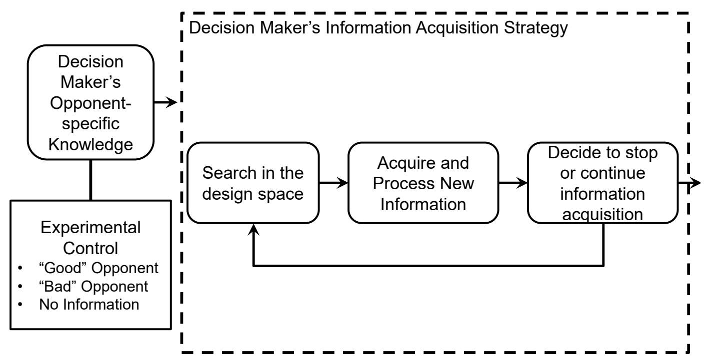


**FIGURE 1**. Overview of the design activities of the previous study [14].

### 2.1 Summary of Our Previous Studies on Strategic Design Search

We summarize the strategic design search scenario as follows. Consider a design problem where individual designers are competing to design a product that optimizes a design objective $f(x)$. They control a set of design variables $x$ in a design space $\mathscr{X}$. However, the designer does not explicitly know the mathematical relationship between the design variables $x$ and the design objective $f(x)$. The designer needs to acquire information about the impact of design variables $x$ on the design outcome $f(x)$. Such information can be acquired by making decisions such as choosing an $x$ and conducting experiments (at that $x$) which incur a certain cost. We assume that the designer updates their state of knowledge about the design space after executing each experiment. Moreover, in order to win, designers need to be strategic. In other words, designers need to account for their opponents' behaviors while making search decisions. We refer to such a scenario as a strategic Sequential Information Acquisition and Decision Making (s-SIADM) scenario.

The motivation for our past studies [14–16] on s-SIADM scenarios is based on the knowledge gap about how designers make strategic decisions while searching for design solutions. Past research emphasis in decision-based design [17, 18] has focused on how designers should make decisions. Much less attention has been given to how designers actually make decisions. Thus, through our previous studies [14–16], we proposed an s-SIADM framework to understand designers' strategic activities in SIADM scenarios.

The s-SIADM framework considers two crucial decisions that an individual makes, namely, what $x$ to choose and when to stop the search. Existing literature has established that an individual's decision to stop in a design search activity is a strategic decision [19–23]. For example, if the opponent is too strong then an individual may decide to not enter the competition, that is, stop at the beginning. Throughout this study, we refer to the process that a designer uses to stop the design search as their stopping *policy.* Moreover, when designers account for opponent-specific information in their stopping policy we refer to such a policy as their stopping *strategy.* Thus, a strategy is a policy but the converse may not be true.

In [14], we use the s-SIADM framework to propose a stopping strategy that predicts how individuals stop in an s-SIADM scenario based on opponent-specific information. In other words, we model how individuals' stopping decisions are influenced based on opponent-specific information. The model is calibrated based on experimental data.

The s-SIADM strategy proposed in [14] is build on the theoretical foundations of game theory and decision theory. However, there lies a need to triangulate (validate) the s-SIADM strategy through an alternative approach such as a protocol analysis. Moreover, through the analysis we hope to find alternative s-SIADM models towards building descriptive theory of strategic decision-making for design search scenarios. Thus, in this study we analyze the interviews conducted with the participants from our previous experimental study [14].

## 2.2 The Experiment

**2.2.1 Overview** Participants are told that they will participate in a series of contests organized by a firm that is interested in designing roller coasters. In every contest, they are required to design a track. They are informed that they are competing against an opponent while solving the design problem as described in Section 2.2.2. The player that achieves a higher value of the design objective for a given contest wins the corresponding prize amount for that contest. Participants are expected to strategize their effort based on the information provided to them about their opponent. For example, if they believe that their opponent has had a "very strong performance history" then they could decide not to expend any effort in a contest.

In reality, the "opponent" was an agent that was designed to have a past performance record. The agent either had a strong performance record or a weak performance record. Moreover, the participants were either given information about their performance record or not. The authors' decision to design the opponent as an agent was made to achieve experimental control in order to quantify the influence of historical information about opponents on a participant's design behaviors and outcomes. The agent was also designed to be consistent with their past performance while competing against a participant in a given contest. Thus, the independent variable was the opponent's past performance and the dependent variable was the participants' decision to stop. An overview of the design activities is shown in Figure 1.

