

SEQUENTIAL INFORMATION ACQUISITION AND DECISION MAKING IN  
DESIGN CONTESTS: THEORETICAL AND EXPERIMENTAL STUDIES

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I dedicate this thesis to my parents Sherifa and Nuruddin Shergadwala whose sacrifices, resilience, and undying love for their children has created more impact in this world than they know.

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## ABSTRACT

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Products are typically designed by accounting for competition. For example, Apple and Samsung competing to design better products. Such competition influences strategic design decisions which, in turn, influence the product design outcomes. Existing literature in Design for Market Systems utilizes behavioral Game Theory to investigate product design competitions to maximize a firm's profit. However, in engineering design contexts, there is a lack of understanding of the influence of competition on designer behaviors and, thereby, the design outcomes.

Consider an example of a design contest such as DARPA's Robotics Challenge. In such a contest, the contest organizer (DARPA) possesses greater freedom as compared to free-market product development competitions because they get to design the contest environment. The organizers need to make contest-design decisions such as, what problem-specific and contest-specific information to share with the contestants. Moreover, the contestants are the designers who solve the design problem. Thus, the contest-design decisions influence how the contestants evaluate the competition as well as make the design decisions such as what information to acquire about the problem and when to stop acquiring information. Information acquisition decisions, in turn, influence decisions about the design artifact and, thereby, the contest outcomes. Such nuances of engineering design behaviors are unaccounted in existing literature on contests. Thus, there is a lack of theoretical foundations to understand how competition influences the decision-making behaviors of designers in engineering design contexts. Establishing such foundations would enable predictions about

product design outcomes as well as aid organizers of design contests to better design competitive environments.

The primary research question of this dissertation is, *How do contestants make sequential design decisions under the influence of competition?* To address this question, I study the influence of three factors, that can be controlled by the contest organizers, on the contestants' sequential information acquisition and decision-making behaviors. These factors are (i) a contestant's domain knowledge, (ii) framing of a design problem, and (iii) information about historical contests. The *central hypothesis* is that by conducting controlled behavioral experiments we can acquire data of contestant behaviors that can be used to calibrate computational models of contestants' sequential decision-making behaviors, thereby, enabling predictions about the design outcomes. The behavioral results suggest that (i) contestants better understand problem constraints and generate more feasible design solutions when a design problem is framed in a domain-specific context as compared to a domain-independent context, (ii) contestants' efforts to acquire information about a design artifact to make design improvements are significantly affected by the information provided to them about their opponent who is competing to achieve the same objectives, and (iii) contestants make information acquisition decisions such as when to stop acquiring information, based on various criteria such as the number of resources, the target objective value, and the observed amount of improvement in their design quality. Moreover, the threshold values of such criteria are influenced by the information the contestants have about their opponent. The results imply that (i) by understanding the influence of an individual's domain knowledge and framing of a problem we can provide decision-support tools to the contestants in engineering design contexts to better acquire problem-specific information (ii) we can enable contest designers to decide what information to share to improve the quality of the design outcomes of design contest, and (iii) from an educational standpoint, we can enable instructors to provide students with accurate assessments of their domain knowledge by understanding students' information acquisition and decision making behaviors in their design



projects. The *primary contribution* of this dissertation is the computational models of an individual's sequential decision-making process that incorporate the behavioral results discussed above in competitive design scenarios. Moreover, a framework to conduct factorial investigations of human decision making through a combination of theory and behavioral experimentation is illustrated.

## 1. TOWARDS A DESCRIPTIVE THEORY FOR DECISION MAKING IN DESIGN UNDER COMPETITION: DISSERTATION OVERVIEW

The primary research question of this dissertation is, *How do designers make sequential information acquisition decisions under the influence of competition?* To motivate the reader for the need to investigate this research question, two key topics are introduced and discussed in this chapter, namely, sequential decision making and human behavior under the influence of competition. Both the topics are discussed in the context of engineering design. Existing literature in Decision-based Design and in Behavioral Economics is leveraged to combine the two topics and discuss the research gaps in sequential decision making in design under competition. Then, I present the overview of this dissertation by discussing the research questions, the research approach adopted to address the questions, the summary of the research findings, and the educational implications of this work. I close the chapter by discussing the organization of this dissertation document.

### 1.1 Design Under Competition: Introduction

Products are typically designed by accounting for competition [1, 2]. By understanding the competition, designers can make design decisions that can improve the competency of their products [3]. Thus, competition influences design decisions and such decisions in turn influence the product design outcomes. Examples of product design under the influence of competition include Apple and Samsung competing to design better products [4]. Moreover, with the decentralization and democratization of digital technologies, open-innovation contests such as crowdsourcing contests have become novel examples of product design under competition [5].

Crowdsourcing is defined as the practice of outsourcing tasks, traditionally performed by employees or suppliers, to a large group of people in the form of open contests [6]. An example of crowdsourced design contests is the DARPA research competitions such as DARPA Robotics Challenge [7] where various teams compete to achieve design objectives. In the context of crowdsourcing contests, organizers possess greater freedom as compared to free-market competitions because the organizers get to design the competition environment and make contest-design decisions such as how to design the incentives, what information to share with the contestants, and deciding the knowledge-background of the contestants.

Currently, there is a lack of theoretical foundations to understand how competition influences decision making behaviors of designers, thereby, influencing product design outcomes such as product innovation, safety, and efficiency. Such knowledge would enable the organizers of design contests to make predictions about contest outcomes by accounting for the influence of competition on the contestants' design decisions. To establish the knowledge gaps for design under competition, I refer to two key research areas: Decision-based Design (DBD) and Behavioral Economics. Within DBD, the primary agent is a designer who is viewed as a decision maker. Within Behavioral Economics, the effects of environmental factors such as competition are studied on the decisions of individuals. Within DBD, there is a lack of descriptive theories, that is, understanding how humans actually make decisions within a design process. Such considerations are important for design under competition to investigate how contestants would actually make design decisions. Within Behavioral Economics, there is lack of consideration of the nuances of engineering design and designer behaviors. Thus, studying design under the influence of competition would bridge the gaps in these research areas while leveraging existing work in both these fields. In the following, I discuss these two research areas as the foundation over which I build my dissertation research.

### 1.1.1 Decision-based Design: Past Research Emphasis

The two distinguishing characteristics of design decision making are that decisions are made by humans and these decisions involve uncertainty [8,9]. Such characteristics make a designer the primary agent that influences a decision making process and its outcomes. Within the context of engineering design, designers make several decisions such as what information to acquire and when to acquire that information which influences the design outcomes. Thus, decision making is widely recognized as an integral activity within design process [8,10].

During the past two decades, decision-based design (DBD) [8,11] has emerged as an important research area focused on supporting a rigorous application of mathematical principles and decision theory to develop computational methods for engineering design. Existing research in DBD has focused on a designers as decision makers by modeling their preferences [12,13], understanding their deviations from rationality [14], investigating group decision making [15], and accounting for customers' decisions in the product design [16]. However, the emphasis of research in decision-based design has primarily been on using normative theory to make artifact decisions using a specified state of information. Much less attention has been given to descriptive theory, that is, understanding how humans actually make decisions within a design process. As humans are an integral part of design processes, descriptive theory is essential to make better predictions about the impact of human decision making on design outcomes.

### 1.1.2 Descriptive Investigations in Decision-based Design: Sequential Decision Making

Although descriptive theories of human decisions have been developed within behavioral economics [17], psychology [18], and cognitive science [19], research in these fields does not address the nuances of systems engineering and design. For example, in typical engineering design processes, designers rarely make artifact decisions solely

based on available information. They also perform information acquisition activities such as executing simulation models and experiments. In such activities, designers make decisions about what new information to acquire and when to stop acquiring information. Such information acquisition decisions heavily influence design outcomes and the resources utilized in the engineering design processes [20].

Currently in design literature, there is a lack of descriptive models of sequential information acquisition and decision making. Existing models of sequential decision making [21–23] do not consider a design context or the cognitive limitations of humans while making sequential decisions. For example, the authors [21, 22] assume that the individual has a finite set of choices. In the context of a design scenario, a design space can be continuous with infinite possibilities of design alternatives. Moreover, there is a lack of computational models that capture the qualitative knowledge that factors such as an individual’s domain knowledge influences their information acquisition process. Thus, it may be qualitatively known that an individual with a greater knowledge about their domain, that is, an expert, typically has a better strategy in problem solving, which includes information acquisition [24]. However, there is a lack of computational models that can quantify such relationships and enable predictions on the outcomes of engineering design scenarios. Therefore, there is a need for understanding how designers make information acquisition decisions within the context of engineering design.

Information acquisition can be broadly categorized into *sequential* or *parallel* processes [25]. In a sequential process, information is acquired in steps, and in each step, the acquired information is used to update past beliefs, resulting in a new state of knowledge at the end of that step. Hence, the information acquired in a sequential process affects the subsequent information acquisition decisions. For example, the information acquisition process is sequential when a designer decides what next experiment to conduct based on the result of previous experiments. In parallel processes, all acquired information is analyzed at the end of the process [25]. For example, the

information acquisition process is parallel when a designer executes a pre-planned set of experiments and analyzes the results of the entire set at the end.

Within the context of design contests, both sequential and parallel information acquisition processes exist. However, in this dissertation, I focus on modeling a single contestant as a decision maker who *sequentially* acquires information to search for an optimal design solution. Focusing on such scenario is a parsimonious starting step in understanding information acquisition as a design behavior under the influence of competition. Moreover, information acquisition in parallel could be regarded as multiple individuals within a competing design team following a sequential process of information acquisition and pooling information at various time steps. Such an investigation is beyond the scope of this dissertation.

### **1.1.3 Behavioral Economics Literature: Competition as A Factor Affecting Decision-making Behaviors**

Existing literature in behavioral game theory has established that the design of a contest influences participant behaviors and, thereby, the outcomes of a contest [26, 27]. The design of a contest includes decisions such as what and how much information to share with the contestants [26]. Examples of various types of contest-specific information include knowledge about the organizers of the contest, the reputation of the contest, the prize of the contest, and the players in the contest [28]. It is intuitive that knowledge about such types of information can heavily influence the strategic decisions of the players. For example, in the field of sports, a lot of data about competing teams' past performance is analyzed to make strategic decisions for a team's gameplay such that it improves their winning probability [29, 30].

While there is extensive literature investigating contests within behavioral economics [26, 31–34], research in behavioral economics does not address the nuances of engineering design scenarios. For example, designers in engineering design processes typically iterate through several design solutions before making artifact decisions.

Each of these iterations involves information acquisition activities that allow the designers to explore the design space and update their state of knowledge about them. Sharing contest-specific information influences a designer’s information acquisition activities, and thereby, the quality of design solutions.

Existing literature in Design for Market Systems utilizes behavioral Game Theory to investigate product design competitions to maximize a firm’s profit [35, 36]. Moreover, it is acknowledged that designers play an important role such that their decisions get influenced based on the structure of market systems [37]. However, the incorporation of designer’s decision-making behaviors through the identification and quantification of contest-specific factors that influence their behaviors in competitive design environments has largely been ignored [38]. Thus, there lies a need to understand how competition influences sequential decision-making behaviors in an engineering design process.

## 1.2 Overview of this Dissertation

The *overarching research goal* of this dissertation is to develop descriptive theory of sequential information acquisition and decision making in design contests. A step towards descriptive theory of information acquisition and decision making under competition is by factorial investigation [39]. Such investigation provides insights on the quantification and the impact of factors that affect information acquisition, decision making process and its outcomes in design contests. Such insights can then be incorporated to develop descriptive models of decision making process that can better predict design contest outcomes.

The research approach adopted in this dissertation for factorial investigation is to utilize a combination of computational modeling and behavioral experimentation. Existing theories from areas such as DBD and Behavioral Economics are utilized to develop computational models of sequential design scenarios under competition. Such models provide abstractions of design contests subjected to some assumptions.

Models provide predictions about contest design outcomes which helps us generate hypotheses about the factorial impact on design decision making process and outcomes. Such hypotheses can then be tested using behavioral experimentation. Results of such hypotheses testing provide us with insights that in turn help us improve existing theory. The research approach adopted in this dissertation is described in Figure 1.1.

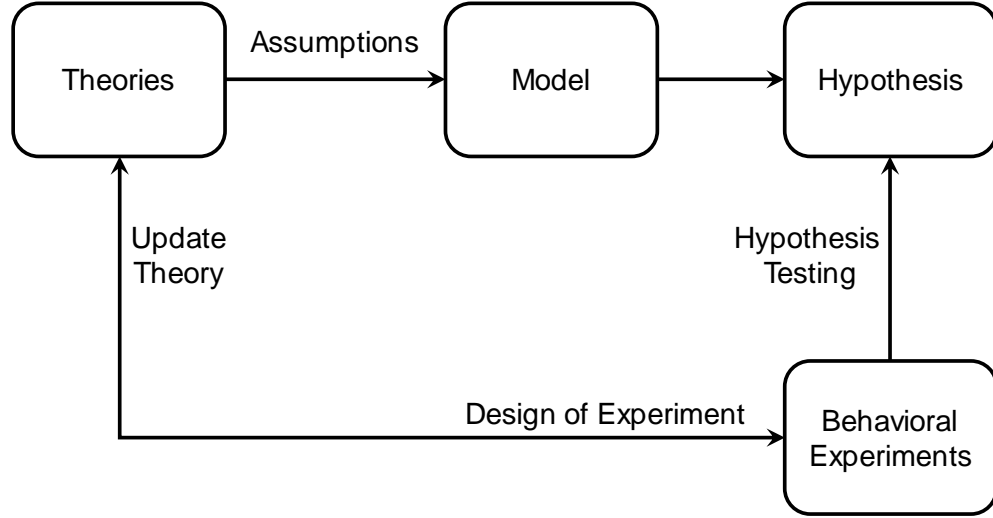


Figure 1.1. : The Research Approach

### 1.2.1 Research Questions Addressed In This Dissertation

In this dissertation, the impact of three factors in an information acquisition and decision making scenario are investigated. These factors are a decision maker's domain knowledge, problem framing, and information about the historical contest's winning performances. In order to conduct investigations of the mentioned factors I aim to address the following research questions (RQs):

RQ1 How can we quantify the impact of a designer's domain knowledge and problem framing on their information acquisition decisions and the corresponding design outcomes?



RQ2 How can we quantify the influence of providing information about historical contests on a participant’s information acquisition decisions in a design contest?

RQ3 How can we study a designer’s cognitive processes that influence their decision to stop acquiring information under the influence of competition?

RQ1 is addressed in Chapter 2. The motivation for RQ1 is that there is a lack of descriptive models that quantify the impact of a designer’s domain-specific knowledge on their information acquisition, decision making, and thereby, the quality of design solutions. For example, it is trivial to predict that an expert roller coaster designer would design better roller coasters than a novice. However, there’s a lack of models that quantify the impact of their knowledge of dynamics, for example, on the quality of the design of the roller coaster.

RQ2 is addressed in Chapter 3. The motivation for RQ2 is that while it is known that opponent-specific information influences participant’s decision-making, there is a lack of understanding on how a boundedly rational agent would utilize such information to make decisions. Thus, there lies a need to quantify the influence of such information on participant’s information acquisition and decision making behaviors. Moreover, computationally quantifying and modeling such influences provides a baseline to study actual behaviors of participants.

RQ3 is addressed in Chapter 4. RQ3 is considered as an extension of the other two research questions that have so far focused on the quantification of factors affecting decision making behaviors. The motivation for RQ3 is that there is lack of understanding of the approach to investigate *how* the cognitive factors influence a participant’s decision making process. Thus, there is a need to synthesize the effect of cognition on design outcomes. Such knowledge is particularly helpful for a designer of a design tournament whose objective is to maximize the quality of the design solutions submitted. The designer of such tournaments can decide what information to reveal about the past contests such as the past participant’s performance data.

Moreover, the approach to answer RQ3 requires both qualitative and quantitative methods. Qualitative methods enable investigating individuals' cognitive processes that can help us infer their preferences, motivations, and mental states. Whereas, quantitative methods can enable quantification of the cognitive factors and their impact of design outcomes. Thus, a mixed methods approach is proposed towards descriptive theory development in DBD.

### **1.2.2 Research Questions: Summary of the Results and Their Implications**

The results from investigating RQ1 suggest that, designers better understand problem constraints and generate more feasible design solutions when a design problem is framed in a domain-specific context as compared to a domain-independent framing of the problem. Moreover, the computational model developed is able quantify the influence of domain knowledge and problem framing on an individual's sequential decision making behaviors. The results imply if contest designers frame the design problem in a domain-specific context, they would receive more feasible design solutions.

The results from investigating RQ2 suggest that, contestants' efforts to acquire information about a design artefact to make design improvements are significantly affected by the information provided to them about their opponent who is competing to achieve the same objectives. Specifically, designers expend higher efforts when they know that their opponent has a history of generating good quality design solutions as compared to when their opponent has a poor performance history. Moreover, the computational model developed is able to quantify such a behavior by accounting for an individual's belief about their opponent. The results imply that sharing opponent-specific information affects contestants perception about the competitiveness of the competition and their willingness to participate in the contest. Thus, contest de-

signers need to strike a balance between how much information to reveal about the opponents and how to ensure sufficient participation.

The results from investigating RQ3 suggest that, contestants make information acquisition decisions such as when to stop acquiring information, based on various criteria such as the amount of resources they have, the target objective value they want to achieve, and the amount of improvement in their design quality in successive iterations. Moreover, the threshold values of such criteria are influenced by the information the contestants have about their opponent. From the identified criteria, contestants' resource expenditure threshold is the most sensitive to the information they have about their opponent. Thus, if the opponent has a strong past performance history, contestants are hesitant to spend more resources as compared to an opponent with a weak performance history. The results imply that contest designers need to strike a balance between the competitiveness of the competition and the resource budget allocation to the contestants.

### **1.2.3 Educational Implications of Investigating Sequential Decision Making Without Competition**

The implications of the factorial investigation of domain knowledge (RQ1) are also investigated in engineering education contexts. Students are considered as sequential decision-makers to understand how classroom activities can impact their ability to acquire and process information. The following educational research question (ERQ) is addressed.

ERQ1 How do students make decisions while acquiring information in a product design process?

ERQ1 is addressed in Chapter 5 where an observational study is discussed. The results of the study indicate that the students recognize the need to acquire information about the physics and dynamics of their design artifact. However, they do not acquire such information during the design process. The factors that contribute to

the failure of information acquired during the product design activity are the lack of (i) explicit learning objectives in the project specifications, (ii) the students' lack of knowledge to do so, and (iii) the time constraints for project completion. Instead, they acquire such information from the prototyping activity as their toy does not satisfy the design objectives and work as intended. Such information acquisition results in the students wanting to have more number of iterations for prototyping activities to improve the achievement of their design objectives. With the given cost and time constraints, the students do not get the opportunity to iterate their prototype. Consequently, the students rely on improvising during prototyping.

### **1.3 Thesis Organization**

In this dissertation, each Research Question (RQ) is addressed by utilizing a computational model of decision making in conjunction with a controlled behavioral experiment. In each of the subsequent chapters, that is, Chapter 2, Chapter 3, and Chapter 4, respectively, I report how RQ1, RQ2, and RQ3 are addressed. These chapters are structured such that, in each, I discuss the theories utilized to address the respective RQs followed by the model formulation. Then, I discuss the design of the experiment and the corresponding hypothesis formulation and results. In Chapter 5, I highlight the implications of this dissertation in engineering educational research contexts by discussing how ERQ1 was addressed. Finally, in Chapter 6, I provide closing remarks for this dissertation along with the intellectual merit and the broader implications of this research.

## 2. QUANTIFYING THE IMPACT OF DOMAIN KNOWLEDGE AND PROBLEM FRAMING ON SEQUENTIAL DECISIONS IN ENGINEERING DESIGN

### 2.1 Chapter Overview

Designers make several decisions within engineering systems design such as what information to acquire and what resources to use. These decisions significantly affect design outcomes, and the resources used within design processes. While decision theory is increasingly being used from a normative standpoint to develop computational methods for engineering design, there is still a significant gap in our understanding of how humans make decisions within the design process. Particularly, there is lack of knowledge about how an individual's domain knowledge and framing of the design problem affects information acquisition decisions. To address this gap, the objective of this chapter is to address RQ1 (Refer to Chapter 1.2), that is, *to quantify the impact of a designer's domain knowledge and problem framing on their information acquisition decisions and the corresponding design outcomes*. The objective is achieved by (i) developing a descriptive model of information acquisition decisions, based on an optimal one-step look ahead sequential strategy, utilizing expected improvement maximization, and (ii) using the model in conjunction with a controlled behavioral experiment. The domain knowledge of an individual is measured in the experiment using a Concept Inventory, whereas the problem framing is controlled as a treatment variable in the experiment. A design optimization problem is framed in two different ways: a domain-specific track design problem, and a domain-independent function optimization problem. The results indicate that when the problem is framed as a domain-specific design task, the design solutions are better and individuals have a better state of knowledge about the problem, as compared to the domain-independent

task. The design solutions are found to be better when individuals have a higher knowledge of the domain and they follow the modeled strategy closely.

## 2.2 Introduction

Factors such as a designer’s domain knowledge and the framing of a design problem affect designers’ decisions [40–43]. However, there is a significant gap in our understanding of *how* these factors affect information acquisition decisions. For example, it is trivial to predict that an expert roller coaster designer would design better roller coasters than a novice. However, there is a lack of descriptive models that quantify the impact of a designer’s domain-specific knowledge, such as, their knowledge of dynamics on the quality of design solutions. Therefore, in this chapter, the objective is to address RQ1 (Refer to Chapter 1.2).

My approach to answer RQ1 consists of two steps. First, I develop a *descriptive model* of a sequential information acquisition activity in an engineering design process. The model is described in Section 2.3. It is based on the assumptions that individuals strive to maximize their expected payoff and use the Bayesian approach to update their state of knowledge based on new information. Second, I design and execute a *behavioral experiment*. I utilize experimental data to estimate parameters in the model, and to test hypotheses about the impact of domain knowledge and problem framing on design outcomes. Before the experiment, I measure an individual’s domain knowledge using a Concept Inventory [44]. Within the experiment, I control for problem framing by presenting a mathematically identical problem in two different ways and observe the decisions made by the participants. The details of the experiment are provided in Section 2.4. The results are discussed in Section 2.5. Finally, I discuss the implications of this work, the validity of the modeling assumptions, and the avenues for future research in Section 2.6.

## 2.3 A Descriptive Model of Sequential Information Acquisition and Decision Making Process

In this section, I abstract design processes as a Sequential Information Acquisition and Decision Making (SIADM) process. Then, a computational model of the SIADM process is formulated that accounts for the influence of domain knowledge.