**2.2.2 Design Problem Statement** We utilize the track design problem statement from our previous study, which has been designed to be representative of a design search problem [15]. The task is to design a roller coaster track where the objective $f(x)$ of the designer is to "maximize enjoyment experienced by the rider of the track". To achieve the objective, a participant needs to design a circular valley segment of the track with an appropriate width $w$. The participants are not provided an explicit mathematical form of the "enjoyment function" $E(w)$. The rationale is that in real design scenarios, design objectives are a combination of qualitative and quantitative factors that seldom have a mathematical form explicitly known to the designers. What the designers may know is the influence of various design parameters such as the width $w$ of the track on the design outcome, that is, "enjoyment". Thus, the participants are informed that a small valley width would make the ride uncomfortable due to high $g$ forces and a wide valley has a high radius of curvature, that is, a "flat" track. Both cases result in reduced enjoyment, which implies that there is an optimal width $w$ for which the enjoyment for the rider is maximized.

**2.2.3 Experimental Design** The experiment [14] involved a total of 36 participants. These participants were undergraduate and graduate students at Purdue University. There were a total of 14 females and 22 males. The experiment was divided into two parts, namely, With Information (WI) and Without Information (WOI) part. As the part name suggests, the WI part is the one where the information about the opponent's past performance (good or bad) was provided, and WOI part is one where it was not. We find that participants decided to stop earlier when they knew their opponent had a poor past performance record as compared to when their opponent had a strong past performance record as well as when they did not have information about their opponent. Moreover, the calibrated model parameters showed statistically significant differences when the opponent was "good" as compared to when the opponent was "bad" enabling us to quantify the influence of opponent-specific information on the participant's stopping decisions.

## 3 The Study

We conducted structured interviews with the participants at the end of the experiment in our previous study [14]. The interviews were structured as opposed to semi-structured in order to limit the total duration of the experimental activities to 60 minutes. We did so to avoid excessive cognitive load on the participants that could have interfered with the reliability of self-reporting data by the participants. In the following, we discuss the interview questions, data collection method, and the data analysis procedure.

### 3.1 Data Collection

The interviews were conducted privately and in person with every individual participant. The interviews were audio-recorded and then professionally transcribed. The participants were asked five questions (Q1 through Q5) sequentially as illustrated in Table 1. The motivation to ask every question has been summarized in the table as well. The interviews lasted for an average of 150 seconds.

**TABLE 1.** Interview structure

| Question | Motivation |
|---|---|
| Q1: What do you think was the purpose of this experiment? | To ensure that the participants were aware of the experimental objectives. |
| Q2: Was the information provided to you about the opponent useful to you? If so how? If not, why not? | To investigate the usefulness of the opponent-specific information to the participants. |
| Q3: How did you decide to stop in the contest? | To investigate the factors that influenced the participants' stopping decision. |
| Q4: Did you have a game play strategy? Please elaborate. | To investigate the participants' response strategies in the game. |
| Q5: Did the information about the opponent affect your stopping decision? Please elaborate. | To investigate the influence of opponent-specific information on the participants' strategic decision, that is, the decision to stop the search. |

### 3.2 Data Analysis

We analyze the individuals' SIADM process from the transcribed interviews through content analysis [24]. Phrases and sentences were coded to identify *when* participants account for opponent-specific information, *how* they account for such information, and *how* they decide to stop. Two coders independently analyzed the interview transcripts. We hypothesize that the participants account for opponent-specific information in their decision to stop the search process.

Through Question 1, we expect the participants to describe the experimental objective which was to study how opponent-specific information influences participants' decision making process. We assess whether they paraphrase the experimental objective by recognizing the independent variable that is the information provided to them about the opponents and the dependent variable that is their decision making process. From the transcripts, specifically the answers to Question 1, we identify words and phrases that refer to casual relationships such as "impact on", "influence on", and "affects". We also search for words such as "information","good/bad opponent", "risk taking", "gambling", "decision making", "continue or not", and "stopping". The words "gambling" and "risk taking" were included after reading the transcripts to realize that participants referred to strategic decisions as "risk taking" and "gambling" which contextually referred to the accounting of the "goodness or badness" of the opponent to expend greater or fewer resources by stopping earlier or later accordingly. Based on the analysis we concluded whether a participant understood the objective of the experiment or not. Moreover, it enabled us to verify the design of the experiment.