### 2.3.1 Sequential Information Acquisition and Decision Making: An Abstraction of Design Processes

Consider a design scenario where a designer has a set of design variables  $x$  that affect a design outcome  $f(x)$  under constraints  $g(x) \geq 0$ . The designer's objective is to achieve the best feasible design outcome. The designer does not explicitly know the mathematical relationship between the design variables and the design outcome, i.e., the function  $f(x)$ . However, they may know the feasibility of the design variables, i.e., the constraint function  $g(x) \geq 0$ , due to factors such as their domain knowledge. In such a scenario, a designer needs to acquire information about the impact of design variables  $x$  on the design outcome  $f(x)$ . Such information can be acquired by running (physical or computational) experiments, which incur certain cost. Consequently, they also receive information about the feasibility of the design variables  $g(x)$ . We assume that the designer updates their state of knowledge about both these functions after executing each experiment. Such a design scenario is referred to as a Sequential Information Acquisition and Decision Making (SIADM) scenario.

We choose such a scenario, where  $f(x)$  is unknown but  $g(x)$  may be known, to decouple the impact of an individual's domain knowledge on the knowledge of the objective  $f(x)$  and the constraint function  $g(x)$ . In reality, designers may have knowledge about the objective function  $f(x)$ . We align the modeled scenario with our experiment by ensuring that the function  $f(x)$  is unknown to the participants.

The SIADM process is illustrated in Figure 2.1. It consists of three main activities: acquiring information, processing information, and making decisions. These activities

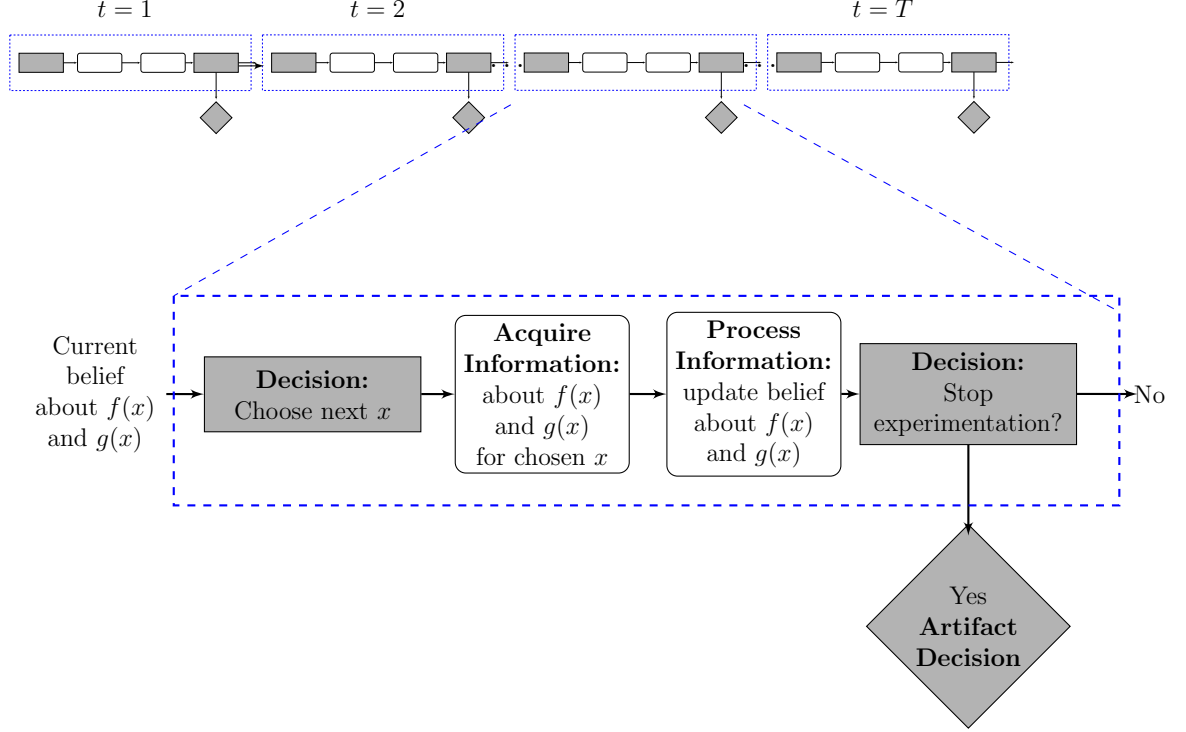


Figure 2.1. : Illustration of Sequential Information Acquisition and Decision Making process. Decisions are highlighted in gray color. Rectangular nodes are information acquisition decisions and the outcome (diamond node) of the SIADM process is making the artifact decision.

are repeated over a sequence of steps,  $t = 1, \dots, T$ . During each step  $t$ , the decision maker chooses a set of design variables  $x_t$  to execute an experiment. Choosing a set of design variables  $x$  is referred to as *sampling*. From the experimental data, the decision maker acquires new information about  $f(x)$  and  $g(x)$ , and processes it to update their state of knowledge. Then, the decision maker decides whether to continue acquiring information (or to stop experimentation). If they decide to continue acquiring information, the decision maker repeats the same set of activities as that of the previous step. If their decision is to stop experimentation, then they make artifact decisions such as selecting an alternative using the current state of knowledge at step  $t$ .



### 2.3.2 Model Formulation

I begin the SIADM model formulation by making assumptions about the representation of an individual’s state of knowledge, how they update their state of knowledge, and how they make information acquisition decisions. I assume the following: A1.1) The state of knowledge of an individual is the belief of that individual. A1.2) Individuals update their state of knowledge through Bayesian updating. A2.1) The decision to choose the “next  $x$ ” (refer to Figure 2.1) is made by maximizing the expected improvement in the objective function. A2.2) Individuals have bounded rationality [45]. A3) The decision maker stops after a fixed number of steps  $T$ .

A1.1 implies that the state of knowledge of an individual is a probability distribution (referred to as a belief) assigned by the individual over the information space. By assuming A2.1 and A2.2 I imply that individuals can only estimate the impact of the information acquired in the immediate next step. In other words, I model a myopic information acquisition decision by accounting for an individual’s bounded cognitive capabilities. Assumption A3 is reasonable in scenarios where the designer has to commit to expending certain resources before conducting any experiments or there is a fixed predefined budget for experiments.

In my model, I account for the impact of domain knowledge and the framing of the design problem on the state of knowledge of an individual. I do so by utilizing a set of parameters called *type* ( $\theta$ ) of an individual. The type  $\theta$  of an individual accounts for their unique characteristics due to which they have varying domain knowledge and different information acquisition strategies. By assuming A1.1 I imply that an individual’s type  $\theta$  impacts their prior beliefs with which they begin the SIADM process. While I make specific assumptions about the information acquisition process of an individual (A1 to A3), I account for their deviation from the process through their type  $\theta$ .

In the following subsections, I mathematically define two concepts: (i) the information acquired at each decision making step (Section 2.3.3) and (ii) the type of

an individual  $\theta$  (Section 2.3.4). I then describe various aspects of an individual's type  $\theta$ , such as, an individual's state of knowledge (Section 2.3.5), how they update their state of knowledge (Section 2.3.6), and how they make information acquisition decisions (Section 2.3.7).

### 2.3.3 Information Acquired at Each Step

At each decision making step,  $t = 1, 2, \dots, T$ , (refer to Figure 2.1) the individual samples an  $x_t$  value and receives information about:

1. The constraint feasibility,  $z_t = \begin{cases} 1, & \text{if } g(x_t) \geq 0 \\ 0, & \text{otherwise.} \end{cases}$
2. The value of the objective function,  $y_t = f(x_t)$ , provided the constraint is satisfied,  $z_t = 1$ . The design outcome is not known,  $y_t = \emptyset$ , if the constraint is not satisfied,  $z_t = 0$ .

I assume that an individual begins the SIADM process at step  $t = 0$  with some initial information  $I_0$  at  $x = x_0$  about the objective function  $y_0 = f(x_0)$  and the constraint feasibility  $z$ . Thus,

$$\mathcal{I}_0 = \{(x_0, y_0, z_0)\}. \quad (2.1)$$

The information  $\mathcal{I}_t$  that the individual observes at the end of step  $t$  is:

$$\mathcal{I}_t = \mathcal{I}_{t-1} \cup \{(x_t, y_t, z_t)\}. \quad (2.2)$$

### 2.3.4 The Type of an Individual

The type  $\theta$  of an individual fully specifies (i) their prior state of knowledge and how it is represented, (ii) how they update their state of knowledge after observing  $\mathcal{I}_t$ , and (iii) how they decide what to observe at each step. Obviously, there are infinitely

many modeling alternatives for items (i)-(iii). In what follows, I have made specific modeling choices, trying to be parsimonious (to keep the number of model parameters as small as possible), while taking into account some of the cognitive limits of humans.

### 2.3.5 Modeling an Individual's State of Knowledge

I utilize Gaussian process prior [46] to model an individual's state of knowledge about the objective function  $f(x)$ . Existing studies support the findings that Gaussian Process models can capture human search process [47,48]. A relevant study conducted by Borji and Itti [49] focuses on investigating the underlying algorithms that humans utilize to optimize an unknown 1D objective function. Their results indicate that Gaussian Process models can capture an individual's state of knowledge about the mathematically unknown objective function  $f(x)$ .

I assume that prior to observing any data, the individual believes that  $f(x)$  could be any sample from a Gaussian process prior [46],

$$f(x)|\theta \sim \text{GP}(0, c(x, x')), \quad (2.3)$$

with a zero mean and covariance function  $c(x, x')$ . The covariance function  $c(x, x')$  defines the process' behavior between any two points  $x$  and  $x'$ . The choice of the covariance function  $c(x, x')$  along with the prior beliefs that the individual has about its parameters are, in general, a part of their type  $\theta$ .

In this work, however, I assume that the individuals use a squared exponential covariance function:

$$c(x, x') = s^2 \exp \left\{ -\frac{(x - x')^2}{2\ell^2} \right\}, \quad (2.4)$$

with unspecified signal strength  $s > 0$  and length scale  $\ell > 0$ , i.e., they assign flat priors. This choice is equivalent to the assumption that the individual believes that  $f(x)$  is infinitely differentiable and that it could have any signal strength or length scale.

The state of knowledge about the constraint function  $z$  is represented as the probability that the constraints are satisfied  $p(z = 1|x, \theta)$ . The simplest such model is the logistic regression:

$$p(z = 1|x, \lambda, b) = \text{sigm}(\lambda(x - b)) := \frac{1}{1 + e^{-\lambda(x-b)}}, \quad (2.5)$$

with parameters  $\lambda$  and  $b$ . As with the parameters of the covariance function, I do not assume that an individual knows the exact values of  $\lambda$  and  $b$ . In other words,  $\lambda$  and  $b$  are not a part of the description of an individual's type  $\theta$ . What is a part of the type  $\theta$ , however, is the individual's prior beliefs about  $\lambda$  and  $b$ . Specifically, I assume that an individual of type  $\theta$  assigns a factorizing prior on  $\lambda$  and  $b$ :

$$p(\lambda, b|\theta) = p(\lambda|\theta)p(b|\theta), \quad (2.6)$$

and that each factor  $\alpha \in \{\lambda, b\}$  is a Gaussian:

$$\alpha|\theta \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2), \quad (2.7)$$

with given mean  $\mu_\alpha$  and variance  $\sigma_\alpha^2$ . In other words, the specification of an individual's type contains these parameters, i.e.,  $\{\mu_\lambda, \sigma_\lambda^2, \mu_b, \sigma_b^2\} \subset \theta$ . While  $\lambda$  quantifies the slope of the regression curve (refer to Equation 2.5), the parameter  $b$  has an intuitive interpretation that correlates with the constraint knowledge of an individual. I discuss the interpretation of  $b$  in Section 2.4.3.

### 2.3.6 Modeling how Individuals update their State of Knowledge

At step  $t$ , after an individual samples  $x_t$ , they receive information  $(x_t, y_t, z_t)$ . The individual processes this information by updating their belief about  $f(x)$  and  $g(x)$ . However, due to their limited cognitive capabilities they may not be able to fully characterize all posteriors. The assumptions A1.2 and A2.2 imply that when they

cannot deal with the computational complexity, they choose to obtain a maximum a posteriori estimate of their hyperparameters. Thus, an individual of type  $\theta$  updates their beliefs about  $f(x)$  to:

$$f(x)|\mathcal{I}_t, \theta \sim \text{GP}(m_t(x), c_t(x, x')) \quad (2.8)$$

where  $m_t(x)$  and  $c_t(x, x')$  are the posterior mean and covariance functions of the GP [46] when it is conditioned on the  $x$ - $y$  input-output pairs contained in  $\mathcal{I}_t$  that satisfy the constraints, i.e., on  $\{(x_i, y_i) : (x_i, y_i, z_i) \in \mathcal{I}_t, z_i = 1, i = 0, \dots, t\}$ . Since I have assumed that the individuals have flat priors on the hyperparameters of the covariance function,  $p(s, \ell|\theta) \propto 1$ , this is equivalent to maximizing the marginal likelihood. Note that at the very first step,  $t = 0$ , the marginal likelihood is flat with respect to the lengthscale. In that case, I assume that they pick  $\ell = 1$ . This may seem ad hoc, but it is inconsequential since their first decision at  $t = 1$  does not depend on  $\ell$ .

Similarly, the individuals use  $\mathcal{I}_t$  to update their state of knowledge about the feasible region, which is modeled as a logistic regression depending on  $b$  and  $\lambda$ . In this part, their prior state of knowledge specified by their type  $\theta$ , and specifically by  $\{\mu_\lambda, \sigma_\lambda^2, \mu_b, \sigma_b^2\} \subset \theta$ , does play a role in their decision to choose the next search point. The modeling assumption is that they choose  $b$  and  $\lambda$  by maximizing the posterior of these hyperparameters, i.e., they choose:

$$\hat{b}(\mathcal{I}_t; \theta), \hat{\lambda}(\mathcal{I}_t; \theta) = \arg \max_{b, \lambda} \prod_{i=0}^t p(z_i | x_i, \lambda, b) p(\lambda, b | \theta). \quad (2.9)$$

### 2.3.7 Modeling how Individuals make Information Acquisition Decisions

To model how an individual of type  $\theta$  samples  $x_t$ , I define a decision function  $\chi_t(\mathcal{I}_t; \theta)$ . In the context of the SIADM scenario, the decision of *what* information to sample can be modeled utilizing a decision function. For example, for a convex search problem, a designer may choose to sample  $x_t$  based on a convex optimization method

such as the bisection method. Then the decision function is modeled such that the next  $x$  is chosen at the mid point of the search space.

To descriptively formulate my decision function, my first assumption is that the decision function is not stationary i.e., it changes with  $t$ . However, it only changes due to the information observed until step  $t$  i.e.  $\chi_t(\mathcal{I}_t; \theta) = \chi(\mathcal{I}_t; \theta)$ . I do so to account for the argument that when  $t$  is small, individuals may wish to explore the space and that when  $t$  gets closer to  $T$ , they wish to exploit their state of knowledge. The second assumption is that the decision function is myopic, i.e., it only considers the optimality of the next decision and not the optimality of the subsequent sequence of decisions. This assumption is reasonable, since individuals do not have the cognitive capabilities to think about many steps ahead [50]. There are many possible choices of myopic decision functions. Here, I opted for one of the most parsimonious models (no new parameters) which is based on the conditional expected improvement [51]. Borji and Itti [49] show that maximization of expected improvement is indicative of how humans make search decisions. It is:

$$\chi(\mathcal{I}_t; \theta) = \arg \max_x \text{EI}(x; \mathcal{I}_t, \theta) p(z = 1 | x, \hat{\lambda}(\mathcal{I}_t; \theta), \hat{b}(\mathcal{I}_t; \theta)), \quad (2.10)$$

where  $\text{EI}(x; \mathcal{I}_t, \theta)$  is the expected improvement (EI) defined via the GP representation of the objective function as modeled by an individual of type  $\theta$  and  $p(z = 1 | x, \lambda(\mathcal{I}_t; \theta), b(\mathcal{I}_t; \theta))$  is the probability that the constraints are satisfied given by the logistic regression function.  $\hat{\lambda}(\mathcal{I}_t; \theta)$  and  $\hat{b}(\mathcal{I}_t; \theta)$  are parameters that the individual has identified as described in Section 2.3.6.

### 2.3.8 A Researcher's Belief about the Individual

A researcher is an individual who is observing the decision maker's decisions but does not know their type  $\theta$ . In Section 2.3.7, I formulate the beliefs of an individual about  $f(x)$  and  $g(x)$ . In this section, I formulate the *researcher's beliefs* about observing the decision data of an individual with type  $\theta$ .

The researcher's probability that an individual of type  $\theta$  selects  $x_t$  at the  $t$ -th step after having observed information  $\mathcal{I}_t$  is:

$$p(x_t|\mathcal{I}_t, \theta) \sim \mathcal{N}(\chi(\mathcal{I}_t; \theta), \sigma^2), \quad (2.11)$$

where  $\sigma^2 \in \theta$  is a type parameter that accounts for the deviation of an individual from the information acquisition strategy modeled in Section 2.3.7. Thus, for a fixed number of tries  $T$ , the researcher's probability of observing a sequence of decisions made by an individual  $x_{1:T} = \{x_1, \dots, x_T\}$  is given by:

$$p(x_{1:T}|y_{1:T}, z_{1:T}, \theta) = \prod_{t=0}^{T-1} p(x_{t+1}|\mathcal{I}_t, \theta) \quad (2.12)$$

I refer to Equation 2.12 as the *likelihood*. Note that the likelihood is also conditioned on fixing the number of tries (assumption A3). Therefore, the probability of an individual for not stopping for  $T - 1$  tries as well as the probability of stopping at  $T$  tries is 1.

The researcher's prior beliefs about the type  $\theta$  of an individual are:

$$p(\theta) = p(\mu_\lambda)p(\sigma_\lambda)p(\mu_b)p(\sigma_b)p(\sigma), \quad (2.13)$$

where, the variances  $\sigma_\lambda^2$ ,  $\sigma_b^2$ , and  $\sigma^2$  are assigned an uninformative Jeffrey's prior, e.g.,  $p(\sigma_\lambda) \propto \frac{1}{\sigma_\lambda}$ ,

$$\mu_\lambda \sim \mathcal{N}(-0.1, 0.001), \quad (2.14)$$

and

$$\mu_b \sim \mathcal{N}(300, 5000). \quad (2.15)$$

I assume that all the participant's prior belief about  $\mu_b$  and  $\mu_\lambda$  is normally distributed as shown in Equation 2.14 and 2.15. These priors are assigned in accordance with the range of values chosen for the design of the experimental constraints as described in Section 2.4.1.

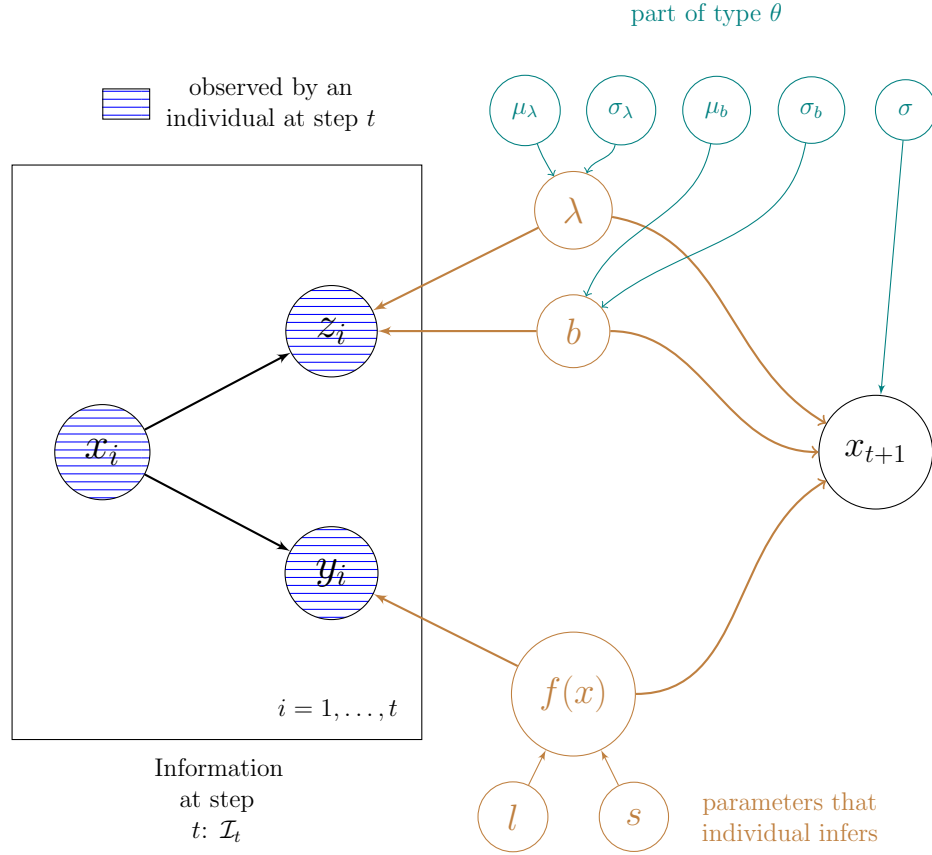


Figure 2.2. : Graphical illustration of Sequential Information Acquisition and Decision Making (SIADM) model at step  $t$ . Parameters  $\lambda$ ,  $b$ ,  $l$ , and  $s$  are inferred by the individual. Parameters  $\mu_b$ ,  $\sigma_b$ ,  $\mu_\lambda$ ,  $\sigma_\lambda$ , and  $\sigma$  are a part of an individual's type  $\theta$ .

Figure 2.2 illustrates the information observed by the individual. Note that the researcher observes the entire information set  $\mathcal{I}_t$ . Figure 2.2 also illustrates the plate diagram of the SIADM model and the influence of various model parameters on the information acquired.

### 2.3.9 Inferring an Individual's Type from Experimental Data

The stochastic model of sequential decision making contains five parameters that specify the type of an individual, i.e.,  $\theta = \{\mu_\lambda, \sigma_\lambda^2, \mu_b, \sigma_b^2, \sigma^2\}$ . In this section, I



discuss how observed decisions  $x_{1:T}$  of the individual can be used to infer their type  $\theta$ . Section 2.3.8 describes a generative model of  $x_{1:T}$  conditioned on  $\theta$ , which enables us to compute the likelihood  $p(x_{1:T}|y_{1:T}, z_{1:T}, \theta)$  and the researcher’s prior beliefs about an individual’s type  $\theta$ . Using Bayes rule, the researcher’s posterior over  $\theta$  conditioned on  $x_{1:T}$  is:

$$p(\theta|\mathcal{I}_T) \propto p(x_{1:T}|y_{1:T}, z_{1:T}, \theta)p(\theta). \quad (2.16)$$

I sample from the posterior using the Metropolis-Hasting algorithm sampling [52] from the PyMC [53] Python module. I run the MCMC chain for 10000 iterations with a *burn-in* period of 2000 samples that are discarded. Equation 2.16 is used to estimate the researcher’s posterior over  $\theta$  for an individual given their (individual’s) search data.

## 2.4 Experimental Study

A behavioral experiment with an SIADM task is required to obtain an individual’s search data for this study. Such data enables us to estimate an individual’s type  $\theta$  from the model formulated in Section 2.3. In order to study the impact of domain knowledge and problem framing in a SIADM scenario, I need to formulate and test related hypotheses. Thus, in this section, I describe the experimental tasks, structure, and design in the context of this work. I then discuss the quantification and measurement of the factors investigated utilizing the experimental study and formulate the hypotheses.

### 2.4.1 Experimental Tasks

I assume that a designer receives information about the design objective  $f(x)$  and constraint  $g(x)$  with certainty i.e., the information sources are not noisy. I also assume that an individual’s domain knowledge does not affect their belief about the objective function. Thus, I assign a GP prior belief about the objective function

for an individual in my model (refer to Section 2.3.7). To ensure consistency of the experiment with the model, the objective function  $f(x)$  is mathematically unknown to the participants. However, I assume that the domain knowledge affects an individual's belief about the constraints  $g(x)$ .

The experimental study has three constrained optimization tasks. The first task is formulated as a domain-dependent track design problem where the feasible design space is not explicitly specified. For brevity, I call this task a Track-Design-Problem where Constraint-is-Not-Specified ( $\text{TDP}_{\text{CNS}}$ ). The second task is the track design problem where the constraint is specified ( $\text{TDP}_{\text{CS}}$ ). The third task is formulated as a domain-independent function optimization problem (FOP). The  $\text{TDP}_{\text{CNS}}$  and FOP are mathematically identical but framed in different domain contexts. I do so to test the impact of problem framing on the participants' decisions in SIADM scenarios. The  $\text{TDP}_{\text{CS}}$  is formulated in order to understand the impact of adding a constraint. Table 2.1 illustrates the differences between each task. I do not consider a domain-independent task where the constraint is specified as it simply becomes a search task without influence of domain knowledge due to lack of a domain context and the constraint. In the following, I discuss the details of each design task.

Table 2.1. : Differences between the Track Design Problem (TDP) and Function Optimization Problem (FOP)

<b>Constraint \ Domain</b>	<b>Domain</b>	
	<b>Dependent</b>	<b>Independent</b>
<b>Specified</b>	$\text{TDP}_{\text{CS}}$	—
<b>Not Specified</b>	$\text{TDP}_{\text{CNS}}$	FOP

## Track Design Problems

The track design problems TDPs are formulated as SIADM tasks. The designer's 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” under the constraint

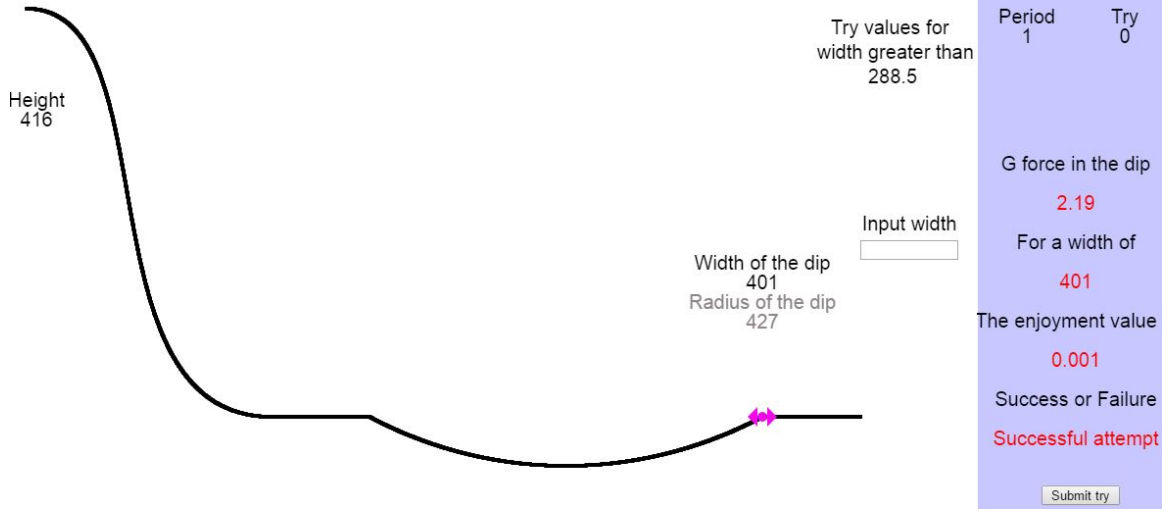


Figure 2.3. : The user interface of track design game where constraint is specified  $TDP_{CS}$

$g(x)$  that the centripetal acceleration should not exceed  $4g$ . To achieve the objective, a participant's task is 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"  $E(w)$ . However, they 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. Both cases result in reduced enjoyment. Thus, there is an optimal width  $w$  for which the enjoyment for the rider is maximized. The participants are provided with an initial height  $H$  of the track and are informed that the circular valley has a constant depth of 50 units as shown in Figure 2.3.

If the participants violate the constraint such that the centripetal acceleration exceed  $4g$  then the track fails because the ride becomes uncomfortable due to high  $g$  forces. In such a case, it is counter intuitive to display an "enjoyment" value. Thus, we chose a modeling scenario where violation of constraints results in no information about the objective function.

We design the objective function  $E(w)$  such that it satisfies requirements such as concavity, non-negativity, function parameterization, and function asymmetry in

order to control for factors such as incentivization, intuition, guessing, and problem difficulty to avoid interference with the experiment results.

We require the enjoyment function to have the following characteristics:

1. The objective function should be concave so that there is a unique maximum value of enjoyment.
2. The objective function should be non-negative to ensure that the enjoyment value is non-negative.
3. The objective function should be sensitive to the values in the design space sampled by the user.
4. The concavity of the function should be such that it is less intuitive for the participant to achieve the maximum by sampling values at random. In this way the participants would also have an incentive in trying to converge to the optimum.
5. The enjoyment value should eventually decrease to zero by moving away from the optimal value.
6. The function should have flexible parameters to adjust its maximum value either on the constraint boundary or somewhere within the design space. This would make it less intuitive for the participant to search for the optimal by guessing.
7. The enjoyment function could be asymmetric with respect to the optimal width value. The rate at which enjoyment decreases due to increase of width could be different from the rate at which enjoyment decreases due to decreasing width.

Considering such characteristics, we model enjoyment function through a Log-Normal function. The enjoyment ( $E(w)$ ) of the track is defined as:

$$E(w) = 0.075 \exp(0.005) \frac{H^2}{w} \exp \left\{ \frac{-(\ln(w) - \ln(H) - \ln(0.6) - 0.01)^2}{0.02} \right\}. \quad (2.17)$$

The maximum value of enjoyment function occurs at the width value  $w_{\max}$ . We model  $w_{\max}$  as a function of the track height  $H$  such that  $w_{\max} = 0.6H$ . The corresponding maximum enjoyment value  $E_{\max}$  is:

$$E_{\max} = \left(\frac{H}{8}\right). \quad (2.18)$$

The function is normalized to have a maximum value dependent on the height of the track. We do so because intuitively a “taller” ride should have a higher maximum possible enjoyment. In the experiment, the height values  $H$  are uniformly chosen from the range of 400 to 800 units. Thus,  $E_{\max}$  values range between 50 to 100. However, the design alternative at  $w_{\max}$  may still be infeasible i.e., not satisfy the acceleration constraint. The constraint is chosen by considering the standard safety measures adopted in general in a roller coaster track design where the  $g$  forces are limited between  $-4g$  and  $4g$ . In the valley, the  $g$  force is always positive and therefore limited between 0 to  $4g$ . The track is also assumed to be frictionless.

Mathematically, the problem can be formulated as an optimization problem as follows:

$$\begin{aligned} \text{maximize} \quad & E(w) = 0.075 \exp(0.005) \frac{H^2}{w} \exp \left\{ \frac{-(\ln(w) - \ln(H) - \ln(0.6) - 0.01)^2}{0.02} \right\}, \\ \text{subject to} \quad & w^2 \geq 200H. \end{aligned} \quad (2.19)$$

Participants were not aware of the explicit form of the objective function  $E(w)$  as seen in Equation 2.17. An understanding of laws of motion, centripetal acceleration and force balance is required to formulate the constraint in Equation 2.19. We assume that an individual with knowledge of the Newtonian concept of force will be able to formulate the constraint in Equation 2.19. This assumption is reasonable as research has shown that individuals with high domain knowledge tend to categorize a problem according to the major concept that could be applied to solve the problem [54].

Consider a randomly chosen  $H$  value of 500. The theoretical maximum value of the function is  $E_{\max} = 62.5$  at the width value of  $w_{\max} = 0.6H = 300$ . However,

for the constraint to be satisfied we need  $w \geq 316.23$ . Thus, the function maximum is not a feasible solution and the optimal lies at the constraint boundary in this case. Such cases are included in order to reduce learning [55] about the relationship between  $w_{max}$  and track parameter  $H$ . For track design problem where constraint is specified TDP<sub>CS</sub> the participants were additionally given the constraint information. We do so by giving the range of width values for which the solution would be feasible. Figure 2.3 illustrates TDP<sub>CS</sub>.

### Function Optimization Problem

We design the function optimization problem by excluding the context of the track design task. In the function optimization problem, the participants are asked to maximize a concave function  $f(x)$  given a constraint function  $g(x)$ . Their task is to sample values to obtain the maximum value of  $f(x)$  as well as ensure that  $g(x) < 2$  for a feasible solution (choosing a set of design variables  $x$  is referred to as *sampling*). The objective function  $f(x)$  remains exactly the same as the objective function of the track design game,  $E(x)$  (Equation 2.17). The constraint in the TDP is such that the centripetal acceleration is less than  $4g$  (and greater than 0). The centripetal acceleration constraint is shown as a constraint function  $g(x)$  in FOP and the values are normalized between 0 and 2 to minimize learning about the mathematical similarity of the tasks.

#### 2.4.2 Experiment Design

The experiment involved a total of 44 participants. These participants were undergraduate and graduate students at Purdue university. The participants were engineering majors from various departments such as mechanical, civil, chemical, and nuclear engineering. Students were recruited via flyers and social media posts in Purdue Engineering groups. The experiment was divided into four parts. In the first part, the participants were required to take a Concept Inventory test (the details are

provided in Section 2.4.3). No time limit was imposed for this part. In the rest of the parts, each participant was required to play the games in a predetermined order.

There were a total of three orders of execution of the experiment tasks. Such ordering of tasks is done to eliminate order effects [56]. There can be six possible permutations of the order of execution of three experimental tasks. However, I eliminated certain cases as follows: In any task I did not want the participants to play  $TDP_{CS}$  before playing  $TDP_{CNS}$ . This was done to eliminate learning effects [55]. As constraints are explicitly specified in  $TDP_{CS}$ , knowledge of the constraints may interfere with the performance in  $TDP_{CNS}$ . Thus, I eliminate three of the permutations of the order of execution of the three experiment tasks.

Table 2.2. : Treatments and number of participants in each treatment

Treatment Order	Number of Participants
$TDP_{CNS} - FOP_{CNS} - TDP_{CS}$	15 participants
$TDP_{CNS} - TDP_{CS} - FOP_{CNS}$	15 participants
$FOP_{CNS} - TDP_{CNS} - TDP_{CS}$	14 participants

Each order of the experimental tasks, as shown in Table 2.2, is termed as a *treatment*. Each participant was a part of one of these three treatments. Each experimental task within a treatment consisted of 7 *periods*. In each period, the objective function was randomly generated. In particular, the objective function parameter  $H$  was randomly chosen from a uniform distribution between 400 to 800 units.

Each period consisted of seven (7) fixed number of tries. A *try* is defined to be a submission of one sampled  $w$  (or  $x$  for FOP) value. A *successful try* is defined as one in which the constraint in Equation 2.19 is satisfied. Otherwise, the try is termed unsuccessful. For all the tasks, at the end of each successful try, the value of the objective function was shown. Additionally, for TDP, an animation of the ride was shown to the participants.

The incentive structure for the participants was designed as follows. Participants were paid based on their performance to align incentives with the task objective of

obtaining the maximum value. I do so by obtaining a ratio of the maximum function value obtained by the participant in a period to the actual maximum achievable value. This ratio is multiplied with a constant value of \$2.5. Thus, the participants can achieve a maximum incentive of \$2.5 in each period. To control for wealth effects [57], the participants are informed that for any task they would be paid for their performance in two randomly chosen periods of that task. As there are a total of three tasks the participants can earn a maximum of \$15. Additionally, they are given \$5 as a participation fee.

### 2.4.3 Metrics Utilized for Hypothesis Formulation and Testing

I describe the metrics utilized to quantify the factors under investigation in this chapter. I list these factors in Table 2.3.

Table 2.3. : List of factors under investigation in this chapter and their method of measurement

Factor	Method of Measurement or Control	Measure or Control	Output
Domain Knowledge	Concept Inventory Scores	$S$	Performance is measured by averaging all the function values sampled in a given period over the total number of tries in the period
Lack of Knowledge	Experimental Data and Model	$\mu_b^{\text{diff}}$	
Deviation from ideal strategy	Experimental Data and Model	$\sigma$	
Constraint Specification	Constraint is either specified or not in the problem statement	Experimental Control	
Problem Framing	Problem is framed as a Track Design Task and a Function Maximization Game	Experimental Control	

I consider domain knowledge as the general conceptual knowledge of an individual about a specific domain. I quantify an individual's domain knowledge through the test-scores of a Concept Inventory. In this specific study, I utilize the test-scores  $S$  of the Force Concept Inventory (FCI) [44]. The FCI quantifies an individual's knowledge



of Newtonian concepts of force. These concepts are required to comprehend the constraints in the track design tasks. The FCI has been validated utilizing Item Response Theory [58]. An FCI score ranges from 0 to 30. A score of less than 15 is considered as a low score [58]. Shergadwala et al. [59] discuss how FCI scores can be utilized to assess the performance of individuals in a design context. Other metrics such as a student's GPA or subject specific grades cannot be utilized to assess their performance as they are inconsistent across universities and lack verification.

An individual's lack of knowledge ( $\mu_b^{\text{diff}}$ ) is defined as the distance of an individual's belief about the location of the constraint boundary from the actual location. The hyperparameter  $\mu_b$  represents an individual's mean prior belief about the location of the constraint boundary. The actual location of the constraint boundary is  $b_{\text{actual}} = \sqrt{200H}$  (refer to Equation 2.19). Thus, an individual's lack of knowledge is quantified as,

$$\mu_b^{\text{diff}} = |\mu_b - b_{\text{actual}}|. \quad (2.20)$$

As  $\mu_b^{\text{diff}}$  estimates the distance between actual constraint boundary  $b_{\text{actual}}$  and the hyperparameter  $\mu_b$ , intuitively a smaller  $\mu_b^{\text{diff}}$  means a lesser lack of knowledge. This implies a better state of knowledge about the constraints. It is to be noted that  $\mu_b^{\text{diff}}$  is specific to the class of problems where there are inequality constraints.

I quantify an individual's deviation from the modeled SIADM strategy through the hyperparameter  $\sigma$ . The decision-making data of the individuals obtained from the experiments is utilized to infer the parameters  $\mu_b$  and  $\sigma$  as discussed in Section 2.3.9. Problem framing is controlled by formulating the Track Design Problem TDP and Function Optimization Problem FOP.

The performance of an individual is measured as follows: For a given objective function in a given period I average the  $f(x)$  values over all the tries (tries and periods are defined in Section 2.4.2). For example, if an individual sampled  $\{x_1, \dots, x_T\}$  sequentially in a design space to receive  $\{f(x_1), \dots, f(x_T)\}$  then the average of the  $f(x)$  values achieved over  $T$  tries is considered as the person's performance. I do so

to reduce the effects of guessing the maximum value or randomly sampling a high function value.

#### 2.4.4 Hypotheses Formulation and Operationalization

I list all the hypotheses and their corresponding operationalization in Table 2.4.

Table 2.4. : Operationalization of Hypotheses

Research Objective	Hypotheses	Operationalized Hypotheses
1.1 To quantify the impact of domain knowledge on SIADM process and outcomes.	H1: Domain knowledge affects the initial state of knowledge of a SIADM task.	H1*: Average $\mu_b^{\text{diff}}$ is a decreasing function of the FCI score.
	H2: Domain knowledge affects design performance.	H2*: Average enjoyment value achieved by a participant in the Track Design Game is an increasing function of their FCI score.
	H3: Domain knowledge affects SIADM strategy.	H3*: Average $\sigma$ value is a decreasing function of the FCI score.
1.2 To quantify the impact of problem framing on the SIADM outcomes.	H4: Participants will have a better state of knowledge about a domain dependent problem as compared to a domain-independent problem.	H4*: Participants will have a lower average $\mu_b^{\text{diff}}$ in the Track Design Game than in the Function Maximization game.
	H5: Participants will have a better performance in a domain dependent problem as compared to a domain-independent problem.	H5*: Participants will have a higher average function value in the Track Design Game than in the Function Maximization game.
	H6: Participants will have a better state of knowledge about the problem where constraints are specified as compared to a problem where constraints are not specified.	H6*: Participants will have lower average $\mu_b^{\text{diff}}$ in the Track Design Game where the information about the constraint is specified (TDP <sub>CS</sub> ) as compared to the Track Design Game where the information about the constraint is not specified (TDP <sub>CNS</sub> ).
	H7: Participants will have a better performance in a problem where constraints are specified as compared to a problem where constraints are not specified.	H7*: Participants will have a higher average enjoyment value in the Track Design Game where the information about the constraint is specified (TDP <sub>CS</sub> ) as compared to the Track Design Game where the information about the constraint is not specified (TDP <sub>CNS</sub> ).
	H8: Problem framing impacts SIADM strategy.	H8*: Participants have a lower average $\sigma$ in the Track Design Game than the Function Maximization game.

I reiterate that the state of knowledge of an individual at each step  $t$  in a SIADM process affects the decisions in the next step ( $t+1$ ). Therefore, I consider H1\* and H2\* where conditional on the design task to encompass the domain knowledge (Newtonian force concept in this case) I hypothesize that the FCI score will negatively correlate with the lack of knowledge parameter  $\mu_b^{\text{diff}}$  and positively correlate with performance.

The “decision making error”  $\sigma$  can be considered as the deviation of an individual’s search strategy from the assumed search strategy. I hypothesize (H3\*) that an individual with a higher domain knowledge will closely follow the modeled strategy.

By framing the same mathematical problem as a track design task and a function maximization task I hypothesize (H4\*) that the participants will have a better understanding about the track design task which implies a smaller  $\mu_b^{\text{diff}}$  for the track design task. As a consequence of better understanding the track design task, I also hypothesize (H5\*) that the participants will have a better performance in the track design task as compared to the function optimization problem.

As  $\mu_b^{\text{diff}}$  quantifies the belief the about constraints, I formulate H6\*. Since the participants are given the constraint boundary in  $\text{TDP}_{\text{CS}}$  the  $\mu_b^{\text{diff}}$  will be smaller as compared to  $\text{TDP}_{\text{CNS}}$ . As the information about the constraint boundary is provided, participants will be able to make better decisions and perform better. Thus, I formulate and operationalize H7\*. I formulate H8\* by hypothesizing that participants will follow the modeled strategy closely for a domain-specific task as compared to a domain-independent task.

## 2.5 Results and Discussion

I utilize the data, collected from the experiment described in Section 2.4, to infer the model parameters  $\theta$ . Based on these parameters and the experimental data, I test hypotheses H1\* to H8\* in this section. I then discuss the implications of each of the hypothesis test results. Table 2.4 categorizes H1\* to H8\* with respect to my research objective that is divided into two parts. The first part of the research objective is

related to the domain knowledge and the second part is concerned with problem framing.

### 2.5.1 Hypotheses Testing

I categorize H1\* through H3\* as hypotheses related to person-specific factors that are conceptual knowledge (FCI Score) and lack of knowledge about the constraints ( $\mu_b^{\text{diff}}$ ). H4\* to H8\* are categorized as hypotheses related to problem-specific factors such as problem framing and constraint specifications in the problem. For each individual, their  $\mu_b^{\text{diff}}$ ,  $\sigma^2$ , and performance are averaged over all but first two periods. As the participant gets familiar with the task I disregard data from the first two periods for each task to reduce the impact of learning effects [55].

#### Hypotheses Testing: Person-specific factors

To understand the impact of person-specific factors (FCI score and  $\mu_b^{\text{diff}}$ ) in a SIADM task, I test H1\* through H3\*. I investigate the impact of knowledge about the Newtonian concepts of force (quantified by the FCI scores) only in the tasks that require that conceptual knowledge. As FOP does not require knowledge of Force Concepts I do not investigate the impact of FCI scores on an individual's performance in FOP.

I test H1\* by conducting a regression analysis between FCI scores and  $\mu_b^{\text{diff}}$ . The results of H1\* indicate that there is no significant linear relationship between FCI score and the lack of knowledge about the constraints  $\mu_b^{\text{diff}}$  ( $p = 0.22 > 0.05$ ). The ANOVA results for FCI score versus  $\mu_b^{\text{diff}}$  is shown in Table 2.5. The scatter plots for FCI score versus  $\mu_b^{\text{diff}}$  are shown in Figure 2.4.

Table 2.5 illustrates that the participant's lack of knowledge about the constraints ( $\mu_b^{\text{diff}}$ ) was not significantly affected by their conceptual knowledge of Newtonian force concepts (FCI scores). I recognize that FCI scores and  $\mu_b^{\text{diff}}$  are direct and indirect measures of an individual's knowledge about the problem, respectively. The impact

Table 2.5. : ANOVA of FCI score and  $\mu_b^{\text{diff}}$  in track design tasks.