Responses to Question 2 were expected to be "yes" or "no" along with the justification for the same. The focus on the "usefulness" of the information provided insights regarding *how* participants process opponent-specific information in terms of its utility while making strategic decisions. The "yes/no" nature of the question enabled us to categorize the participant pool on the basis of whether the participants recognized the value of the provided information.

Question 3 was designed to identify factors that influenced participants' stopping decisions. Decisions are characterized by investigating a decision maker's preferences, various alternatives they choose from, and the information they have about the alternatives as illustrated in Figure 2. The factors were coded by understanding participants' preferences and the recognition of the problem-specific and the contest-specific information they highlighted while describing their decision to stop.

The answers to Question 4 were coded as participant's approach to solving SIADM problems. The transcriptions for the answers to Question 4 were analyzed several times over to inductively identify common approaches described by the participants. It is to be noted that a participant's "game play strategy" may be different from their stopping strategy. In [14] we model an s-SIADM strategy which assumes that an individual's game play strategy is the same as their stopping strategy. However, we expect the answers to Question 4 to

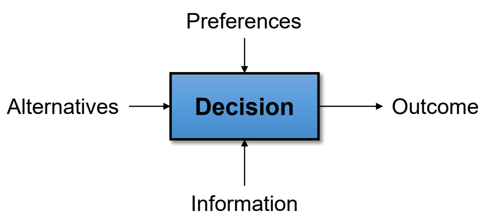


**FIGURE 2**. Characteristics of a decision.

highlight the differences between policies and strategies as participant's descriptions of a "game play strategy" may not account for opponent-specific information at all.

The answers to Question 5 were coded as stopping strategies or stopping policies depending on whether participants respond with a yes or a no to the question. It is expected that they will elaborate on how they make stopping decisions by considering opponent-specific information (or not). We used content analysis [24] to elicit phrases and sentences that represent the conditions based on which participants include opponent-specific information. Moreover, the answers to Questions 3, 4, and 5 are considered in conjunction using the coding scheme as described in Table 2 to categorize potential descriptive stopping strategies.

The inter-rater reliability (IRR) was calculated by taking the ratio of the number of agreements among the coders while analyzing answers to every question to the overall sum of agreements and disagreements [25]. A coded instance is considered as an agreement if no clarification was requested amongst the coders towards identifying that instance. The IRR is given by,

$$IRR\% = \frac{Agreements}{Agreements + Disagreements} * 100\% \quad (1)$$

The disagreements were resolved by the coders through discussions, and the consensus of the results are presented. However, the IRR scores include the disagreements amongst the coders prior to the discussion aimed towards reaching a consensus. Thus, the IRR score quantifies the reliability of the content analysis.

## 4 Results

We present the results of the interview questions and our synthesis of the identified stopping policies. The results of the responses to Question 1 and 2 are presented as the verification of the controlled experiment on the basis of participants' understanding of the experiment as well as their acknowledgement of the influence of opponent-specific information in their decision-making process. The results of Questions 3,4, and 5 are synthesized to describe the search strategies of the participants in a sequential information acquisition problem under the influence of opponent-specific information.

### 4.1 Experimental Verification: Influence of Opponent-specific Information

**4.1.1 Usefulness of Opponent-specific Information** In the context of stopping decisions, we find that twenty-eight out of thirty-six (28/36) participants (77%) clearly stated that they were influenced by the information about the opponent's past performance history (IRR 100%). Two participants gave contradictory answers where they believed that the information about the opponent was not "useful" but they mentioned that they did account for the information while making a stopping decision. Six participants clearly stated that they did not get influenced based on opponent-specific information.

From the experimental data of our previous study [14], we compare the participants' efforts, that is their number of searches, when information about the opponent was provided versus when no information was provided. We find that thirty-three participants expended higher efforts when information about the opponent was provided as compared to when no information was provided. The remaining three participants who did not expend greater efforts based on opponent-specific information were also participants that mentioned in the interviews that they did not get influenced based on opponent-specific information. Thus, three out of six (3/6) participants who clearly stated that were not influenced by opponent-specific information seemed to have been influenced by opponent-specific information on the basis of expending higher efforts when information about the opponent was available.

**4.1.2 Understanding the Experimental Objective** We find that twenty-eight out of thirty-six (28/36) participants (77%) were able to recognize the experimental objective (IRR 100%). For example, one of the participants described the experimental objective as follows. *"Um, I think the purpose was to understand how performance of other groups influenced our uh. our own performance in the experiment. So if other groups performed better, then we would try to perform better and if other groups performed poorly, then we wouldn't try as hard to perform better."*

Out of the eight participants who could not recognize the experimental objectives, five participants acknowledged that the information provided to them about the opponents was useful. However, they did not mention such information while describing the experimental objective. The remaining three participants (out of the eight), were also those who did not consider the opponent-specific information to be useful. Moreover, they described the experimental objective in an optimization context. For example, one of the (three) participants described the experimental objective as follows. *"to study how it come to an optimal solution for... a relationship between the*

**TABLE 2**. Coding scheme for identifying how and when participants decided to stop.

| Criterion | Details | Coded Example |
|---|---|---|
| Stopping Policy or Stopping Strategy | Based on the responses to Question 5, if opponent-specific information was utilized for stopping decision then answers to Question 4 are marked as "strategy" else it is coded as "policy". Instances of this category are coded verbatim from the transcripts. | *"No, the [opponent-specific] information was not helpful"* *"Definitely, it [opponent-specific information] helped"* |
| Factors | Based on the responses to Questions 3, 4, and 5 we identify the factors/reasoning provided by the participants that influenced their stopping decisions. Instances of this category are coded coded inductively after reading through the transcripts several times. | *"for the most part, [for stopping] I was looking for a relatively high numeric answer"* - objective value is a factor for stopping. *"most of the time I decided to stop, uh, once I saw a point before and after, uh, the peak, where it had sort of leveled out "* -function visualization as a basis for stopping. |
| Time Step | Based on the responses to Questions 3, 4, and 5, we categorize when they account for opponent-specific information as 1) in the beginning of the search process, 2) at the end of a search process, or 3) switching from searching to stopping strategy at some time step. Instances of this category are coded inductively after reading through the transcripts several times. | *The participant used the information as they began the search process.* *The participant used the information at the end of the search process.* |

*width and the height of the [roller coaster]."*

## 4.2 Stopping Policies

In this section, we discuss the stopping policies identified through the content analysis. We first describe stopping policies that are solely based on the achievement of the design objective. Then, we discuss the stopping strategies that account for opponent-specific information. We conclude this section by discussing influential factors other than opponent-specific information that several participants mention while executing their stopping policies.

We differentiate between the terms *search policy* and *stopping policy*. We use the term search policy to refer to the process that an individual uses to search the design space. Whereas, a stopping policy refers to the process an individual uses to stop their design search. We acknowledge that such policies may not necessarily be decoupled. For example, *where* one searches in the design space may influence *when* one decides to stop. Moreover, in the interviews, we find that participants describe their search policies while discussing their stopping policies. For instance, thirteen participants explicitly mention bisection approach as a search policy while searching for the function optimal. For example, a participant mentions *"Um, I tended to pick towards the middle, so maybe, like, 550 to 650, around that range, to get started."* Six other participants indirectly mention bisection approach by describing the numbers such as 650 where they typically searched. 650 represents the approximate midpoint of the design range $[350, 1000]$. For example, a participant mentions *"I started with 600, um, [proceeded] higher or lower based on that."* While it is important to consider various search policies that participants utilize, in this study we consolidate the results of the interviews by focusing primarily on the stopping policies.

### 4.2.1 Stopping Based on Objective Achievement

All the participants for whom opponent-specific information did not influence stopping decisions mention that they decide to stop solely based on the achievement of the design objective. Moreover, participants who did mention that opponent-specific information influenced their stopping policy, described several objective achievement policies that they combine with their stopping strategies. We identify three stopping policies that are based on the design objective achievement (IRR 90%). Participants stop 1) once they achieve a target design objective value, 2) when objective achievement stopped improving in successive tries, and 3) when they visualized a function "peak" based on their past searches.