Metric	ANOVA with $\mu_b^{\text{diff}}$	
	TDP <sub>CNS</sub>	TDP <sub>CS</sub>
FCI Score	$r = 0.19$	$r = -0.24$
$S$	$p = 0.22$	$p = 0.11$

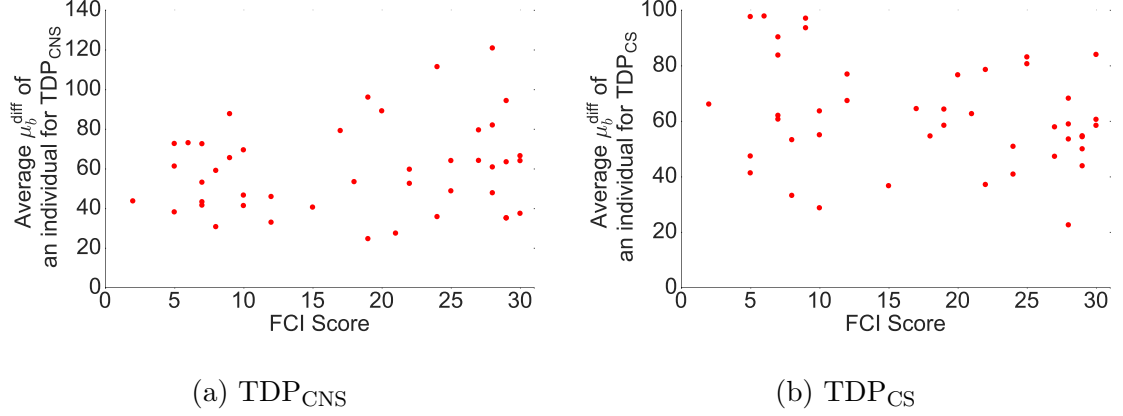


Figure 2.4. : Scatter plots for H1\*

of domain knowledge on the state of knowledge may be reduced due to learning effect [55].

I test H2\* by conducting a regression analysis between FCI scores and performance. The ANOVA results for FCI score versus performance are shown in Table 2.6. The scatter plots for FCI score versus performance are shown in Figure 2.5. The figure illustrates that individuals with a greater FCI score have a higher performance with lesser variation. This implies that individuals with a higher FCI score are likely to perform better. In both the track design tasks, the results of H2\* indicate a significant ( $p < 0.05$ ) weak positive linear relationship ( $0.25 < r \leq 0.5$ ) between FCI scores and performance.

Table 2.6 indicates that there is a significant ( $p < 0.05$ ) linear relationship between an individual's conceptual knowledge of the Newtonian Concepts of Force and the TDP tasks that require such knowledge. However, as the correlation is weak ( $0.25 < r \leq 0.5$ ) the FCI scores cannot be solely utilized to predict an individual's performance

Table 2.6. : ANOVA of FCI score and performance in track design tasks.

	ANOVA with performance	
Metric	TDP <sub>CNS</sub>	TDP <sub>CS</sub>
FCI Score	$r = 0.31$	$r = 0.48$
$S$	$p = 0.042$	$p < 0.001$

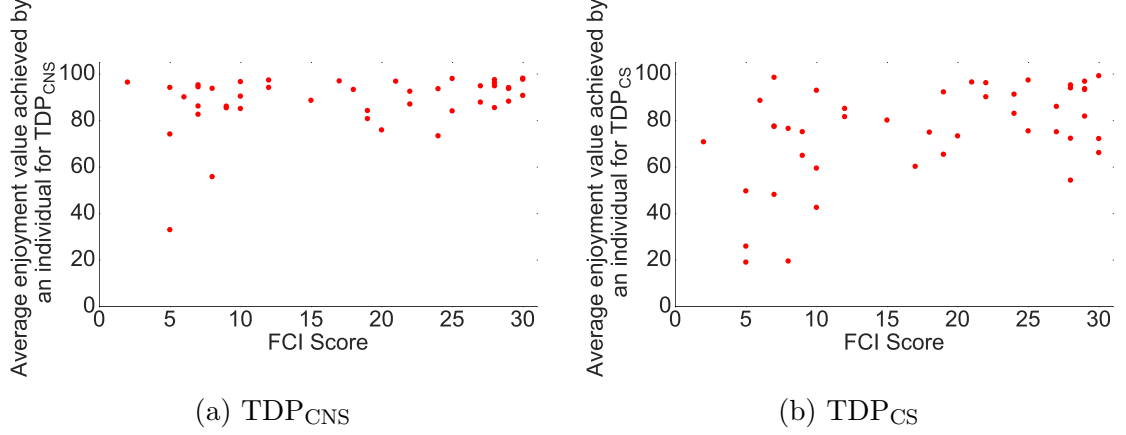


Figure 2.5. : Scatter plots for H2\*

in different SIADM scenarios. While FCI score may be a good metric for conceptual knowledge quantification, further investigation is required to differentiate direct and indirect measures of knowledge and their subsequent impact on SIADM outcomes.

I test H3\* by conducting a regression analysis between FCI scores and  $\sigma$ . The results of H3\* indicate that there is a significant ( $p < 0.05$ ) linear relationship between FCI score and the deviation ( $\sigma$ ) of an individual from the modeled strategy for TDP<sub>CS</sub>. However, as the correlation is weak ( $0.25 < r \leq 0.5$ ) the FCI scores cannot be solely utilized to predict an individual's deviation from the SIADM model. The p-value for TDP<sub>CNS</sub> is less than the level of significance  $\alpha = 0.05$ . The ANOVA results for FCI score versus  $\sigma$  are shown in Table 2.7. The scatter plots for FCI score versus  $\sigma$  are shown in Figure 2.6.

Table 2.7 illustrates that when the constraints are specified, an individual's domain knowledge affects how closely the individual followed the modeled strategy. The variation of performance of the individuals with low FCI score is indicated in Fig-

Table 2.7. : ANOVA of FCI score and  $\sigma$  in track design tasks.

Metric	ANOVA with $\sigma$	
	TDP <sub>CNS</sub>	TDP <sub>CS</sub>
FCI Score	$r = -0.26$	$r = -0.38$
$S$	$p = 0.09$	$p = 0.01$

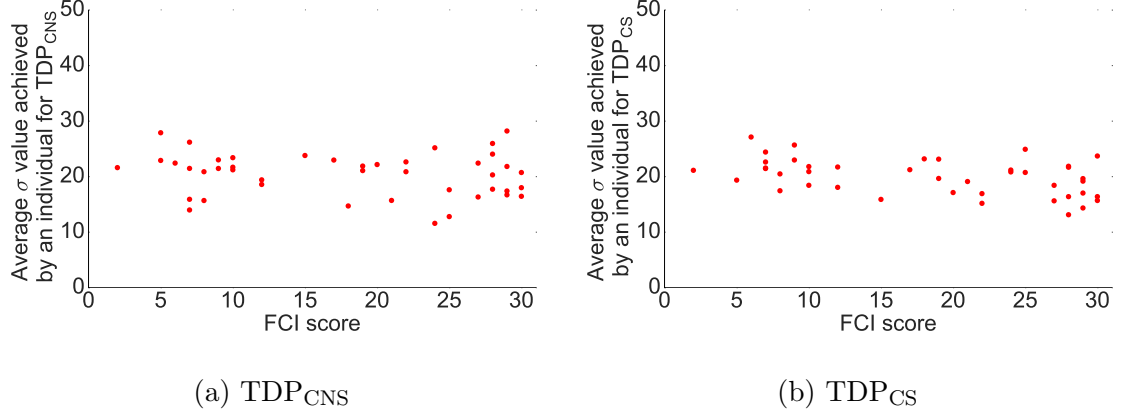


Figure 2.6. : Scatter plots for H3\*

ure 2.5. This variation may be explained by the results of H3\* that people with higher FCI score tend to follow the modeled strategy closely, and that may impact their performance. A greater and significant correlation in the track design task where constraints are specified may be due to the order of the track design tasks. As TDG<sub>CS</sub> is always played after TDG<sub>CNS</sub>, it may result in learning effect [55] such that the participants get closer to the modeled strategy after repeatedly playing the track design task.

### Hypotheses Testing: Problem-specific factors

To test H4\* I compare the average  $\mu_b^{\text{diff}}$  of an individual in TDP and FOP by conducting a paired two sample t-test. The hypothesis test results for H4 indicate that  $\mu_b^{\text{diff}}$  is indeed lower in the Track Design Games than the Function Maximization Game ( $p < 0.05$ ). Therefore, the state of knowledge about the constraints in the

Track Design Game is better than the Function Maximization Game. I conclude that problem framing impacts the lack of knowledge about the constraints. The results are shown in Table 2.9. The mean and variance of the average  $\mu_b^{\text{diff}}$  value for TDP ( $\alpha_\mu^{\text{TDP}}, \gamma_\mu^{\text{TDP}}$ ) and the mean and variance of the average  $\mu_b^{\text{diff}}$  value for FOP<sub>CNS</sub> ( $\alpha_\mu^{\text{FOP}}, \gamma_\mu^{\text{FOP}}$ ) are shown in Table 2.8.

Table 2.8. : Mean ( $\alpha$ ) and variance ( $\gamma$ ) of the average  $\mu_b^{\text{diff}}$  values in TDP and FOP

Game	Average $\mu_b^{\text{diff}}$	
	Mean $\alpha$	Variance $\gamma$
<b>TDP<sub>CNS</sub></b> Sample size=44	$\alpha_\mu^{\text{TDP}} = 59.59$	$\gamma_\mu^{\text{TDP}} = 499.46$
<b>TDP<sub>CS</sub></b> Sample size=44	$\alpha_\mu^{\text{TDP}} = 61.95$	$\gamma_\mu^{\text{TDP}} = 353.51$
<b>FOP<sub>CNS</sub></b> Sample size=44	$\alpha_\mu^{\text{FOP}} = 79.11$	$\gamma_\mu^{\text{FOP}} = 1694.84$

Table 2.9. : Summary of the two sample t-test for H4\*

	Alternate Hypothesis	t stat.	p-value
<b>Two sample t-test for TDP<sub>CNS</sub></b>	$\alpha_\mu^{\text{FOP}} > \alpha_\mu^{\text{TDP}}$	-2.66	0.0054
<b>Two sample t-test for TDP<sub>CS</sub></b>	$\alpha_\mu^{\text{FOP}} > \alpha_\mu^{\text{TDP}}$	-2.33	0.012

I failed to reject the null for H6\* ( $p = 0.6$ ) and H7\* ( $p = 0.59$ ). This means that while  $\mu_b^{\text{diff}}$  is indicative of an individual's lack of knowledge about the constraints in domain dependent and independent task, it does not capture the effect of providing information about the constraints for the same task. Learning about the task may interfere with providing information about constraints in one task and not in the other. If the lack of knowledge about the constraints is descriptively captured through  $\mu_b^{\text{diff}}$ , its value should ideally be zero when the participants know exactly where the constraint boundary lies. However, I do not observe a significant difference between  $\mu_b^{\text{diff}}$  values in TDP<sub>CNS</sub> and TDP<sub>CS</sub>.

To test H5\* I compare the performance of the participants in both the track design games with the function maximization game. I conducted a paired two sample t-test.



The results are shown in Table 2.10. Both the p-values are less than the level of significance ( $\alpha = 0.05$ ). This indicates that the performance of the participants was indeed better in both the track design tasks as compared to the function maximization task. The mean and variance of the average enjoyment value for TDP ( $\alpha_E, \gamma_E$ ) and the mean and variance of the average function value for FOP<sub>CNS</sub> ( $\alpha_F, \gamma_F$ ) are shown in Table 2.11.

Table 2.10. : Summary of the two sample t-test for  $H5^*$

	<b>Alternate Hypothesis</b>	<b>t stat.</b>	<b>p-value</b>
<b>Two sample t-test for TDP<sub>CNS</sub></b>	$\alpha_E > \alpha_F$	12.10	$< 0.00001$
<b>Two sample t-test for TDP<sub>CS</sub></b>	$\alpha_E > \alpha_F$	5.90	$< 0.00001$

Table 2.11. : Mean ( $\alpha$ ) and variance ( $\gamma$ ) of the average enjoyment values  $E$  in TDP and average function values  $F$  in FOP

<b>Game</b>	<b>Average output value</b>	
	<b>Mean</b> $\alpha$	<b>Variance</b> $\gamma$
<b>TDP<sub>CNS</sub></b> <b>Sample size=44</b>	$\alpha_E = 88.54$	$\gamma_E = 141.75$
<b>TDP<sub>CS</sub></b> <b>Sample size=44</b>	$\alpha_E = 75.36$	$\gamma_E = 428.34$
<b>FOP<sub>CNS</sub></b> <b>Sample size=44</b>	$\alpha_F = 58.61$	$\gamma_F = 369.43$

The results shown in Table 2.10 indicate that problem framing of the same mathematical task does indeed affect the task performance [43]. I do not find a significant difference between performance in the two track design tasks. The result indicates that providing information about the design space did not significantly impact the task outcome. The result could be influenced due to lack of control over search strategies of different individuals in the track design tasks as well as the learning effect [55]. There could also be a potential for bias in the second track design game play (TDP<sub>CS</sub>) due to the previous track design game play (TDP<sub>CNS</sub>).

I failed to reject the null of  $H8^*$  ( $p = 0.23$ ). Thus, there is no significant difference of the average  $\sigma$  in the Track Design Games and the Function Maximization Game.

Table 2.12. : Summary of Hypothesis Results.  $\checkmark$  indicates rejection of null and  $\times$  indicates failure of null rejection.

Hypotheses	Results	Hypotheses	Results
(H1*)	For $TDP_{CS}$ : $\times$ For $TDP_{CNS}$ : $\times$	(H5*)	$\checkmark$
(H2*)	For $TDP_{CS}$ : $\checkmark$ For $TDP_{CNS}$ : $\checkmark$	(H6*)	$\times$
(H3*)	For $TDP_{CS}$ : $\checkmark$ For $TDP_{CNS}$ : $\times$	(H7*)	$\times$
(H4*)	$\checkmark$	(H8*)	$\times$

I cannot conclude that problem framing impacts an individual's deviation from the modeled SIADM strategy.

### 2.5.2 Hypotheses Tests: Discussion

I summarize the results of the hypothesis test in Table 2.12. The hypothesis test results indicate that framing a SIADM task in a domain specific context decreases an individual's lack of knowledge about the problem constraints. Such problem framing also positively impacts an individual's performance. I conclude that the FCI scores a weak but a significant correlation with an individual's performance in a SIADM task and therefore can be utilized as preliminary indicator of the impact of domain knowledge on performance. Also, I do not find any significant differences in participant's performance across treatments.

It is to be noted that the participants take the FCI test before solving the design problem. This may result in the participants inferring that the design problems involve Newtonian concepts of force. Such inference minimizes the impact of a participant's ability to recall the force concepts and thus, it strengthens the validity of the results of the correlations between FCI scores and performance. The weak correlations indicate the need towards developing descriptive measures of knowledge such as  $\mu_b^{\text{diff}}$ .

From Hypothesis 4, I wanted to leverage the truth that participants will have a better state of knowledge about the domain-specific track design problem than about the function optimization problem due to problem framing. I indeed find that  $\mu_b^{\text{diff}}$  is lower in the track design game than the function optimization game. Based on this, I verify that  $\mu_b^{\text{diff}}$  is indicative of an individual’s state of knowledge. This result justifies the most important modeling assumption in this study that the distance of an individual’s belief about the location of the constraint boundary from the actual location represents their lack of knowledge about the task constraints.

I do not observe a relationship between conceptual knowledge and an individual’s lack of knowledge about the problem constraints. This observation may be because the FCI score of an individual remains the same throughout the study whereas  $\mu_b^{\text{diff}}$  varies over successive periods. The variation of  $\mu_b^{\text{diff}}$  implies variation of the lack of knowledge about the feasible design space. This variation may be due to the randomization of feasible design space and its impact on learning about the task problem over multiple periods of the game play.

## 2.6 Discussion

In this section, I discuss the SIADM framework as a contribution of this study. Then, I discuss about the validity of the research results and the generalizability of the model for extending the proposed framework.

### 2.6.1 Contributions

The primary contribution of this study is a SIADM framework which is instantiated by presenting a SIADM model in conjunction with a behavioral experiment for a class of design problems. Such a framework enables us to understand how individuals sequentially acquire information and make decisions in a design context. I quantify the impact of factors, such as problem framing and an individual’s lack of domain knowledge, on the SIADM outcomes of a design search problem with constraints.

I find that problem framing impacts an individual’s knowledge about the problem constraints as well as their performance.

I represent a SIADM process as one that consists of three activities as illustrated in Figure 2.1 and described in Section 2.3.1. I make specific modeling choices for these three activities in my SIADM model as discussed in Section 2.3.7. Specifically, I assume that individuals maximize the expected improvement in the objective function, and follow a myopic one-step look-ahead strategy for calculating the expected improvement. Based on these assumptions, I study the impact of factors, such as problem framing and an individual’s lack of domain knowledge, on the SIADM outcomes.

The proposed model can be utilized to investigate behavioral similarities and differences among individuals. Specifically, individuals can be categorized based on the combinations of  $\mu_b^{\text{diff}}$  and  $\sigma$ . In the future, their behavior and SIADM outcomes can be compared across such categorizes to study the influence of both domain knowledge and following a particular SIADM model.

### 2.6.2 Validity

The experimental study has high internal validity as it is a controlled behavioral experiment [60]. Internal validity refers to ensuring that the observed effect on the SIADM activities is attributable to the factors identified as a cause. I control for other factors such as an individual’s learning, intuition, the order of experiment task execution, incentivization of the experiment tasks, and the similarity of the search tasks in TDP and FOP that also affect a participant’s decision-making (refer to Section 2.4).

External validity refers to the generalization of the research study [61]. As in any controlled experiment, the external validity depends on how well the experimental conditions represent the target setting. The SIADM framework that consists of the three activities of a SIADM process, as illustrated in Figure 2.1, is highly general. Any

sequential information acquisition activity in the design process can be represented using this framework. The SIADM model, on the other hand, is more specific because it has been instantiated for a particular class of design problems. These problems have a single objective and a single constraint with a single design variable. Consequently, the defined model parameter  $\mu_b^{\text{diff}}$  is specific to the problems with single inequality constraints. In order to utilize the model in more complex design scenarios, various aspects of the proposed model such as its parameters and the SIADM activities will have to be appropriately considered. For example, in a design problem with multiple constraints,  $\mu_b^{\text{diff}}$  could be considered as a set of parameters. Similarly, a problem with multiple objectives will impact the way an individual updates their beliefs about the objectives using Bayesian updating. Further investigation is required to evaluate the effects of complexity on the SIADM model formulation. I also acknowledge that in reality, individuals may cognitively execute the three activities in a SIADM scenario differently. I do not test whether the proposed model is representative of how individuals follow a SIADM process. To investigate the representativeness of an individual's SIADM process by the proposed model there lies a need to develop alternate descriptive models of SIADM. Then, such models can be compared using Bayesian model comparison to evaluate which model best represents the decision making strategy followed by the individuals. This is a promising avenue for further research in this direction.

The external validity of the proposed framework can also be assessed by how well the model applies to different experimental settings such as (a) different populations (b) different design problems, and (c) different SIADM factors. The experimental study has been carried out with undergraduate and graduate engineering students. It is not clear how well these results will extend to practicing engineers who have other implicit as well as procedural knowledge. In real life settings, SIADM scenarios are more complex with multiple objectives and multiple constraints. My study does not account for the effects of complexity as a factor on SIADM scenarios. I do believe that it is likely that different ways of increasing complexity affects behaviors in different

ways. As the complexity grows, other factors such as the manner in which information is presented also affects the behaviors. For example, if there are two or more variables, the visual representation of the acquired data ( $x$  and  $f(x)$ ) affects how individuals process information and make decisions. With increasing complexity, computational tools (e.g., surrogate models) are needed to support designers. The behavior then depends on the types of computational tools used. To assess the ecological validity in such settings, I can not only perform experiments but also conduct interviews, surveys, and case studies. All these effects cannot be captured in a single experiment. Therefore, the complexity of the problem and its effects on information acquisition strategies adopted by humans requires further investigation.

While the SIADM framework is developed for individual SIADM scenarios, in the subsequent chapters, it is used as a component within the design contests. Also, more complex design settings can be studied such as design teams where multiple designers make decisions in parallel. For example, my framework can be used to model a team member making sequential decisions within a team. However, further investigation would be required to understand how the three activities of a SIADM process would be affected based on the interactions of an individual with their team members on every iteration step of a team member's SIADM process. Studying design teams is out of the scope of this dissertation.

### 3. QUANTIFYING THE INFLUENCE OF INFORMATION SHARING ABOUT COMPETITOR'S PERFORMANCE ON A PARTICIPANT'S SEQUENTIAL DESIGN BEHAVIORS IN DESIGN CONTESTS

#### 3.1 Chapter Overview

Existing literature on information sharing in contests has established that sharing contest-specific information influences participant behaviors, and thereby, the outcomes of a contest. However, in context of engineering design contests, such as crowdsourcing, there is still a significant gap in our understanding of how the contest design decisions, such as what information to share, influence participants' decision-making behaviors. Particularly, there is a lack of knowledge about how information about historical performances of competitors influences a participant's decision making behaviors and the outcomes of a design contest. To address this gap, the objective of this chapter is to investigate RQ2, that is, *to quantify the influence of information about competitors' past performance on a participant's decision to stop acquiring information and on the design outcomes*. The objective is achieved by (i) developing a descriptive contest model of strategic information acquisition decisions, based on an optimal one-step look-ahead strategy, utilizing expected improvement maximization, and (ii) using the model in conjunction with a controlled behavioral experiment. A behavioral experiment is conducted where design contests with design optimization problems were considered. The results in Chapter 2 indicate that domain-dependent contexts better inform contestants while making design decisions. Thus, the behavioral experiments leverage the domain-dependent task discussed in Section 2.4.1 for this study. The participants were subjected to agents with strong or weak performance records such that they were either made aware of these records or not. The results indicate that participants spend greater efforts when they are aware that their

opponent has a strong performance record than when the opponent has a weak performance record. Moreover, the model parameter is able to quantify the influence of the contest-specific information sharing on a participant’s sequential decision-making behaviors. It is observed that sharing information about an opponent with a strong past performance record “polarizes” the participants such that, some participants expend greater efforts while others choose to not compete. Thus, participants’ average performance distribution has a higher variation when they know that the opponent has a strong past performance than when they do not have information about the opponent as well as when they know that their opponent has a weak performance record. Based on the parametric inferences, it is suggested that contest designers are better off not providing historical performance records if past design qualities do not match the expectations set up for a given design contest.

### 3.2 Introduction

Existing literature in behavioral game theory has established that the design of a contest influences participant behaviors and, thereby, the outcomes of a contest [26, 27]. The design of a contest includes decisions such as what and how much information to share with the contestants [26]. Examples of various types of contest-specific information include knowledge about the organizers of the contest, the reputation of the contest, the prize of the contest, and the players in the contest [28]. It is intuitive that knowledge about such types of information can heavily influence the strategic decisions of the players. For example, in the field of sports, a lot of data about competing teams’ past performance is analyzed to make strategic decisions for a team’s gameplay such that it improves their winning probability [29, 30].

In the context of engineering design contests, such as crowdsourcing contests, a lot of information about past design contests already exists. In the previous study [62], we analyzed publicly available data on a crowdsourcing platform called GrabCAD [63]. It hosts crowdsourcing contests by organizations such as NASA and DARPA. The



GrabCAD data included information about past contests such as the winning solutions, the associated winners, and the overall participants [62]. A cursory visit to other crowdsourcing platforms such as Innocentive [64] and Ennomotive [65] also established that the past contests' information is readily available. Similarly, product design contests between companies such as Apple and Samsung are also influenced based on the information about the past products of their competitors. Availability of such information educates the participants about the history of such contests which influences their behavior [66]. There is a lack of understanding of how such information about past contests influences a participant's decision-making behaviors. 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.