**Stopping based on the achievement of a target design objective**: A couple of participants described their stopping policy in reference to a target design objective achievement. For example, a participant mentioned *"for the most part, I was looking for a relatively high numeric answer for the, uh, entertainment or excitement value prolly over like a 100, 120."* Similarly, another participant mentions *"So if I, generally if I was over about a score of 100, it seemed that would be very close."* This observation is intriguing because participants did not know a priori the value of the maximum achievable design objective. This observation hints to a possible cognitive activity that results in individuals developing beliefs about design performance targets. Such beliefs are dependent on individual characteristics such as their domain knowledge. Existing literature has discussed evaluation of such belief structures for decision-making [26]. Further investigation is required to understand why individuals tend to formulate design objective targets when there is lack of information about the maximum achievable optimal. We rule out learning behaviors about the experimental design space because the objective function in the experiment was randomized such that the optimal design value ranged from $[60, 130]$. However, the observation that people are likely to think about the number 100 or a value greater than that as a possible optimal value requires further investigation. We hypothesize that individuals have a systematic bias towards certain numbers as representatives of the quantification of "design quality."

**Stopping based on the improvement of successive design objective achievement**: Several participants described their stopping decision on the basis of the amount of improvement of their design objective in their successive searches. For example, a participant mentions *" A lot of times I would just go until I felt like that the value, like, I couldn't get it much higher. Like, I would try to get, uh, higher values, and then lower values, and then... Like, if I got somewhere in the middle, regardless of how hard the opponent was."* Similarly, another participant mentioned *"once I sort of was getting the hang of how the trends were working I could take larger incremental guesses, or smaller incremental guesses based on the, based on the data."* Such a policy has been computationally formulated and referred to as the Expected Improvement maximization policy [27]. While cognitively individuals may not search in design space by maximizing the expected improvement over the entire design space, they certainly tend to think about the successive improvements to decide whether to stop or not.

**Stopping based on the visualization of design objective achievement**: Participants describe their stopping decisions based on the visualization of the "function peak". A participant describes the following. *" most of the time I decided to stop, uh, once I saw a point before and after, uh, the peak, where it had sort of leveled out, and uh, I picked a point right in the middle."* Several participants mention similar search policy towards objective achievement irrespective of their stopping decision. Our previous study using eye-tracking data has shown that participants do look at the function graph as a source of information stimuli [28]. It is interesting to note how participants use mixed approaches while executing their game play. For example, a participant mentions, *"So I kept myself above* \$5.00 *but um it was not based on the opponent. It was based on the shape of the parabola that I was forming in the graph."* Such a participant is adopting a resource-heuristic that fixes the amount of resources they are willing to spend. Consequently they fix the number of design iterations they are willing to make. Moreover, they are also visualizing the function objective to situationally decide whether they want to stop earlier than the expenditure of \$5.00. Such a visual information stimulus is also utilized in assessing improvement of the successive design objective as mentioned above.

#### 4.2.2 Stopping Strategies

We analyze strategies described by the participants who mention that they account for opponent-specific information. These strategies are characterized along two dimensions. Namely, *when* and *how* they account for opponent-specific information. On the basis of these two dimensions, we discuss the analysis of such strategies.

**When does a participant account for the information?** We find that participants account for opponent-specific information at various time steps in a design search process (IRR 100%). We categorize when they account for opponent-specific information as 1) in the beginning of the search process, 2) at the end of a search process, or 3) switching from searching to stopping strategy at some time step. For example, one of the participants mentions how they utilized opponent-specific information in the beginning of the search process as follows. *"given the information I was able to make a decision about whether or not I thought the competition was worth pursuing, or if I should quit early in order to save my money."* Another participant mentions how they utilized opponent-specific information at the end. They mention that *"if they did very well on a certain contest, I knew my [design quality] would be more, uh, precise by measurement, at least towards the end."* Participants who described both a search and a stop strategy as their game play strategy were considered to adopt a mixed strategy such that they would switch from a searching to a stopping decision. For example, a participant described the following strategy. *"if I was close to [the target], then, um, if the opponent was strong, I might track a couple ones nearby. Um, and if the opponent was weak, then I would've probably just be satisfied with a threshold number like 121."* Here, the participant is describing a switch from exploration to exploitation strategy on the basis of opponent-specific information. The participant was searching for a target design objective value that they developed for themselves. Once they reach closer to the value, they switch their strategy to search "a couple ones nearby" depending upon the opponent-specific information and then stop.