There is extensive literature on information sharing in contests within behavioral economics [26,31–34]. However, research in behavioral economics does not address the nuances of engineering design scenarios. For example, designers in engineering design processes typically iterate through several design solutions before making artifact decisions. Each of these iterations involves information acquisition activities that allow the designers to explore the design space and update their state of knowledge about them. Sharing contest-specific information influences a designer's information acquisition activities, and thereby, the quality of design solutions. Thus, there lies a need to understand how contest-specific information sharing influences designer behaviors in an engineering design process.

In this study, I investigate the influence of information about the past performance of opponents on participants' design behaviors. The influence of such type of contest-specific information is investigated as it is readily available to the participants on popular crowdsourcing platforms that host engineering design contests. Qualitatively, it is intuitive that a contestant can believe that contests with opponents who have “strong” past performance records would be more competitive than contests

where opponents’ past performances have been “poor.” However, in the context of engineering design, there is a lack of contest models that quantify the influence of such information on designer behaviors. Therefore, in this study the objective is to *quantify the influence of information about competitors’ past performance on a participant’s design behaviors and outcomes.*

My approach consists of two steps. First, I model the influence of past performance record of an opponent on a participant’s strategic decisions. I extend the SIADM model as discussed in Chapter 2, by considering a design contest. The extended model is described in Section 3.3. It is based on the assumptions that individuals strive to maximize their expected payoff and use the Bayesian approach to update their state of knowledge based on new information. Second, I design and execute a *behavioral experiment*. The results in Chapter 2 indicate that domain-dependent contexts better inform contestants while making design decisions. Thus, the behavioral experiments utilize the domain-dependent task discussed in Section 2.4.1 for this study. I utilize experimental data to estimate parameters in the model and to test hypotheses about the influence of past performance record on design outcomes. In the experiment, I control for past performance information by designing an agent as an opponent to the participants. The details of the experiment are provided in Section 3.4. The results are discussed in Section 3.5. Finally, I discuss the implications of this study, the validity of the modeling assumptions, and the avenues for future research in Section 3.6.

### **3.3 A Descriptive Model of Strategic Sequential Information Acquisition and Decision Making Process**

In this section, I describe the design contest scenario, and the specific modeling choices for the type of contest, problem, and individual in the design scenario. Then, I formulate a strategic model of sequential information acquisition and decision making.

It is to be noted that uppercase notations represent random variables, such as  $X$ . Whereas, lowercase notations represent real numbers, that is, the instantiation of a random variable observed as data. For example,  $x$  is a real number observed by the researcher as an instantiation of the random variable  $X$ .

### 3.3.1 The Design Contest Scenario

In order to model a design contest scenario, I need to consider the class of design problems, the activities of the designer as a participant, and the type of contest. In the following, I make contest-specific, problem-specific, and individual-specific modeling choices by considering a typical crowdsourcing contest for engineering design problems.

#### Contest-specific modeling considerations

In this study, I model the design contest by assuming that the participant is competing against a single opponent; that is, I assume a two-player contest. I make such an assumption for three reasons. First, there are several design competition scenarios that are two-player contests such as product design competitions between Apple vs. Samsung and Boeing vs. Airbus. Similarly, subcontracting engineering design problems often have two competitors for which the modeling scenario is applicable. Second, multiplayer contests can be modeled as two-player contests where multiple opponents are reduced to a single opponent who is assumed to be the best competition that the participant encounters. This modeling assumption is reasonable if I consider a contest where the best design solution wins the contest prize. Such an incentive structure implies that participants are essentially competing against the best performing opponent in the crowd. Third, for game-theoretic modeling of design contests, it is typical to assume a two-player contest as a stepping stone for more complex scenarios [67].

Moreover, the information about the past performance records of contests typically comprises of the best past design solutions generated by the winner. Such information influences a participant’s belief about the quality of the best competing solutions that may be generated in a contest and by extension, the belief about the best competitor in the “crowd” or a participant population. Such information influences a participant’s design decisions.

### **Problem-specific modeling considerations**

A class of design problems is considered where participants are required to optimize a given design objective. For example, crowdsourcing contests organized by NASA provide a clear “figure of merit,” such as the weight for a given design artifact, that needs to be minimized. In such scenarios, participants typically utilize an engineering design process where they perform information acquisition activities, such as executing simulation models and experiments. In such activities, participants make decisions about what new information to acquire and when to stop acquiring information. Such information acquisition decisions heavily influence design outcomes and consequently, the success of a design contest.

I consider a design scenario where a designer has a design  $x$  that affects the design performance  $f(x)$ . The designer’s objective is to achieve the best design outcome. The designer does not explicitly know the mathematical relationship between the design variables and the design outcome, i.e., the function  $f(x)$ . However, they may know the qualitative relationship between the design  $x$  and the design outcome  $f(x)$  due to factors such as their domain knowledge. In such a scenario, a designer needs to acquire information about the impact of design  $x$  on the design outcome  $f(x)$ . Such information can be acquired by running (physical or computational) experiments, which incur a certain cost. Moreover, the information can be acquired sequentially or in parallel. In Section 3.3.1, I make modeling choices about how an individual acquires information.

I assume that the designers are aware of the feasible design space and the qualitative relationship between the design variables and the design outcome. I make such an assumption to control for the influence of domain knowledge on designer behaviors and outcomes in the experiment. I also align the modeled scenario with the experiment by ensuring that the function  $f(x)$  is unknown to the participants. Further details are provided about the design of the experiment in Section 3.4.

### Individual-specific modeling considerations

An individual’s information acquisition process can be broadly categorized into *sequential* or *parallel* processes [25]. An information acquisition process is sequential when information is acquired in steps, and in each step, the acquired information is used to update prior knowledge, resulting in a new state of knowledge at the end of that step. Hence, the information acquired in a sequential process affects subsequent information acquisition decisions. For example, when a designer decides what next experiment to conduct based on the result of previous experiments, the process is sequential. In parallel processes, all acquired information is analyzed at the end of the process [25]. For example, the information acquisition process is parallel when a designer executes a pre-planned set of experiments and analyzes the results of the entire set at the end. Within the context of engineering systems design, I recognize that both sequential and parallel information acquisition processes exist. However, in this chapter, I focus on modeling a single designer as a decision-maker who *sequentially* acquires information to search for an optimal design solution.

In my previous work [68], I have modeled an individual’s sequential information acquisition and decision making (SIADM) behavior. The SIADM framework consists of three main activities: acquiring information, processing information, and making decisions about where to search and when to stop the search. These activities are repeated over a sequence of steps,  $t = 1 \dots T$ . In this study, I extend the model to account for the contest-specific information known to the individual and the influ-

ence of such information on their SIADM process. I call the extended framework as a Strategic-SIADM (S-SIADM) framework because contest-specific information influences a contestant's gameplay strategy in SIADM scenarios. The S-SIADM framework is illustrated as an extension to the SIADM framework in Figure 3.1.

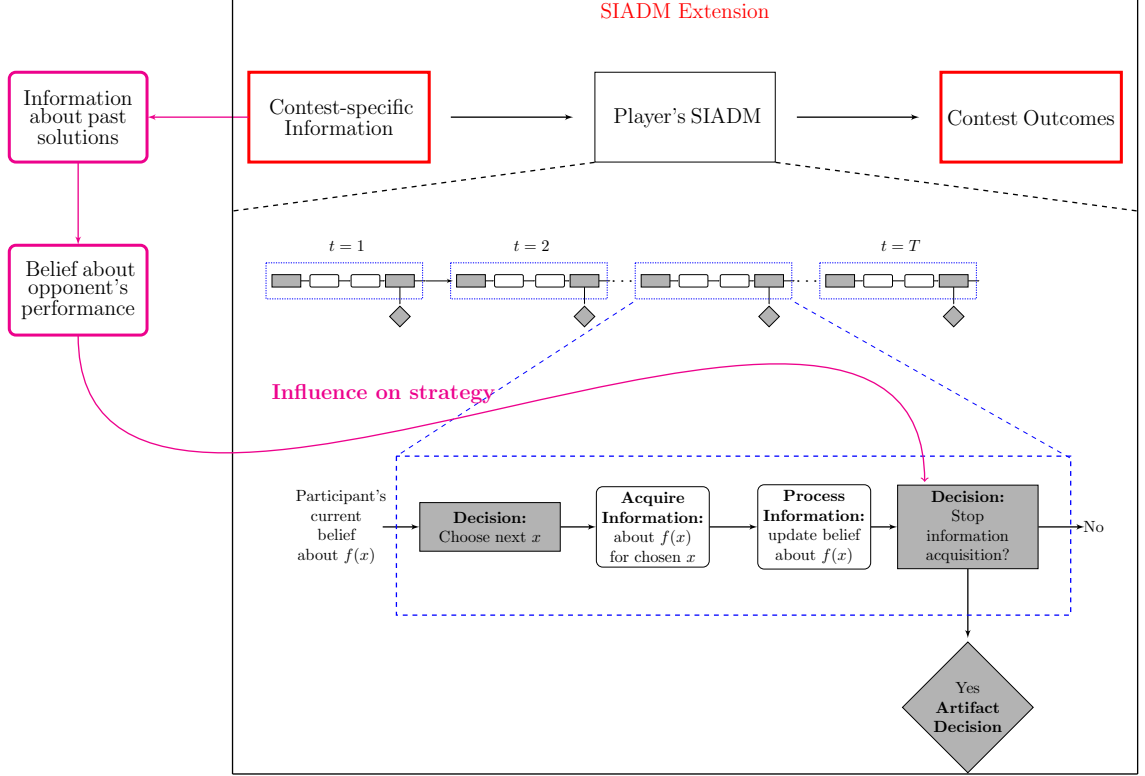


Figure 3.1. : Illustration of the Strategic Sequential Information Acquisition and Decision Making (S-SIADM) framework (red) and model (magenta). The S-SIADM framework considers the influence of contest-specific information on a player's SIADM and contest outcomes. The framework (red) is shown as an extension to the SIADM framework as discussed in Chapter 2. Decisions are highlighted in gray color. Gray rectangular nodes are information acquisition decisions, and the outcome (diamond node) of the SIADM process is making the artifact decision which is also the contest outcome for the S-SIADM framework. The modeling instance of the S-SIADM framework (magenta) considers the influence of information about past solutions on an individual's strategic decision of when to stop the search.

In this study, I assume that the cost associated with acquiring information is independent of the information that is acquired. That is, the value of the “next  $x$ ” to

choose and the experiment cost do not influence each other. Moreover, I assume that the decision to choose  $x$  is a problem-specific decision which does not get influenced by the contest-specific information, such as an opponent's historical performance records. The decision to stop, on the other hand, does get influenced by an opponent's historical performance records. For example, a participant may decide to stop in the very beginning (not participate) in a contest if they know that their opponent is "very strong". Thus, I term the decision to stop as a strategic decision made by the participant in an S-SIADM scenario. It is intuitive that the decision to stop the search influences the total cost incurred for the search problem, that is, the greater the number of experiments, the higher the cost. I control for the variability of the experimental costs by assuming that the cost associated with each information acquisition step is constant.

### 3.3.2 Information Acquired at Each Step

At each decision making step,  $t = 1, 2, \dots, T$ , the individual chooses a design  $X_t$  and receives information about the value of the objective function to be maximized,

$$Y_t = f(X_t). \quad (3.1)$$

They also decide whether to stop or not at time step  $t$ ,  $S_t = 1$  or  $0$ .

I assume that an individual begins the S-SIADM process at step  $t = 0$  with some initial information history  $\mathcal{H}_0$  which includes a single design  $X_0$  and the associated performance  $Y_0 = f(X_0)$ . At  $t = 0$  they are given a choice to enter the contest or not ( $S_0 = 1$  or  $0$ ), which is a special case of the stopping decision they consider at any other time step. Thus,

$$\mathcal{H}_0 = \{(X_0, Y_0, S_0)\}. \quad (3.2)$$

The information history  $\mathcal{H}_t$  that the individual has by the end of step  $t$  is:

$$\mathcal{H}_t = \mathcal{H}_{t-1} \cup \{(X_t, Y_t, S_t)\}. \quad (3.3)$$

The best performance (quality)  $Q_t$  of the individual at time step  $t$  is given by:

$$Q_t = \max_{1 \leq i \leq t} Y_i \quad (3.4)$$

It is to be noted that the initial information history  $H_0$  at time step  $t = 0$  is not considered to calculate  $Q_t$  as participants do not expend any effort for the given information. In other words, if participants do not enter the contest, their best quality is null.

### **The Type of an Individual**

The type  $\theta$  of an individual (i) fully specifies their prior state of knowledge about the opponent, the design objective, and how they are represented in the model, (ii) influences how they update their state of knowledge after observing  $\mathcal{H}_t$ , (iii) influences how they decide to acquire information at each time step, and (iv) influences how they decide to stop. In what follows, I have made specific modeling choices, trying to be parsimonious (to keep the number of model parameters as small as possible), while taking into account some of the cognitive limits of humans.

I leverage the SIADM model discussed in Chapter 2 to model (i) an individual's state of knowledge about the objective function, (ii) how they decide to choose the “next  $x$ ,” and (iii) how they update their state of knowledge about the objective function. It is to be noted that these activities are problem-specific. However, an individual's state of knowledge about the opponent and their decision to stop are a part of their strategic decision-making, and its modeling is an extension to the previous work.

### **Modeling an Individual's State of Knowledge**

I model the influence of providing information about the historical performance record  $R$  of an opponent as follows. By observing past information, an individual



develops “belief” about the opponent’s best solution  $B$  that they are capable of generating in a contest. I model the belief about the best solution  $B$  as a sample from a Gaussian distribution with a mean best performance  $\mu_b$  and deviation  $\sigma_b$ ,

$$B \sim N(\mu_b, \sigma_b), \quad (3.5)$$

where,  $\mu_b$  and  $\sigma_b$  are hyperparameters which are a part of the participant’s type  $\theta$ .

### Summary of the previous work

As in Chapter 2, I model an individual’s belief about the objective function as a Gaussian process (GP),

$$f \sim \text{GP}(m, c), \quad (3.6)$$

where  $m$  and  $c$  are the mean and covariance functions.

I utilize a convex mean function  $m(x)$  to model the prior belief about the objective function given by,

$$m(x) = (-0.0014 \cdot x^2 + 2.048 \cdot x - 633.7), \quad (3.7)$$

where,  $x \in \mathbb{R}$  and takes values in the range  $[350, 1000]$ . The domain of  $x$  is consistent with the domain of the design parameter given to the participants in the experiment. Moreover, the mean function is also consistent with the initial state of knowledge of the participants who know that the objective function is convex and assumed that the design objective would be maximized around the mid range of  $x$ .

The covariance function  $c(x, x')$  defines the Gaussian process’ behavior between any two points  $x$  and  $x'$ . Consistent with the previous work, I assume that the individuals use a squared exponential covariance function:

$$c(x, x') = s^2 \exp \left\{ -\frac{(x - x')^2}{2\ell^2} \right\}, \quad (3.8)$$

with unspecified signal strength  $s > 0$  and length scale  $\ell > 0$ , i.e., they assign flat priors. This form of covariance function is equivalent to the assumption that the individual believes that  $f(x)$  is infinitely differentiable and that it could have any signal strength or length scale. I am also assuming that the individuals identify the best signal strength and length scale  $\ell$  by maximizing the likelihood of the data, i.e., by solving:

$$s_t, \ell_t = \arg \max_{s, \ell} \mathcal{N}(Y_{1:t} | m(X_{1:t}), c(X_{1:t}) + \lambda I_t), \quad (3.9)$$

where  $\mathcal{N}(\cdot | \mu, \Sigma)$  denotes the PDF of the multivariate normal distribution with mean  $\mu$  and covariance  $\Sigma$ . Also, I have introduced the notation  $X_{1:t} = (X_1, \dots, X_t)$  and  $Y_{1:t} = (Y_1, \dots, Y_t)$  for the collection of all observed designs and the corresponding performances up to step  $t$ . Furthermore, I use  $m(X_{1:t}) = (m(X_1), \dots, m(X_t))$  for the mean function evaluated at all designs, and  $c(X_{1:t}) = \{c(X_i, X_j)\}$  is the covariance matrix of the designs. Finally, the matrix  $I_t$  is the  $t \times t$  identity matrix, and  $\lambda$  is a fixed parameter (I use  $\lambda = 10^{-6}$ ) added to the diagonal to ensure numerical stability.

The posterior state of knowledge of the individual about  $f(x)$  is also a GP:

$$f | \mathcal{H}_t \sim \text{GP}(m_t, c_t), \quad (3.10)$$

where,  $m_t$  and  $c_t$  are the posterior mean and covariance functions of the GP [46] when it is conditioned on  $\mathcal{H}_t$ . Specifically, the posterior mean is given by,

$$m_t(x) = m(x) + c(x, X_{1:t}) [c(X_{1:t}) + \lambda I_t]^{-1} (Y_{1:t} - m(X_{1:t})), \quad (3.11)$$

where the row vector  $c(x, X_{1:t}) = (c(x, X_1), \dots, c(x, X_t))$  is the cross covariance between the test point  $x$  and the designs observed so far  $X_{1:t}$ . The posterior covariance is:

$$c_t(x, x') = c(x, x') - c(x, X_t) [c(X_t, X_t) + \lambda I_t]^{-1} [c(x, X_{1:t})]^T, \quad (3.12)$$

where  $A^T$  is the transpose of matrix  $A$ .

I use maximization of Expected Improvement (EI) to model how humans make search decisions. EI is defined as the improvement in design performance at  $x$  over the current best quality  $Q_t$  integrated over the possible values of  $f(x)$ . The mathematical definition of EI is given by,

$$\begin{aligned} \text{EI}(x; \mathcal{H}_t) &= \mathbb{E} [\max(0, f(x) - Q_t) | x, \mathcal{H}_t] \\ &= (m_t(x) - Q_t) \Phi(Q_t | m_t(x), c_t(x, x)) + c_t(x, x) \mathcal{N}(Q_t | m_t(x), c_t(x, x)) \end{aligned} \quad (3.13)$$

Borji and Itti [49] show that maximization of expected improvement is indicative of how humans make search decisions. Thus, I model the point they choose next by:

$$X_{t+1} = \arg \max_{x \in \mathbb{R}} \text{EI}(x; \mathcal{H}_t) + \sigma Z_t, \quad (3.14)$$

where,  $Z_t$  are independent standard normal random variables, and  $\sigma > 0$  sets the level of the deviation of an individual from EI, that is, the modeled strategy to “choose  $x$ .”

### Modeling how Individuals make Stopping Decisions

As discussed earlier, the decision to stop is a strategic decision. I assume that the individual is rational from the perspective that they are trying to maximize their payoff  $\Pi$  in the contest. The stopping payoff  $\Pi_t$ , that is, the payoff a participant would receive if they were to stop at time step  $t$  is given by:

$$\Pi_t = \pi \mathbb{1}_{[B, \infty)}(Q_t) - Kt, \quad (3.15)$$

where,  $\pi$  is the prize,  $\mathbb{1}_{[B, \infty)}(Q_t)$  is an indicator function such that its value is unity if the best quality  $Q_t$  at time step  $t$  is higher than opponent’s best quality  $B$ ,  $K$  is the assumed constant cost associated with each time step  $t$ .

With the specification of the contest-specific parameters such as prize and cost, we are now in a position to visualize the plate diagram of the S-SIADM model and the

influence of various model parameters on the information acquired by the individual as illustrated in Figure 3.2.

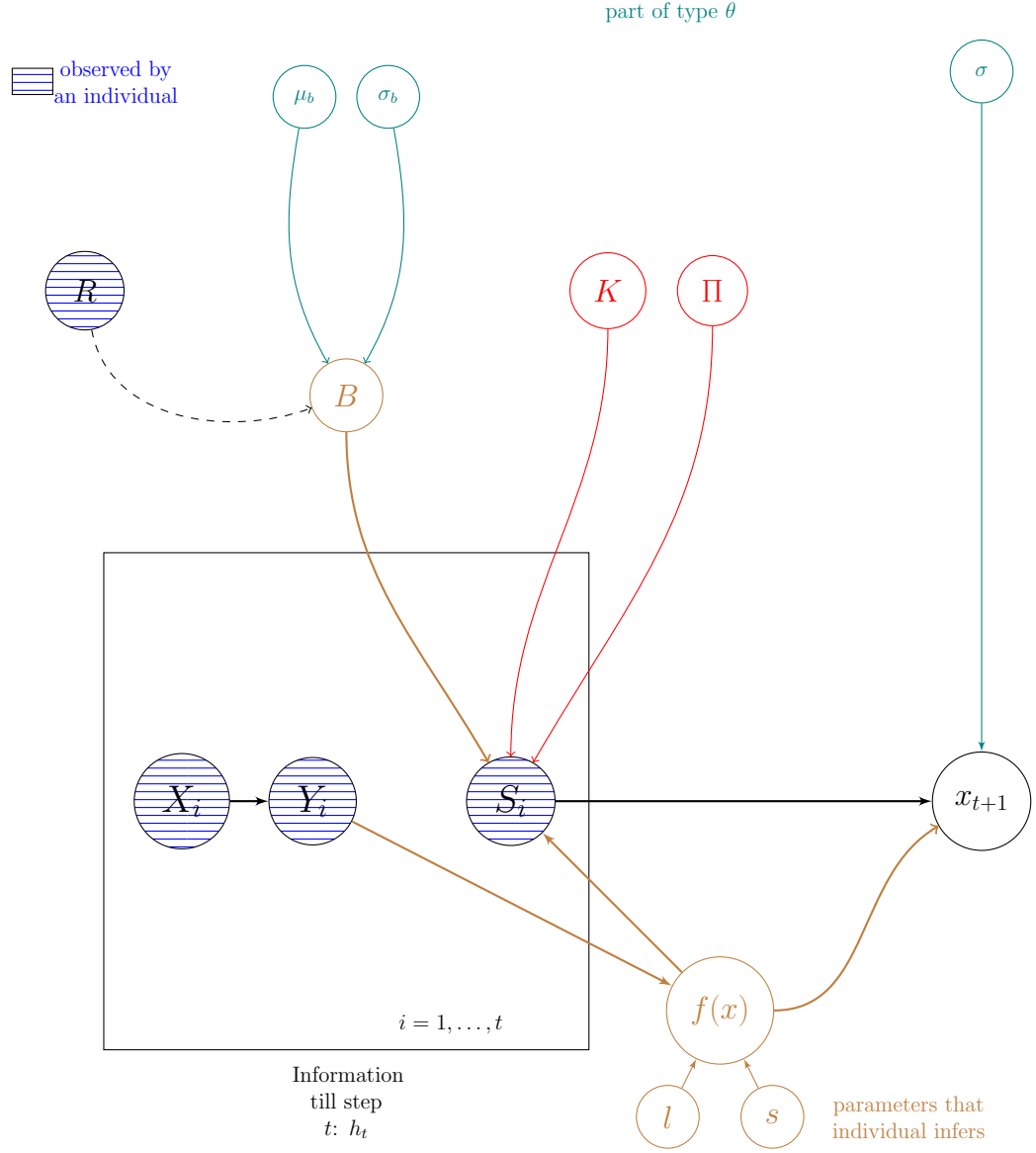


Figure 3.2. : Graphical illustration of Strategic Sequential Information Acquisition and Decision Making (S-SIADM) model at step  $t$  of the process. Individual observes an opponent's past performance ratings ( $R$ ).  $R$  is qualitative and takes discrete values of poor, average, fair, good, and great. Parameters such as participant's belief about an opponent's quality  $B$  and objective function  $l$ , and  $s$  are inferred by the individual. Parameters  $\mu_b$ ,  $\sigma_b$ , and  $\sigma$  are a part of an individual's type  $\theta$ . Based on the inferred parameters, information  $h_t$  about the function till step  $t$ , the information about the cost  $K$  of each try, and prize  $\Pi$ , the individual decides to stop  $S_i$  or not.