**How does a participant account for the information?** We identify 3 strategies that describe *how* participants accounted for opponent-specific information (IRR 90%). We find that participants utilize opponent-specific information to 1) develop a target value of the function objective that they need to achieve, 2) decide the amount of resources they need to spend, and 3) develop an intuition of the amount of improvement they seek in successive searches.

**Developing a target value for the objective achievement.** Participants mention that they developed a target value of the function objective that they need to achieve based on the "goodness" or "badness" of the opponent. This implies that the participants made an assessment of the competitiveness of the opponent based on the opponent history and then developed beliefs about the opponent's performance such that they were required to perform slightly better than that assessment. A few of the participants decided to stop by making an assessment of whether their opponent with the given history would be able to achieve their current best performance. For example, a participant mentions *"So if the opponent had poor to average ratings, I could sort of find an okay value and just like submit with sufficient confidence that I would win."*

**Deciding the resources.** Based on the opponent-specific information, participants decided the amount of iterations they would perform. In other words, participants decided to allocate resources to their search and therefore indirectly deciding when to stop. A participant mentions, *"based on how well my opponent had done in the past. So if, uh, he did really well then I would aim, I would spend a lot more money on tries to really make sure I have the highest optimum."* Another participant mentions, *"so, if it was a, like, a really, really good opponent, I knew that I had a smaller chance of beating them. So, I didn't wanna waste a whole bunch of resources."* A participant describes a resource optimization strategy influenced by opponent-specific information. They discuss, *"o the strategy I was using, was mainly to try to guess in as few guesses as possible, I was trying to get all of them in less than five. Uh, that didn't work out most of the time. Uh, but I would take less guesses if I was up against, uh, a poorer opponent. Uh, if I was up against an opponent that was, uh, more skilled I would take a few more guesses, or I would try to."*

**Deciding the amount of improvement in the objective achievement.** Based on the opponent-specific information, participants decided how much improvement in successive design iterations they would like to achieve before deciding to stop. For example, a participant mentions *"If I had a very strong opponent I would want to make sure my guess is much more accurate."* Moreover, participants also utilized visual information stimuli in conjunction with opponent-specific information to stop. For example, a participant mentioned *"If I knew that they [opponent] were probably gonna get a bad score then I would stop, even if I wasn't at the very top, and uh, if I knew that they were gonna get a good score then I would keep going till I could get it as high as possible."* Another participant explained *"if they [opponent] had relatively low scores, then I probably only needed to get, uh, close to the peak, I didn't actually need to find, uh, to optimize my peak."* Participants also associated their risk behaviors to the opponent-specific information towards deciding improvement in the objective value achievement. A participant mentions *"it helped me decide what, whether or not to be more risky, or to be to be more assured that my guess was correct."*

### 4.3 Accounting for Other Factors

Participants also mention several other factors such as the cost of information acquisition and the initial data point that they consider while making stopping decisions. For example, a participant mentions *"Um, at first, I did the first few tasks, or the first few contests I decided to stop after only spending $1.00 because I wanted to maximize ah how much I would get back."* Another participant mentions, *"my general strategy was to, er, to start with around the minimum value plus 150-ish when, when the performance at, er, the initial value of 850 was closer to say 0.1 or something."* Moreover, there are various individual-specific factors such as the situated cognition of an individual that enables them to develop beliefs about the expected target value for the objective achievement and their risk preferences that also influence their stopping decisions. However, due to the controlled nature of the behavioral experiments, we only focused on eliciting stopping policies based on the influence of opponent-specific information or the lack thereof.

## 5 Discussion: Towards Descriptive Modeling of Sequential Decision Making

In this study, we analyzed the influence of opponent-specific information on the stopping policies, as described by the participants of a behavioral experiment, in a design search scenario. From the stopping policies, we identify stopping strategies. We characterize the strategies on the basis of when the participants account for the information and how they account for the information. The results suggest that if participants account for opponent-specific information, they do so at varying search steps. We identify three stopping strategies, that is, the process via which participants account for opponent-specific information to stop. We find that individuals develop thresholds for stopping criteria, such as a target design quality, the amount of resources they want to spend, and the amount of design objective improvement they seek in sequential search. The threshold values for such criteria are influenced by the contestant's perception about the competitiveness of their opponent. Such insights can enable contest designers to make decisions about sharing opponent-specific information with participants, such as the resources utilized by the opponent towards purposefully improving the outcomes of an engineering design contest.