I model a participant's stopping decision as follows. If the expected marginal improvement in their payoff from step  $t$  to  $(t + 1)$  is negative, then they are more likely to stop. The expected marginal improvement in the payoff  $\Delta\Pi_t$  is given as,

$$\Delta\Pi_t := \mathbb{E}[\Pi_{t+1} - \Pi_t | \mathcal{H}_t] = \mathbb{E}[\Pi_{t+1} | \mathcal{H}_t] - \mathbb{E}[\Pi_t | \mathcal{H}_t]. \quad (3.16)$$

The conditioning on the history at time  $t$  indicates that the individual constructs  $\Delta\Pi_t$  after having observed it. In the language of probability theory, I say that the stochastic process  $\Delta\Pi_t$  is *filtered* by the history  $\mathcal{H}_t$ . In other words,  $\Delta\Pi_t$  is known by time  $t$ . Note that the payoff at time  $t$ ,  $\Pi_t$ , is not completely determined from the history  $\mathcal{H}_t$  up to that point because the performance of the opponent,  $B$ , has not yet been observed. I now proceed to calculate  $\Delta\Pi_t$ . I have for the first term:

$$\begin{aligned} \mathbb{E}[\Pi_t | \mathcal{H}_t] &= \mathbb{E}[\pi \mathbb{1}_{[B, \infty)}(Q_t) - Kt | \mathcal{H}_t] \\ &= \pi \mathbb{P}[Q_t \geq B | \mathcal{H}_t] - Kt \end{aligned} \quad (3.17)$$

where,  $\mathbb{P}(Q_t \geq B | \mathcal{H}_t)$  is the probability that the individual assigns to winning at step  $t$ . It is given by:

$$\mathbb{P}[Q_t \geq B | \mathcal{H}_t] = \Phi\left(\frac{Q_t - \mu_b}{\sigma_b}\right), \quad (3.18)$$

where  $\Phi$  is the cumulative distribution function of the standard normal. Note the dependence of the right-hand side on the best performance  $Q_t$  which, at time  $t$ , is completely determined by the history  $\mathcal{H}_t$ . For the other term defining  $\Delta\Pi_t$ , I have:

$$\begin{aligned} \mathbb{E}[\Pi_{t+1} | Q_t, X_{t+1}] &= \mathbb{E}[\pi \mathbb{1}_{[B, \infty)}(Q_{t+1}) - K(t+1) | \mathcal{H}_t], \\ &= \pi \mathbb{P}[Q_{t+1} \geq B | \mathcal{H}_t] - K(t+1), \end{aligned} \quad (3.19)$$

where  $\mathbb{P}[Q_{t+1} \geq B|\mathcal{H}_t]$  is the probability that the individual assigns to winning at step  $(t+1)$ . This is given by:

$$\begin{aligned}
\mathbb{P}[Q_{t+1} \geq B|\mathcal{H}_t] &= \mathbb{E} [\mathbb{P} [Q_{t+1} \geq B|\mathcal{H}_{t+1}]|\mathcal{H}_t] \\
&= \mathbb{E} \left[ \Phi \left( \frac{Q_{t+1} - \mu_b}{\sigma_b} \right) \middle| \mathcal{H}_t \right] \\
&= \mathbb{E} \left[ \Phi \left( \frac{\max\{Q_t, Y_{t+1}\} - \mu_b}{\sigma_b} \right) \middle| \mathcal{H}_t \right] \\
&= \int_{-\infty}^{\infty} \Phi \left( \frac{\max\{Q_t, y\} - \mu_b}{\sigma_b} \right) \mathcal{N}(y|m_t(X_{t+1}), \sigma_t^2(X_{t+1})) dy,
\end{aligned} \tag{3.20}$$

where  $\mathcal{N}(\cdot|\mu, \sigma^2)$  denotes the probability density function of a standard normal. Note that the integration in the last step is over the point predictive probability density of the GP at  $X_{t+1}$  with mean given by Equation 3.11 and variance given by Equation 3.12 representing the individual's knowledge about  $f(x)$ . Furthermore, the next point to choose  $X_{t+1}$  is completely determined from the history at time  $t$ ,  $\mathcal{H}_t$ , see Equation 3.14. The integral is evaluated via Monte Carlo integration using 10,000 random samples from the point predictive probability density.

Having fully specified the expected marginal payoff after stopping,  $\Delta\Pi_t$ , we are now in a position to model the individual's decision to stop. My premise is that the probability of stopping increases as  $\Delta\Pi_t$  increases. To reflect this, I model the stochastic process  $S_t$  as follows:

$$S_t = \begin{cases} 1, & \text{with probability } \text{sigm}(-\alpha\Delta\Pi_t - \beta) \\ 0, & \text{otherwise,} \end{cases} \tag{3.21}$$

and, the stopping probability is given by,

$$\text{sigm}(-\alpha\Delta\Pi_t - \beta) = \frac{1}{1 + \exp(-\alpha\Delta\Pi_t - \beta)} \tag{3.22}$$

where,  $\alpha$  and  $\beta$  are type parameters to be determined.

### 3.3.3 Inferring an individual's type from experimental observations

The goal of this section is to describe how one can infer the type of an individual  $\theta$  given a set of experimental history observations

$$h_t = h_{t-1} \cup \{(x_t, y_t, s_t)\}. \quad (3.23)$$

I proceed in a Bayesian way which requires the specification of a prior for  $\theta$ ,  $p(\theta)$ , a likelihood for  $h_t$  given  $\theta$ ,  $p(h_t|\theta)$ . The posterior state of knowledge about the type  $\theta$  is simply given by Bayes' rule:

$$p(\theta|h_t) \propto p(h_t|\theta)p(\theta), \quad (3.24)$$

and I characterize it approximately via sampling. I now describe each of these steps in detail.

Following the discussion of the previous section, I associate the type with the vector of parameters  $\theta = (\mu_b, \sigma_b, \sigma, \alpha, \beta)$ , all of which have already been defined. From a Bayesian perspective, I describe the prior state of knowledge about  $\theta$  by assigning a probability density function to them, i.e.,  $\theta$  now becomes a random vector modeling the epistemic uncertainty about the actual type. However, to highlight the distinction between  $\theta$  and the random variables I defined in the previous section, I do not capitalize  $\theta$ . Specifically, the random variables,  $X_t, Y_t, S_t$ , are associated with the subject's behavior, whereas  $\theta$  is associated with the beliefs about the statistics of  $X_t, Y_t, S_t$ .

Having no reason to believe otherwise, I assume that all components are a priori independent, i.e., the prior probability density (PDF) factorizes as:

$$p(\theta) = p(\mu_b)p(\sigma_b)p(\sigma)p(\alpha)p(\beta), \quad (3.25)$$



where,  $\sigma_b^2$ ,  $\sigma^2$ ,  $\alpha$ , and  $\beta$  are assigned an uninformative Jeffrey's prior, i.e.,  $p(\sigma_\lambda) \propto \frac{1}{\sigma_\lambda}$ , and

$$\mu_b \sim \mathcal{U}[50, 200]. \quad (3.26)$$

The range of the uniform distribution was chosen based on the design of the experiment. Note that here I have silently introduced a convenient notational convention, namely  $p(v)$ , which is the PDF of the related random variable evaluated at a given point  $v$ .

The second ingredient required for Bayesian inference of the type is the likelihood of the data  $h_t$  conditioned on  $\theta$ . This was implicitly defined in the previous section. I have:

$$p(h_t|h_0, \theta) = \prod_{r=1}^t p(h_r|h_{r-1}, \theta), \quad (3.27)$$

since the model is Markovian. For each term within the product I have:

$$p(h_r|h_{r-1}, \theta) = p(x_r|h_{r-1}, \theta)p(y_r|x_r, h_{r-1}, \theta)p(s_r|x_r, y_r, h_{r-1}, \theta), \quad (3.28)$$

where I simplify using the definition of  $h_r$ , and the fact that, according to the model, the next design point is fully determined by the previous history, the next observed performance fully determined by the design, and the stopping decision fully determined by all design-performance pairs observed thus far.

I note that while an individual's belief about the design performance  $Y$  is dependent on their type  $\theta$ , the inference about an individual's type does not depend on the value of the design performance  $y_r$  which is beyond the participant's control. From a decision-making perspective, a participant decides to choose  $x$  and decides to stop  $s_r$ . However, they do not decide the design performance. Thus, the middle term is constant with respect to  $\theta$ , and it is dropped from Equation 3.28. The first term in Equation 3.28 is,

$$p(x_r|h_{r-1}, \theta) \sim \mathcal{N}\left(\arg \max_{x \in [0, 1000]} \text{EI}(x; h_t), \sigma^2\right), \quad (3.29)$$

where, the range of  $x$  is based on the design range available to the participants in the experiment. From Equation 3.22 I get that the last term is,

$$p(s_r|x_r, y_r, h_{r-1}, \theta) = [\text{sigm}(-\alpha\delta\pi_r(\mu_b, \sigma_b) - \beta)]^{s_r} [1 - \text{sigm}(-\alpha\delta\pi_r(\mu_b, \sigma_b) - \beta)]^{1-s_r}, \quad (3.30)$$

where  $\delta\pi_r(\mu_b, \sigma_b)$  is the realization of  $\Delta\Pi_r$  of Equation 3.3.2 when  $X_r = x_r, Y_r = y_r, \mathcal{H}_{r-1} = h_{r-1}$  and for  $\mu_b$  and  $\sigma_b$  as in the conditioning  $\theta$ .

I sample from the posterior using the No-U-Turn Sampler (NUTS) [69], a self-tuning variant of Hamiltonian Monte Carlo [70] from the PyMC3 [71] Python module. I run the MCMC chain for 4000 iterations with a *burn-in* period of 500 samples that are discarded. Equation 3.24 is used to estimate the researcher's posterior over  $\theta$  for an individual given their (individual's) search data.

### 3.4 Experimental Study

To ensure consistency of the experiment with the model, the objective function  $f(x)$  is mathematically unknown to the participants. I assume that a designer receives information about the design objective  $f(x)$  with certainty; that is, the information sources are not noisy. I assume that all the participants have the same amount of problem-specific information and that an individual's domain knowledge does not affect their belief about the objective function. Thus, I assign the same GP prior belief about the objective function for all individuals in the model (refer to Section 3.3.2).

#### 3.4.1 The Track Design Game

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 track design problem as described in Section 3.4.1. 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. Further details about the design of the opponent and achieving control are provided in Section 3.4.3.

## The Task

I utilize the track design problem statement as discussed in Chapter 2. However, I modify the objective function design for the problem-context. The objective function  $E(w)$  is designed such that it satisfies requirements such as concavity, non-negativity, function parameterization, and function asymmetry in order to control for factors such as incentivization, intuition, guessing, and problem difficulty to avoid interference with the experimental results. Considering such characteristics, I model the enjoyment function through a Log-Normal function. The enjoyment ( $E(w)$ ) of the track is defined as:

$$E(w) = (0.25H^2 - 80H) \exp(0.00405) \frac{f}{w} \exp \left\{ \frac{-(\ln(w) - \ln(H) - \ln(f) - 0.0081)^2}{0.0162} \right\}. \quad (3.31)$$

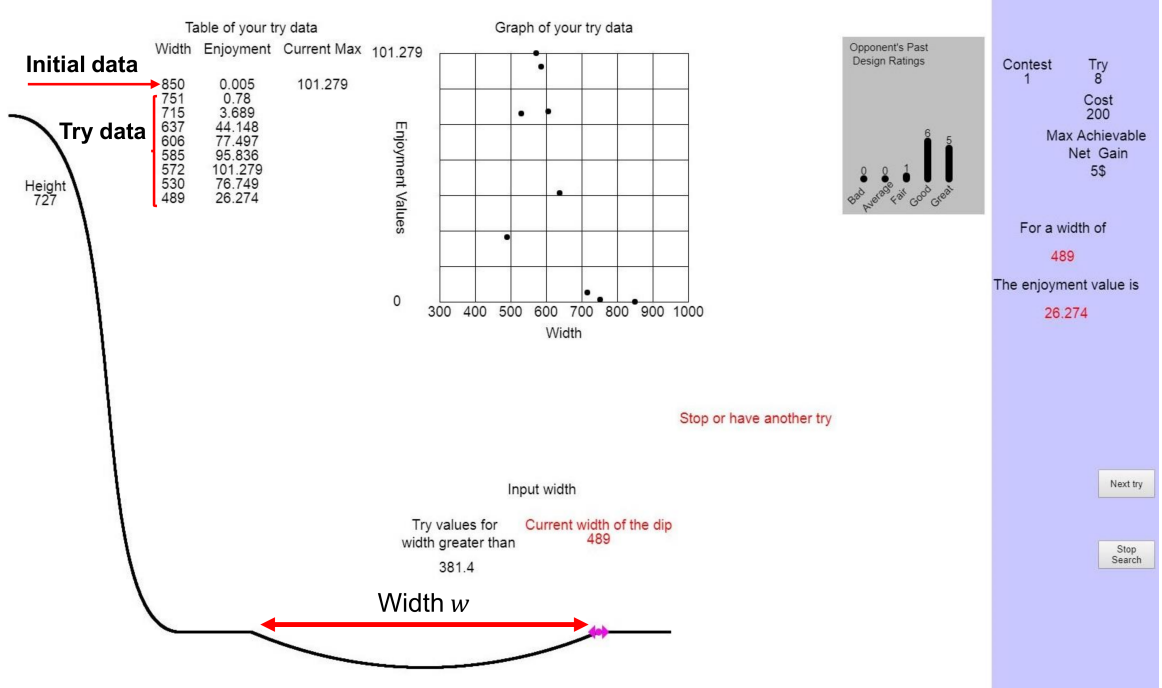


Figure 3.3. : The user interface of track design game where constraint is specified  $TDP_{CS}$

The maximum value of enjoyment function occurs at the width value  $w_{\max}$ . I model  $w_{\max}$  as a function of the track height  $H$  and a factor  $f$  such that  $w_{\max} = fH$ . The corresponding maximum enjoyment value  $E_{\max}$  is:

$$E_{\max} = (0.25H - 80). \quad (3.32)$$

The function is normalized to have a maximum value dependent on the height of the track. I do so because intuitively a “taller” ride should have a higher maximum possible enjoyment. To reduce the effect of learning about optimal width value  $w_{\max}$  as a function of height  $H$ , I introduced a factor  $f$  that was uniformly sampled from the range of  $[0.6, 0.9]$ . In the experiment, the height values  $H$  are uniformly chosen from the range of 600 to 1000 units. Thus,  $E_{\max}$  values range between 70 to 170. The  $E_{\max}$  range was carefully chosen to ensure that participants do not develop misconceptions about the maximum achievable enjoyment value. For example, participants may believe that the maximum achievable enjoyment value for a track is 100. By ran-

domizing objective function parameters, I reduced the influence of such preconceived notions.

Participants are expected to iteratively search for width  $w$  values of the track such that it maximizes the enjoyment experienced by the rider. A *try* is defined to be a submission of one  $w$  value. For each trial, participants incur a cost, and they are shown the corresponding enjoyment value, that is, the value of the objective function. For example, Figure 3.3 shows that a participant has tried 8 times, the cost for which is 200 cents. Further details on the design of the incentive structure are provided in Section 3.4.3. A table and a graph of search data are also provided to the participants to reduce the cognitive load of having to remember their search history. The participants are also provided with an initial height  $H$  of the track and are informed that the circular valley has a constant depth of 50 units. Participants are explicitly provided the feasible design space in this study, and the information appears as “Try values for width greater than  $X$ ” as shown in Figure 3.3. I do so for experimental control such that I reduce the influence of problem-specific information on a participant’s design behaviors and outcomes. In other words, there is no variance in participants’ knowledge about the design space.

### 3.4.2 Opponent Specific Information: Past Design Ratings

The information about an opponent’s performance record is termed as the “design ratings” given by the firm to the design solutions generated by the opponents in the past. A design rating is the firm’s assessment of the goodness of the opponent’s past design solutions. The rating is given on a *Bad-Average-Fair-Good-Great* scale, where “Bad” rating is the worst possible rating, and “Great” rating is the best possible rating. If information about the opponent is provided, participants are shown a histogram of the design ratings of the best design solutions submitted by the opponent in the past 10 to 15 contests as shown in Figure 3.4. Such information is intended for the participants to develop judgment about their opponent’s past performance.

For example, Figure 3.4 reflects that the opponent has a predominantly “great” performance history. Moreover, to control for the effect of design fixations, I did not provide information about the design artefact. Instead, the design ratings provided qualitative information about the design solutions without explicitly revealing the past designs.

To generate past performance data of an opponent, I utilized a quantitative measure of design ratings and created an agent’s performance distribution. From such a distribution, performance data was sampled and then converted to a qualitative scale as seen by the participants.



Figure 3.4. : The information about opponent’s past performance as seen by a participant.

For design search problems, theoretically, an opponent’s true design quality achievement (TDQ) can be quantitatively formulated as follows:

$$\text{True Design Quality Achievement} = \frac{\text{Design objective value achieved for a problem}}{\text{Optimal design objective value for a problem}} \times 100\% \quad (3.33)$$

In reality, assessments of design quality in the context of design search problems are not trivial. The firms organizing design contests themselves do not know the maximum achievable design objective value for a problem. However, I assume that the

contest organizers (in this case, the firm) are capable of making an accurate assessment of the true design quality of the design solutions generated by the opponent. I term this assessment by the firm of the true design quality achieved by an individual, as the “quantified design rating”. For example, a quantified design rating of 90% for a track design problem with maximum enjoyment value of 120 implies that the opponent achieved an enjoyment value of 108.

Table 3.1. : Qualitative and Quantitative Mapping Scheme for Design Ratings of an Opponent.

Qualitative Rating	Quantitative Mapping
Great	Design Rating $\geq 95\%$
Good	$95 > \text{Design Rating} \geq 90\%$
Fair	$90 > \text{Design Rating} \geq 85\%$
Average	$85 > \text{Design Rating} \geq 80\%$
Bad	Design Rating $< 80\%$

For the opponent’s past performance data, quantified design ratings were sampled from a Gaussian distribution with some mean design rating  $\mu_{\text{opp}}$  and a standard deviation of  $\sigma_{\text{opp}} = 3\%$ . As discussed earlier, such ratings are purely theoretical. In order to realistically reflect the past assessments by the firm of the design solutions generated by the opponent, the quantitatively sampled ratings are categorized into a qualitative scale through a mapping scheme. The mapping scheme is tabulated in Table 3.1. It is to be noted that the participants are not aware of the quantitative design rating and the mapping scheme. Such metrics were developed for internal analysis by the authors for various experimental control scenarios as described in Section 3.4.3.

The quantitative distribution utilized to generate past performance design ratings is also used to sample the opponent’s (agent’s) enjoyment value achieved for a given contest. The evaluated performance value of the agent is then utilized to decide whether a participant wins or loses a given contest. When a participant decides to stop their search in a contest, their corresponding performance, as well as their opponent’s performance is shown and the winner is displayed for the contest. The consistency in

utilizing the performance distribution of the agent is crucial to studying the influence of past performance record on participant behaviors. The goal was not to create an agent that is dishonest. It can be argued that an opponent’s performance may vary over a period of time. However, for a controlled experiment scenario, a dishonest agent would result in learning behaviors confounding with strategic decision-making behaviors of the participants. To reduce the influence of learning about the dishonesty of the agent over successive contests, the agent was designed to have a performance distribution honest to its past performance record.

### 3.4.3 Experiment Design

The experiment involved a total of 36 participants. These participants were undergraduate and graduate students at Purdue University. Students were recruited via flyers and social media posts in Purdue Engineering groups. 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, WI part is one where the information about the opponent’s past performance was provided, and WOI part is one where it was not. The experiment was executed with the two possible orders of the two parts. Such ordering of the tasks is done to eliminate order effects [56].

Table 3.2. : Treatments order and the number of participants in each treatment.

Treatment Order	Number of Participants
WI - WOI	18 participants
WOI - WI	18 participants

Each order of the experimental parts, as shown in Table 3.2, is termed as a *treatment*. Each participant was assigned to only one of these two treatments. The WOI part had 10 contests and the WI part had 20 contests. Overall, every participant played a total of 30 contests. In the WI part, a participant was presented with op-



ponent’s past performance information such that they either had a “strong” past history or a “poor” one. A mean design rating  $\mu_{opp}$  in the range of  $[80, 84]\%$  was utilized for generating “poor” opponent history and a range of  $[95 - 99]\%$  for generating “strong” opponent history. These ranges were chosen based on observations of past performances of human subjects in the design search problems and their achievement of true design quality TDQ. It might seem that, in reality, a range of  $[80, 84]\%$  for design rating is a “strong” performance. However, in the context of a convex search problem, I observed in the pilot experiment that human subjects are able to achieve such quality (TDQ) in 2 to 3 tries on an average. For such low effort, I consider this range of TDQ achievement to be a “poor” performance.

Table 3.3. : Contest conditions experienced by every participant.

Contest Condition	Number of Contests
WI and “strong” opponents	10 contests
WI and “poor” opponents	10 contests
WOI and “strong” opponents	5 contests
WOI and “poor” opponents	5 contests

For the WI part, I randomized a total of 10 strong and 10 poor past performance information about the opponents making it a total of 20 contests. Thus, overall, every participant played ten contests with opponents with strong past performance, with poor past performance, and without knowledge about the past performance, respectively. Table 3.3 illustrates various conditions of a contest experienced by every participant. I randomized strong and poor performance information in the WI part in order to reduce anchoring effects of successively presenting poor (or strong) opponent history. Moreover, it might result in an apparent belief of high (or low) probability of wins, thereby, further compounding the effect of anchoring bias along with the gambler’s fallacy. With 36 participants, I collected data of 1080 contests (360 for each of the three conditions). To reiterate the objective, I want to study the influence of information about the past performance of opponents on an individual’s design behaviors. By designing experimental treatments where strong, poor, and no

information about the past performances is provided, I can generate controlled data sets of participant behaviors in various treatments.

The incentive structure for the experiment was designed as follows. The prize for winning a contest was set to be \$7. The cost for a *try* was set to be \$0.25. The prize to cost ratio was deliberately high to reduce the influence of a high cost of experimentation on design behaviors. For the payments, the net gain or loss for any three contests out of the thirty contests was chosen at random. This was done in order to minimize the wealth effects [57]. The theoretical maximum net gain was calculated to be \$20.25. This calculation was done by considering the best case scenario such that the participant tries once, costing them \$0.25 cents, and they win the contest such that it gives them a maximum gain of  $\$7 - \$0.25 = \$6.75$  for the contest and  $6.75 \times 3 = 20.25$ . Moreover, participants were given a show-up fee of \$5. Theoretically, participants could earn a maximum total of \$25.25 for a session that lasted for approximately 75 minutes.

#### 3.4.4 Metrics Utilized for Hypothesis Formulation and Testing

I summarize the metrics utilized in this study to test the hypothesis in Table 3.4. These metrics are the qualitative and quantitative design ratings of the agent, the performance of a participant in a given contest, a participant’s belief about their opponent’s performance, and a participant’s effort.

I describe the qualitative and quantitative design ratings in detail in Section 3.4.2. The strong and poor past performance record is created by utilizing an agent with a performance distribution that is Gaussian with parameters  $[\mu_{\text{opp}}, \sigma_{\text{opp}}]$ . It is to be noted that an individual’s belief about the opponent is also modeled as a Gaussian distribution but with parameters  $[\mu_{\text{b}}, \sigma_{\text{b}}]$ . The parameters  $[\mu_{\text{opp}}, \sigma_{\text{opp}}]$  serve as control variables to control an opponent’s past performance record while  $[\mu_{\text{b}}, \sigma_{\text{b}}]$  are the dependent variables estimated as model parameters using experimental data. In the context of a design search problem, I refer to an individual’s effort as their design

Table 3.4. : List of metrics used in this study and their method of measurement or control.

Metric	Method of Measurement or Control	Measure or Control	Outcome
Qualitative Design Rating	Mapping from quantitative samples	Bad-Average-Fair-Good-Great	Performance is measured by using the maximum enjoyment value achieved by a participant in a contest and normalizing the value according to Equation 3.33
Quantitative Design Rating	Gaussian sampling	Samples from Gaussian distribution with parameters $[\mu_{\text{opp}}, \sigma_{\text{opp}}]$	
Strong past performance record	Controlling the quantitative design rating by limiting $\mu_{\text{opp}}$ between 95% to 99%	Experimental Control	
Poor past performance record	Controlling the quantitative design rating by limiting $\mu_{\text{opp}}$ between 80% to 85%	Experimental Control	
Belief about the opponent's performance in a contest	Experimental Data and Model	Belief is quantified as a Gaussian distribution with parameters $[\mu_b, \sigma_b]$	
Effort	Number of tries	Number of tries $T$	

behavior. The individual's effort is measured as the number of tries  $T$  they expend in a design search problem.

### 3.4.5 Hypothesis Generation

I list all the hypotheses and their corresponding operationalization in Table 3.5. I recall the discussion in Section 3.2 and reiterate that the opponent-specific information influences participant behaviors (H1) and design outcomes (H2). Thus, I formulate Hypotheses H1 and H2. Hypothesis H3 is formulated based on the modeling considerations such that the information about opponents influences a participant's belief about their opponent's performance. In the following, I discuss the hypothesis formulation.

Table 3.5. : Hypotheses and their corresponding operationalization based on the influence of an opponent's past performance on an individual's efforts, performance, and beliefs.

Hypotheses	Operationalized Hypotheses
H1: Opponent's past performance information influences a participant's efforts in a design contest.	<p>H1.1*: The number of tries (<math>T</math>) expended by a participant is higher when they are given that an opponent has a strong past performance record (<math>\mu_{opp}</math> between 95% to 99%) as compared to when they are given that an opponent has a poor past performance record (<math>\mu_{opp}</math> between 80% to 85%).</p> <p>H1.2*: The number of tries (<math>T</math>) expended by a participant is higher when no information is given about an opponent as compared to when they are given that an opponent has a poor past performance record (<math>\mu_{opp}</math> between 80% to 85%).</p> <p>H1.3*: The number of tries (<math>T</math>) expended by a participant is lower when no information is given about an opponent as compared to when they are given that their opponent has a strong past performance record (<math>\mu_{opp}</math> between 95% to 99%).</p>
H2: Opponent's past performance information influences a participant's performance in a design contest.	<p>H2.1*: The maximum enjoyment value achieved by a participant in a contest is higher when they are given that an opponent has a strong past performance record (<math>\mu_{opp}</math> between 95% to 99%) as compared to when they are given that an opponent has a poor past performance record (<math>\mu_{opp}</math> between 80% to 85%).</p> <p>H2.2*: The maximum enjoyment value achieved by a participant in a contest is higher when no information is given about an opponent as compared to when they are given that an opponent has a poor past performance record (<math>\mu_{opp}</math> between 80% to 85%).</p> <p>H2.3*: The maximum enjoyment value achieved by a participant in a contest is lower when no information is given about an opponent as compared to when they are given that an opponent has a strong past performance record (<math>\mu_{opp}</math> between 95% to 99%).</p>
H3: Opponent's past performance information influences a participant's belief about the opponent's achievement of the design objective value in a contest.	<p>H3.1*: The <math>\mu_b</math> value estimated for an individual when they are given that their opponent has a strong past performance record (<math>\mu_{opp}</math> between 95% to 99%) is higher as compared to the <math>\mu_b</math> value estimated when they are given that their opponent has a poor past performance record (<math>\mu_{opp}</math> between 80% to 85%).</p> <p>H3.2*: The difference between the <math>\mu_b</math> value estimated for an individual when they do not know that their opponent has a strong past performance record (<math>\mu_{opp}</math> between 95% to 99%) and the <math>\mu_b</math> value estimated when they do not know that their opponent has a poor past performance record (<math>\mu_{opp}</math> between 80% to 85%) is zero.</p>

Hypothesis 1 is operationalized by comparing the influence of the modeled agent in various contest conditions as described in Table 3.3 on participant efforts. This results in the formulation of three operationalized hypotheses, namely, H1.1\*, H1.2\* and H1.3\*. I hypothesize that when the participant knows that the opponent is strong, they spend higher efforts than any other test condition (H1.1\* and H1.3\*). This hypothesis stems from existing literature on information sharing in contests which shows that there is significant over-expenditure of efforts (compared with theoretical predictions) when information about a strong opponent is known [26]. I formulate H1.2\* by considering risk-behavior literature that the majority of the population is risk-averse in nature. Thus, I hypothesize that when there is a lack of information about the opponent, participants will behave conservatively and expend greater efforts than when they know that their opponent has a poor past performance record. Moreover, testing H1.1\* also serves as a verification test for the experiment design.

I formulate H2 on the basis of H1 such that greater efforts expended would result in better design performance. In the context of a design search problem, it is intuitive that the greater the exploration of the design space, the more likely it is to search for an optimal design solution. Thus, I map the operationalization of hypothesis 2 to the corresponding operationalized hypothesis 1. Hypotheses H2.1\*, H2.2\*, and H2.3\* are formulated in accordance with H1.1\*, H1.2\*, and H1.3\* respectively. I hypothesize (H2.1\* and H2.3\*) that the maximum enjoyment value achieved by a participant while competing against an opponent that has a strong past performance record is higher than an opponent that has a poor past performance record or when no information is known about the opponent. Hypothesis H2.2\* is formulated on the basis of H1.2\* such that conservative behavior when the opponent is unknown would result in higher performance than when the opponent is known to have a poor past performance record.

Hypotheses H3 is formulated based on the S-SIADM model. I quantify the influence of opponent-specific information on a participant's SIADM behaviors via a belief (probability distribution) about the opponent's design performance. I hypoth-

esize (H3.1\*) that an individual's belief  $\mu_b$  about an opponent should be higher when the opponent has a strong past performance as compared to an opponent with poor past performance. To further validate the sensitivity of  $\mu_b$  to the information provided to the opponents, I hypothesize (H3.2\*) that there is no difference in a participant's belief about an unknown opponent irrespective of whether they actually have a strong or poor past performance record.

### 3.5 Results and Discussion

I utilize the data, collected from the experiment described in Section 3.4, to infer the model parameters  $\theta$ . Based on these parameters and the experimental data, I test hypotheses H1.1\* to H3.2\* in this section. I then discuss the implications of each of the hypothesis test results.

#### 3.5.1 Hypotheses Testing: Influence of Past Performance Information

I categorize H1.1\* to H1.3\* as hypotheses related to the influence of an opponent's past performance on an individual's efforts in a contest. The hypotheses H2.1\* to H2.3\* are related to the influence of an opponent's past performance on an individual's performance in a contest. To validate the model that quantifies the influence of an opponent's past performance via the beliefs that an individual develops about their opponent, I test hypotheses H3.1\* and H3.2\*. Table 3.5 lists H1.1\* to H3.2\* with respect to the influence of an opponent's past performance on an individual's efforts, performance, and beliefs about the opponent in a contest.

#### Influence on Efforts

To test H1.1\* to H1.3\*, I compare the average number of tries  $T$  of the participants across contests where they knew that their opponent had a strong past performance, where they knew that their opponent had a poor past performance, and where they

did not know their opponent's performance record. I do so by conducting paired two-sample two-tailed t-tests. The hypotheses test results for H1.1\*, H1.2\*, and H1.3\* are shown in Table 3.7. The results for H1.1\* indicate that the participants indeed try higher number of times when they know that their opponent had a strong past performance record as compared to a weak one ( $p < 0.0001$ ). Therefore, knowledge about an opponent's past information does influence a participant's efforts. I also reject the null for H1.2\* ( $p < 0.01$ ) which implies that the participants expend higher effort when no information is provided to them about their opponent as compared to when they know that their opponent has had a poor performance record. However, I failed to reject the null for H1.3\* ( $p > 0.05$ ) that the participants expend higher effort when they have information that the opponent has a strong past performance record as compared to when there is no information provided to them about their opponent. In other words, the difference between the expenditure of efforts when the opponent is known to have a strong performance record and when the opponent is unknown is not statistically significant.

The results for H1.3\* indicate that a majority of the individuals behave conservatively while making strategic decisions against an unknown opponent. While theoretically a total lack of information about the opponents is possible, in reality, information about past contests and by extension, information about the best past performances, is typically available. The results suggest that if such information is available and the participants enter the contest, then they will expend higher effort when they know that the opponents in the past have had a strong performance record.

Table 3.6 lists the mean  $\mu$  and standard deviation  $\sigma$  of the average number of Tries of the participants when they know the opponent is Good ( $\mu_T^G, \sigma_T^G$ ), when they know the opponent is Bad ( $\mu_T^B, \sigma_T^B$ ), and when they have No information ( $\mu_T^N, \sigma_T^N$ )

Table 3.6. : The mean  $\mu$  and standard deviation  $\sigma$  of the average number of tries  $T$  of the participants.

Condition	Average tries $T$	
	Mean $\mu$	Standard Deviation $\sigma$
Information given Strong past performance record Sample size=360	$\mu_T^G = 5.17$	$\sigma_T^G = 2.00$
Information given Poor past performance record Sample size=360	$\mu_T^B = 4.15$	$\sigma_T^B = 1.8$
No Information given Sample size=360	$\mu_T^N = 4.77$	$\sigma_T^N = 2.12$

Table 3.7. : Summary of the paired two-sample t-test for H1.1\*, H1.2\*, and H1.3\*.

	Alternate Hypothesis	t stat.	p-value
<b>H1.1*</b>	$\mu_T^G > \mu_T^B$	-4.85	< 0.0001
<b>H1.2*</b>	$\mu_T^N > \mu_T^B$	-3.43	0.0016
<b>H1.3*</b>	$\mu_T^G > \mu_T^N$	1.61	0.1165

## Influence on Performance

To test H2.1\* to H2.3\*, I compare the average of the normalized maximum enjoyment value  $E$  achieved by the participants across contests where they knew that their opponent had a strong performance record, where they knew that their opponent had a poor performance record, and where they did not know their opponent's performance record. I do so by conducting paired two-sample two-tailed t-tests. I failed to reject the null for all the hypotheses associated with H2, that is, H2.1\*, H2.2\*, and H2.3\*. The results are counter-intuitive as greater efforts in a design search problem (H1) typically implies better achievement of the design objectives.

The results are shown in Table 3.9. The mean  $\mu$  and standard deviation  $\sigma$  of the normalized average Enjoyment value achieved by the participants when they know the opponent is Good  $\mu_E^G, \sigma_E^G$ , when they know the opponent is Bad  $\mu_E^B, \sigma_E^B$  and when they have No information  $\mu_E^N, \sigma_E^N$  are shown in Table 3.8.



I note the high variance in performance distribution  $\sigma_E^G$  when the participants know that their opponent has a had a strong past performance record. I believe that such high variance in performance is due to the influence of the information about the “goodness” of an opponent which results in a “polarizing effect” such that some participants choose not to participate resulting in a zero design rating whereas some expend greater efforts to increment their existing performance. On averaging across individuals, the mean of the performances does not significantly vary, however, it does result in a spread (high variance) of design quality.

Table 3.8. : The mean  $\mu$  and standard deviation  $\sigma$  of the average number of tries  $T$  of the participants.

Condition	Average enjoyment value $E$	
	Mean $\mu$	Standard Deviation $\sigma$
Information given Strong past performance record Sample size=360	$\mu_E^G = 95.27\%$	$\sigma_E^G = 10.49$
Information given Poor past performance record Sample size=360	$\mu_E^B = 95.71\%$	$\sigma_E^B = 4.27$
No Information given Sample size=360	$\mu_E^N = 96.11\%$	$\sigma_E^N = 5.73$

Table 3.9. : Summary of the paired two-sample t-test for H2.1\*, H2.2\*, and H2.3\*.

	Alternate Hypothesis	t stat.	p-value
<b>H2.1*</b>	$\mu_E^G > \mu_E^B$	0.28	0.7821
<b>H2.2*</b>	$\mu_E^N > \mu_E^B$	-0.43	0.6689
<b>H2.3*</b>	$\mu_E^G > \mu_E^N$	-0.50	0.6177

### Influence on the Belief about the Opponent

To test H3.1\* I compare the estimated belief parameters  $\mu_b$  of the participants across contests where they knew that their opponent had a strong past performance record and a poor past performance record. I do so by conducting paired two-sample

two-tailed t-tests. The hypothesis test results for H3.1\* indicate that the participants indeed believe that their opponent's performance is better when they have had a strong past performance record as compared to a weak past performance record ( $p < 0.05$ ). This implies that the modeled parameters are sensitive to the information provided to the participants about their opponent's past performances. To further test the sensitivity of the modeled parameters, I test H3.2\*. I compare the estimated belief parameters  $\mu_b$  of the participants across contests where their opponent had a strong past performance record and a poor past performance record but the participants did not know about the opponent's performance record. The hypothesis test results for H3.2\* indicate that there is no statistically significant difference between the estimated belief parameters  $\mu_b$  in the two scenarios. This further supports the claim that the modeled parameters are influenced based on the information provided to the participants about their opponent's past performance record.

The results are shown in Table 3.11. The mean  $\mu$  and standard deviation  $\sigma$  of the average of the estimated Belief parameters of the participants about their opponent's performance With Information that the opponent is Good ( $\mu_{B-WI}^G, \sigma_{B-WI}^G$ ), With Information that the opponent is Bad ( $\mu_{B-WI}^B, \sigma_{B-WI}^B$ ), WithOut Information that the opponent is Good ( $\mu_{B-WOI}^G, \sigma_{B-WOI}^G$ ), and WithOut Information that the opponent is Bad ( $\mu_{B-WOI}^B, \sigma_{B-WOI}^B$ ), are shown in Table 3.10.

### 3.5.2 Hypotheses Tests: Discussion

I summarize the results of the hypotheses tests in Table 3.12. The hypotheses test results from H1.1\* to H1.3\* and H2.1\* to H2.3\* indicate that information about the past performance record of an opponent influences a participant's decision to stop a sequential search process. However, such information results in high variance of the quality of the design outcomes for a participant population. This implies that different participants respond differently to the given information about the opponent such that some participants may expend higher efforts and generate higher quality while

Table 3.10. : The mean  $\mu$  and standard deviation  $\sigma$  of the average  $\mu_b$  of the participants.

Condition	Average belief $\mu_b$	
	Mean $\mu$	Standard Deviation $\sigma$
Belief With Information Strong past performance record Sample size=360	$\mu_{B-WI}^G = 90.51\%$	$\sigma_{B-WI}^G = 17.62$
Belief With Information Poor past performance record Sample size=360	$\mu_{B-WI}^B = 87.70\%$	$\sigma_{B-WI}^B = 16.68$
Belief Without Information Strong past performance record Sample size=180	$\mu_{B-WOI}^G = 88.59\%$	$\sigma_{B-WOI}^G = 16.63$
Belief Without Information Poor past performance record Sample size=180	$\mu_{B-WOI}^B = 88.77\%$	$\sigma_{B-WOI}^B = 18.55$

Table 3.11. : Summary of the paired two-sample t-test for H3.1\*, and H3.2\*.

	Alternate Hypothesis	t stat.	p-value
<b>H3.1*</b>	$\mu_{B-WI}^G > \mu_{B-WI}^B$	-2.20	0.0283
<b>H3.2*</b>	$\mu_{B-WOI}^G > \mu_{B-WOI}^B$	0.99	0.9211

some participants may lose motivation to expend resources and efforts resulting in no submissions or low quality solutions. This results in a large distribution over the quality of submitted design solutions as compared to scenarios where participants do not have information about the opponents and generate solutions that do not have a high variance in design quality. Existing literature on open-innovation has investigated crowdsourcing scenarios where variance dominates quality of solutions [72]. The results contribute to the conditions that can be facilitated by contest designers, such as, information provision about the opponents, in order to generate high variance in design outcomes.

Moreover, the results indicate that the contest designers are better off not providing information to the participants about past contests if the corresponding winning design solutions do not meet the standards defined by the organizers for the given contest. However, regulations may prevent contest organizers from withholding such

information from the participants. In such scenarios, the contest designers need to account for the influence of such information on participant behaviors and contest outcomes. Further research is required towards understanding how to catalyze participant motivations towards expending higher efforts as well as generating higher design quality given that they have knowledge about the historical information.

The test results from H3.1\* and H3.2\* indicate that I can quantify an individual's belief about an opponent through the parameter  $\mu_b$  such that higher the  $\mu_b$  parameter greater is the belief about an opponent's performance in a given contest. Such parameters can be utilized by contest designers to incorporate the influence of participant beliefs about the competitiveness of a contest based on its participants and to predict the corresponding influence on their design behaviors and contest outcomes. Such parameters contribute to the much needed quantification of qualitative knowledge about the design of contests for engineering design scenarios.

Table 3.12. : Summary of Hypothesis Results. ✓ indicates rejection of null and ✗ indicates failure of null rejection.

Hypotheses	Results
(H1)	H1.1* : ✓ H1.2* : ✓ H1.3* : ✗
(H2)	H2.1* : ✗ H2.2* : ✗ H2.3* : ✗
(H3)	H3.1* : ✓ H3.2* : ✓

### 3.5.3 Observations

I plot the belief parameters  $\mu_{B-WI}^G, \mu_{B-WI}^B$  estimated for every individual when they have information about the strong and poor performing opponents. I do so to categorize every individual's sensitivity to the information provided to them about

their opponents. Figure 3.5 illustrates every individual as a scatter point  $(x, y)$  such that the x-value represents an individual's average belief about their opponent's performance when they are given that their opponent has had a poor performance record and y-value represents that individual's belief about their opponent's performance when they are given that their opponent has had a strong performance record. Individuals whose average belief about the strong opponent is higher than that of the poor performing opponent are labeled as sensitive to the given information as estimated by the model while others are termed as insensitive. The model estimates 22 individuals out of 36 as sensitive. Thus, the model estimates approximately 60% of the participants as sensitive to the provided information about their opponent based on their estimated beliefs from experimental data.

Such categorization of individuals can inform design decisions of contest designers such as the need to conservatively frame the problem if majority of the participants are insensitive to particular types of information. To do so, further model validation is required by incorporating other informational factors that influence participant behaviors as well as develop confidence that the model predictions are representative of people behavior. This study serves as the stepping stone towards developing descriptive models of design contests with quantified relationships between strategic information and design behaviors.

#### 3.5.4 Validity

The experimental study has high internal validity as it is a controlled behavioral experiment [60]. Internal validity refers to ensuring that the observed effect on the S-SIADM activities is attributable to the past performance information identified as a cause. I control for other factors such as an individual's learning, intuition, the order of experiment task execution, incentivization of the experiment tasks, and domain knowledge that also affect a participant's decision-making (refer to Section 3.4).