In Table 3 we categorize s-SIADM strategies along the two dimensions identified that characterize how and when designers use opponent-specific information to stop. Each cell represents an s-SIADM strategy that can be modeled to represent a player type. We note that "Strategy 1" as described in Table 3 is the s-SIADM strategy that was modeled based on the theoretical foundations in our previous study [14]. In [14] we found that the model parameters that quantify an individual's belief about an opponent's performance are statistically different when individuals are informed that their opponent has had a good performance history as compared to when their opponent had a bad performance history. However, in the interview, the participants did not explicitly mention that they developed beliefs about the opponent. Nevertheless, by characterizing how and when participants accounted for opponent-specific information we are able to identify a search strategy that is reflective of

**TABLE 3**. Characterizing s-SIADM strategies based on how and when opponent-specific information is utilized to stop the design search.

| When / How | **Sequentially** | **At Some Time Step** |
|---|---|---|
| **Decide Resource Expenditure** | Strategy 1: Stop if the improvement in the expected payoff is not positive. | Strategy 2: Use a search policy. Then, switch at some time step to decide how much additional resources to spend based on the opponent-specific information. |
| **Set Objective Achievement Target** | Strategy 3: Stop if the opponent would not be able to achieve the current best design. | Strategy 4: Use a search policy. Then, switch at some time step to make stopping decisions based on the belief about the opponent's achievement of the design objective. |
| **Set Objective Improvement Target** | Strategy 5: Sequentially decide the amount of improvement one wishes to have in their design objective achievement based on the opponent-specific information. | Strategy 6: Use a search policy. Then, switch at some time step to make stopping decisions by deciding the amount of improvement one wishes to have in their design objective achievement based on the opponent-specific information. |

the existing literature on strategic decision making in design search. Moreover, there are several other strategies identified that suggest further investigations towards identifying individual differences in design search strategies towards better predictions of design outcomes.

The authors believe that, as future work, modeling the identified strategies computationally would enable us to develop predictive models of designer behaviors in sequential information acquisition and decision making scenarios. Specific modeling choices along the two dimensions, as described in Table 3, can enable us to theoretically formulate computational strategies of design search. For example, an individual's decision about whether they should stop ($s_i = 1$) or not ($s_i = 0$) at step $i$ would be modeled via a likelihood (probability) function such as a sigmoid function as follows:

$$p(s_i = 1|\theta, \mathscr{I}, \mathbb{D}_i) = \text{sigm}(f(\theta, \mathscr{I}), \mathbb{D}_i), \qquad (2)$$

where, $\theta$ represents individual-specific parameters, $\mathscr{I}$ represents opponent-specific information, and $\mathbb{D}_i$ represents participant's search data until given search step $i$. The threshold function $f(\theta, \mathscr{I})$ would be modeled to represent how individuals pick a threshold value for the stopping criteria. The threshold value and the current search data would then determine the likelihood $p(s_i = 1|\theta, \mathscr{I}, \mathbb{D}_i)$ that an individual would stop. Such models would serve as decision-support tools for contest designers to facilitate the search activities of the participants based on their search styles.

In context of conducting controlled behavioral experiments for engineering design research, we highlight the need to collect design debriefing data through methods such as structured and semi-structured interviews. Our study illustrates the value of the analysis of such data in conjunction with behavioral modeling and experimentation methods towards validation of behavioral studies in engineering design contexts. Such data collection enables triangulation method as a validation technique towards developing descriptive theories of designer behaviors in engineering design contexts.

The limitations of this study are as follows. The interviews provide a source of self-evaluated data which may consist of hindsight bias from the interviewees who could modify their game play strategy while describing them in hindsight at the end of the experiment. Nevertheless, their explanation of their SIADM strategies sheds light on the factors that participants consider while making information acquisition decisions. Moreover, it enables us to assess their perceived influence of opponent-specific information which is consistent with the goal of this study. Another limitation is that if subjects highlight factors that are not a part of the controlled experimental variables (see Section 4.3), it is not possible to verify their claims solely from the experimental data. However, such factors provide opportunities for future work wherein the results of this study can be utilized as a basis for hypotheses formulation.

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