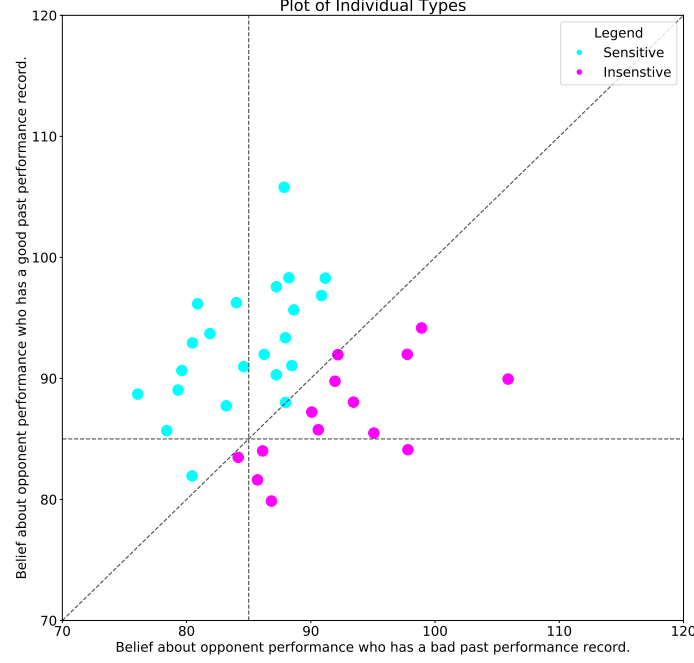


Figure 3.5. : Plot categorizing individuals

External validity refers to the generalization of the research study [61]. The external validity is dependent on how well the experimental conditions represent the target setting. The extension of the SIADM framework to include the influence of contest-specific information as illustrated in Figure 3.1, is highly general. Any sequential information acquisition activity in a design contest can be represented using this framework. The S-SIADM model, on the other hand, is more specific because it has been instantiated based on contest-specific, process-specific, and individual-specific considerations. The contest's incentive structure is assumed to be a winner-takes-it-all structure such that a two-player contest can be reasonably assumed. The problems have a single objective with a single design variable. Consequently, the defined model parameter  $\mu_b$  is specific to the problems where belief about a single quality metric can be modeled. In order to utilize the model in more complex design contest scenarios, various aspects of the proposed model such as its parameters and the S-SIADM activities will have to be appropriately considered. For example, in a design problem with multiple winners as an incentive structure, a multi-player contest would need to

considered. Similarly, a problem with multiple objectives will impact the way an individual updates their beliefs about the objectives using Bayesian updating. Further investigation is required to evaluate the effects of complexity on the S-SIADM model formulation. I also acknowledge that in reality, individuals may cognitively execute the activities in a S-SIADM scenario differently. I do not test whether the proposed model is representative of how individuals follow a S-SIADM process. To investigate the representativeness of an individual's S-SIADM process by the proposed model there lies a need to develop alternate descriptive models of S-SIADM. Then, such models can be compared using Bayesian model comparison to evaluate which model best represents the decision making strategy followed by the individuals. This is a promising avenue for further research in this direction.

The external validity of the proposed framework can also be assessed by how well the model applies to different experimental settings such as (a) different populations (b) different design problems, and (c) different contest-specific factors. The experimental study has been carried out with undergraduate and graduate engineering students. It is not clear how well these results will extend to the “crowd” who have other implicit as well as procedural knowledge. In real life settings, SIADM scenarios are more complex with multiple objectives and multiple constraints. The study does not account for the effects of complexity as a factor on SIADM scenarios. I do believe that it is likely that different ways of increasing complexity affects behaviors in different ways. As the complexity grows, other factors such as the manner in which information is presented and various stages of a contest also affects the behaviors. For example, if contest has a preliminary stage which eliminates a fraction of the participation pool, then participants will need to update their belief distribution to correspond to the next stage. With increasing complexity, computational tools (e.g., surrogate models) are needed to support designers. The behavior then depends on the types of computational tools used. To assess the ecological validity in such settings, I can not only perform experiments but also conduct interviews, surveys, and case studies. All these effects cannot be captured in a single experiment. Therefore,

the complexity of the problem and its effects on information acquisition strategies adopted by humans requires further investigation.

### 3.6 Closing Remarks

An S-SIADM process is represented as one that consists of three activities as illustrated in Figure 3.1 and described in Section 3.3. I make specific modeling choices for these three activities in the S-SIADM model as discussed in Section 3.3.1. Specifically, it is assumed that individuals maximize their improvement in payoff, decide to stop when they do not see an improvement in their payoff, and follow a myopic one-step look-ahead strategy for design search. Based on these assumptions, the influence of past performance records, on the SIADM outcomes is studied.

The primary contribution of this study is the finding that the influence of an opponent's past performance on a participant's decision to stop acquiring information in an SIADM problem solved under competition can be quantified using the S-SIADM model. Moreover, it is found that, if possible, contest designers are better off not providing historical performance records if past design qualities do not match the expectations set up for a given design contest. I also provide an extension to the SIADM framework which is done by presenting a Strategic-SIADM model in conjunction with a behavioral experiment for a class of design contests. Such a framework enables us to understand how participants get influenced based on the performance information in past contests on their sequential information acquisition and decision making process in a design contest.

In the future, the S-SIADM model can be utilized to investigate behavioral similarities and differences among contestants. Specifically, individuals can be categorized based on the combinations of  $\mu_b$  and  $\sigma_b$ . Such categorizes could be used to compare participants' behaviors and the S-SIADM outcomes to study the influence of historical information on the design performance.



## 4. SEQUENTIAL DECISION MAKING UNDER THE INFLUENCE OF COMPETITION: A MIXED METHODS APPROACH

### 4.1 Chapter Overview

In the previous chapter, the influence of opponent-specific information on contestant's decision making behaviors was computationally quantified by assuming a boundedly rational model based on an optimal one-step look-ahead strategy, utilizing expected improvement maximization. In this study, I investigate *how information about historical performances of competitors influences a participant's information acquisition behaviors and the outcomes of a design contest*. To fill this knowledge gap, I am leveraging both qualitative and quantitative data from protocol analysis and controlled behavioral experimentation respectively. Such use of multiple data sources enables the characterization of the opponent, the contest history, and the influence of such characterization on designer behaviors and their design outcomes. The central hypothesis is that by conducting a mixed-methods approach where I conduct a controlled behavioral experiment and a protocol study, I can elicit and model the designers' cognitive processes while making information acquisition decisions. I 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, which are computationally inferred based on experimental data, are influenced by the contestant's perception about the competitiveness of their opponent. The results indicate that the threshold value for individuals' expenditure of efforts is influenced the most by opponent-specific information such that it is the most sensitive factor in deciding to stop information acquisition activities. This study illustrates that the cognitive factors that influence an

individual's preferences can be investigated via a mixed-methods approach, thereby, enabling predictions of behaviors towards bridging the gap between cognition and decision making.

## 4.2 Introduction

In Chapter 3.2, I discuss the need to quantify the influence of information sharing on a participant's decision making behaviors. To further investigate this topic, the research question of this study is: *How does information about historical performances of competitors influence a participant's information acquisition behaviors and thereby the outcomes of a design contest?* The central hypothesis is that by conducting a mixed-methods approach where I conduct a controlled behavioral experiment and a protocol study, I can elicit and model the designer's cognitive processes while making information acquisition decisions. Qualitative analysis such as protocol analysis, provides cognitive insights by investigating people's thought process while making decisions [73]. Whereas, quantitative analysis such as computational modeling of the influence of cognition on design processes, enables better prediction of design outcome [74]. In context of behavioral investigations, it is acknowledged that a combination of qualitative and quantitative data supports the most robust theory and scientific knowledge developments [75]. Thus, I choose a mixed-methods approach towards theory building of contest design in engineering design scenarios.

The remainder of this chapter is structured as follows. In Section 4.3, I present a mixed-methods approach that combines qualitative and quantitative data for descriptive analysis of the influence of designers' cognition and behaviors on design outcomes. Then, in Section 4.4, I illustrate the approach through a study that investigates designers' information acquisition behaviors under the influence of competition. In Section 4.5, I discuss the qualitative method and its analysis. In Section 4.6, I discuss the quantitative method to computationally model designer behaviors by considering the results of the qualitative analysis. In Section 4.7, I discuss the mixed-methods

analysis by testing hypotheses based on both the qualitative and quantitative data. I conclude this chapter in Section 4.8 by discussing the information acquisition behaviors of designers under the influence of competition as well as emphasizing the need for adopting mixed-methods research approaches for theory building in design research.

### 4.3 Analyzing Designer Behaviors: A Mixed-methods Approach

In this section, I present a mixed-methods research approach that enables us to leverage both qualitative and quantitative data for cognitive analysis and modeling of the factors that influence decision-making behaviors and outcomes in engineering design contexts. Consequently, the research approach is suitable for descriptive analysis of engineering design behaviors. The approach consists of three steps that are, 1) variable identification, 2) leveraging existing literature, and 3) mixed-methods behavioral experimentation. In the following, I discuss these three steps with a particular emphasis on the mixed-methods analysis in Step 3.

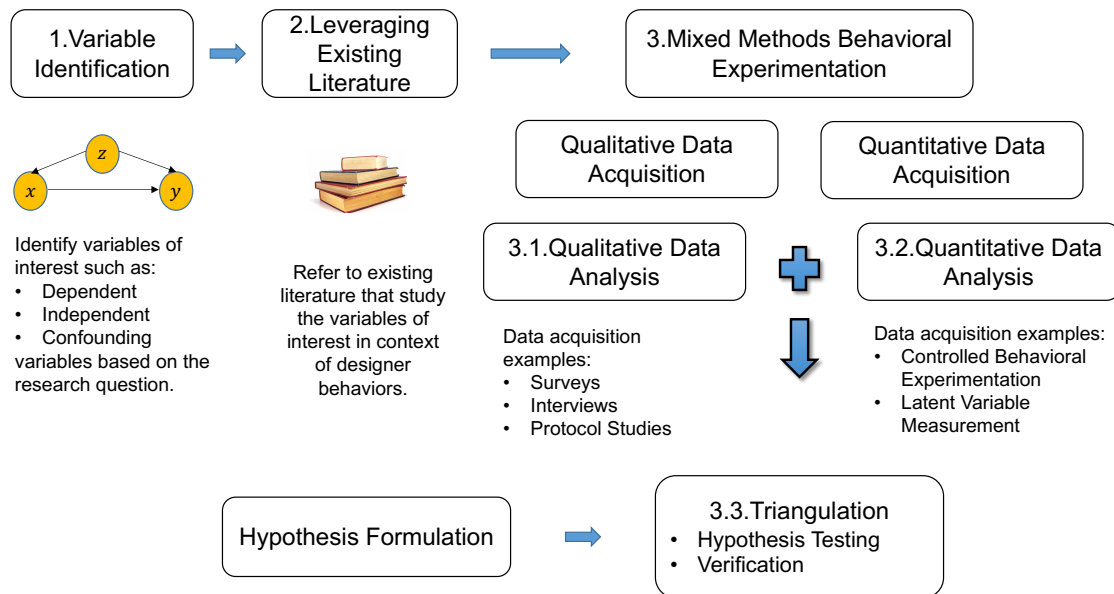


Figure 4.1. : An illustration of the mixed-methods research approach with an emphasis on the mixed-methods analysis.

### 4.3.1 Variables Identification and Leveraging Existing Literature

The first step in a descriptive research study is to identify the variables of interest. In engineering design behavioral context, such variables would include the factors that can provide a descriptive account of why or how people's behavior gets influenced in engineering design scenarios. Moreover, the behavior under study or the behavior of interest is also a part of the variables of interest. For example, in a product design scenario under competition, information about the opponent's past performance can influence how designer's design their future products. In such a scenario, information about the opponent is a factor that affects how products are designed. Such information becomes a variable of interest. Moreover, the behaviors of interest such as designers' decision making is also a part of the variables of interest. I utilize the process of systematically identifying all the experimental variables of interest from existing literature on the design of experiments [76,77]. Based on the literature, I suggest categorizing experimental variables of interest as dependent, independent, and confounding variables. Factors that influence behaviors are typically categorized as independent variables. The behaviors of interest are the dependent variables. Confounding variables are those variables that also influence the behaviors of interest such that they may alter the apparent influence of the independent variables on the dependent variables in the experimental observations.

In the context of behavioral design research, independent variables would typically be the design variables that can be controlled by designers in engineering design environments. Dependent variables would typically be designer behaviors such as decision making, communication, and reasoning behaviors. Confounding factors include, but are not limited to, the cognitive biases of designers that need to be controlled such as anchoring bias that may alter the apparent effect of the experimental conditions on the observed behaviors. For further details, refer to Cash et al. [78] where they discuss various experimental design approaches specifically for design research.

After identifying the variables of interest, one should refer to existing literature for the theoretical foundations for such variables. Researchers would need to develop an understanding of the boundaries of existing knowledge about the variables of interest to identify research gaps that include quantifying variables of interest [68], relationships between the variables of interest [79], the underlying cognitive mechanisms that stimulate behavioral responses [80], and the domain-specific nuances of engineering design contexts [81]. Such understanding would facilitate the formulation of hypothesis about how the behaviors of interest influence the outcomes of interest. Moreover, existing literature aids in the analysis of qualitative data as described in Section 4.3.2.

### **4.3.2 Mixed-methods Behavioral Experimentation**

After identifying variables of interest and establishing research gaps, an approach is required to bridge the research gaps between a designer's cognitive processes, engineering design behaviors, and their influence on the engineering design outcomes. To do so, I suggest leveraging both qualitative and quantitative data with an aim to better analyze engineering design scenarios. Such data should be acquired, processed, and analyzed. I collectively term these activities as conducting mixed-methods experimentation. In the following, I discuss both qualitative and quantitative data acquisition and processing as a part of the approach. I then discuss an approach to mixed-methods analysis where I introduce the process of triangulation.

### **Qualitative Data Acquisition and Analysis**

The goal of qualitative data analysis is to identify the underlying cognitive processes that influence individual's decision making activities. Based on the identified variables that include factors that influence people's behaviors (refer to Section 4.3.1), researchers would need to investigate why and how the variables of interest influence people's behavior. Such investigation involves observing and probing an appropriate sample of human population. Such observations result in generation of qualitative

data that enable us to characterize and describe the identified factors and their possible influence on the outcomes of interests. Researchers should be able to either acquire existing qualitative data from prior investigations or conduct experiments to do so.

Various methods exist for qualitative data acquisition and analysis such as protocol analysis of interviews and think aloud studies, self reports from people about their activities while executing various tasks, reflections from experts as well as novices, and surveys from a sample that is representative of a population of interest [82]. While these methods are not a comprehensive list, I emphasize that the outcomes of the qualitative analysis, irrespective of the data acquisition method, should reveal latent variables such as motivation, rationale, preferences, personality traits, prior knowledge, and beliefs of human subjects at various levels such as individual, group, community, and global level.

### **Quantitative Data Acquisition and Analysis**

Following the outcomes of the qualitative analysis, researchers need to work towards quantifying the identified latent variables (cognitive factors) and their relationships to the outcomes of interest. In context of engineering design, I believe that qualitative analysis is a first step towards descriptive research and not necessarily an end goal. Quantitative analysis provides the foundations required to make predictions about the design outcomes while accounting for the qualitative knowledge about human behavior in engineering design. Researchers should be able to either acquire existing quantitative data or conduct experiments to do so. It is to be noted that researchers would need to quantify the identified latent variables from qualitative analysis. Data for such variables of interest may not be readily available in existing literature. Therefore, it is vital for researchers to appropriately design behavioral experiments to acquire quantitative data.

Various methods exist for quantitative data analysis such as existing open data repositories and conducting behavioral experiments to measure specific quantities of interest. Moreover, such data is typically analyzed via statistical approaches such as t-tests in experimental conditions, correlations, and analysis of variance (ANOVA) [83]. While these methods are not a comprehensive list, I emphasize that the outcomes of the quantitative analysis, irrespective of the data acquisition method, should quantify relationships between latent variables and observable behaviors at various levels such as individual, group, community, and global level. Such analyses would provide researchers with a triangulation strategy to test hypotheses about possible cognitive mechanisms that influence designer behaviors and therefore the outcomes of an engineering design process. I discuss triangulation in Section 4.3.2.

## **Triangulation**

In this section, I explain the process of triangulation in the context of my approach. Triangulation refers to a multi-method approach of data collection and analysis. Key idea supporting the concept of triangulation is that the phenomena under study can be understood best when approached with a variety of research methods [84]. Data Triangulation specifically refers to drawing evidence from several data sources to study the variables of interest [84]. In this study, data triangulation, is referred to simply as triangulation and it is considered as the process of leveraging the results of the qualitative and quantitative analysis to test experimental hypotheses. Such process aims towards establishing relationships between cognitive factors and engineering design outcomes.

The process of triangulation can be conducted in parallel or in series. However, the implications of choosing the process of execution needs to be highlighted. Triangulation in parallel refers to collecting both qualitative and quantitative data in parallel via independent studies. This implies that independent subject population is utilized for collecting different types of data. Triangulation through such data im-

proves the reliability of experimental conclusions. However, triangulation in parallel is typically resource intensive as human-subjects recruited for one study cannot be leveraged for the other. Triangulation in series refers to collecting both qualitative and quantitative data from the same pool of human subjects. The advantage of such an approach is generation of richer data sets from every individual as well as better use of human-subject participants as compared to triangulation in parallel. However, the dependency of the data sources results in a potential threat to validity such that the actions of the human-subjects in a behavioral experiment may influence their description of their behavior while studying the phenomenon of interest. In such a scenario, existing literature can be leveraged to corroborate data analysis. Referencing literature can help mitigate threats to validity by preventing formulation of hypotheses about behaviors which may be specific to the particular study in concern but otherwise not generalizable.

As discussed in Section 4.3.2, the outcomes of qualitative analysis include identification of latent variables associated with cognition. Such variables can be leveraged in conjunction with existing literature to formulate hypotheses about how and why people’s behavior influence design outcomes. Furthermore, by quantifying the variables identified from the qualitative analysis (refer to Section 4.3.2) researchers would be able to operationalize the formulated hypotheses. Operationalization is a process of defining the measurement of a phenomenon that is not directly measurable [85]. I note that the process of operationalization in context of engineering design in and of itself is worthy of detailed investigation. By including operationalization as a part of the approach I do not intend to create a false impression that this process is a minor task within the umbrella of activities for designing behavioral experiments. Instead, I highlight that operationalization is the crucial bridge between qualitative and quantitative data analysis. Moreover, operationalization is dependent on a researcher’s expertise to identify the suitable measures that serve as a proxy for the identified latent variables. The triangulation activities culminate by hypotheses testing which provides the verification that the operationalized metrics are indicative of the cogni-



tive activities of interest. Such verification establishes confidence in the utilization of the quantified latent variables. I note that validation of such metrics would require multiple investigations to study their efficacy in varying domain-specific contexts.

#### **4.4 A Mixed-methods Experiment: Interviews and Controlled Experimentation**

In this section, I illustrate the approach in Section 4.3 in context of the research question: *How does participants' decision to stop searching for a design solution get influenced by the knowledge about their opponent's past performance?* I identify the variables of interest, refer to existing literature that study these variables, and design a mixed-methods experiment to acquire and analyze qualitative and quantitative data from human subjects using triangulation in series.

##### **4.4.1 Variable Identification**

I identify the *independent variable* as the historical or prior information about the contests that is available to the participants. I consider this information as independent variable as the contest organizers can make a decision about how much information they should avail to the contestants. Thus, such information availability can be controlled by the contest organizers. The *dependent variable* is the contestant's decision to stop acquiring information. Such decisions include considerations such as how much effort to expend including resources such as time and money as well as cognitive load. I also identify other factors that influence the dependent variable and may act as potential confounding variables. Factors such as an individual's domain knowledge, the complexity of the design problem, and the incentive structure can also influence a participant's stopping decisions. In Section 4.4.3, I refer to the controlled behavioral experiment discussed in Chapter 3 as well as discuss the interview study conducted with the participants of the experiment.

#### 4.4.2 Existing Literature: Information Acquisition and Decision Making

Existing literature in cognitive psychology and behavioral economics describes various descriptive models of human decision makers [86, 87]. Examples of these decision-making models include bounded rationality-based models [88], fast and frugal heuristics [87], models based on deviations from rationality [86], and cognitive architecture-based models [89].

Within engineering design, some efforts have been made to address nuances of information acquisition in context of designer behaviors [90]. The authors in [90] identify decision to stop information acquisition decisions using criteria such as resource expenditure, objective achievement, and improvement in objective achievement in sequential steps. Such stopping decision strategies are also acknowledged in cognitive psychology literature that refers to information acquisition as evidence accumulation [91]. Moreover, the dependency of such evidence accumulation on the level of confidence of a decision-maker is also acknowledged [92]. Thus, existing literature on the decision to stop information acquisition has identified that individuals decide to stop using threshold-based criteria such that if the value of the criteria surpasses a particular threshold value, then individuals decide to stop.

#### 4.4.3 Mixed-Methods Experimentation: The Track Design Behavioral Experiment and Interviews

The same experiment and experimental data set as described in Chapter 3 is utilized for this study. The rationale is that for studying the effect of opponent-specific information, the same behavioral data set can be leveraged. What changes is the research approach to investigate latent factors that influence participants decision-making process. Such latent factors shed light on how participants made stopping decisions, thereby, facilitating hypothesis formulation using existing literature.

The participants of the behavioral experiment described in Chapter 3 were interviewed at the end of the previous study. The interviews were structured as opposed

to semi-structured in order to limit the total duration of the experimental activities to 60 minutes. I 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, I discuss the interview questions, data collection method, the data analysis procedure, and the latent variables identified as a part of the results of the analysis. The variables are corroborated with existing literature and then utilized as a basis for quantitative modeling and analysis.

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 4.1. The motivation to ask every question has been summarized in the table as well. The interviews lasted for an average of 150 seconds.

Table 4.1. : 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.

## 4.5 Interviews: Qualitative Analysis

In this section, I discuss the analysis procedure and the results of the interview analysis. The results enable us to identify stopping strategies by the participants based on various stopping criteria which are identified as the latent variables.

#### 4.5.1 Data Analysis

I analyze the individuals' SIADM process from the transcribed interviews through content analysis [93]. 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. I hypothesize that the participants account for opponent-specific information in their decision to stop the search process.

Through Question 1, I expect the participants to describe the experimental objective which was to study how opponent-specific information influences participants' decision making process. I 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, I identify words and phrases that refer to casual relationships such as "impact on," "influence on," and "affects." I 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 I 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 or 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. 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 [79] I model an s-SIADM strategy which assumed that an individual's game play strategy is the same as their stopping strategy. However, I expected the answers to Question 4 to 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 a yes or a no to the question. It was expected that they would elaborate on how they make stopping decisions by considering opponent-specific information (or not). I used content analysis [93] to elicit phrases and sentences that represent the conditions based on which participants include opponent-specific information. Moreover, the answers to Question 3, 4, and 5 are considered in conjunction using the coding scheme as described in Table 4.2 to categorize potential descriptive stopping strategies.

The inter-rater reliability (IRR) was calculated by taking the ratio of the number of agreements among three coders while analyzing answers to every question to the overall sum of agreements and disagreements [94]. 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,

$$IRR\% = \frac{Agreements}{Agreements + Disagreements} * 100\% \quad (4.1)$$

Table 4.2. : 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.	<ul style="list-style-type: none"> <li>• “No, the [opponent-specific] information was not helpful”</li> <li>• “Definitely, it [opponent-specific information] helped”</li> </ul>
Factors	Based on the responses to Questions 3, 4, and 5 I identify the factors/reasoning provided by the participants that influenced their stopping decisions. Instances of this category are coded inductively after reading through the transcripts several times.	<ul style="list-style-type: none"> <li>• “for the most part, [for stopping] I was looking for a relatively high numeric answer” - objective value is a factor for stopping.</li> <li>• “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.</li> </ul>
Time Step	Based on the responses to Questions 3, 4, and 5, I 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.	<ul style="list-style-type: none"> <li>• The participant used the information as they began the search process.</li> <li>• The participant used the information at the end of the search process.</li> </ul>

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.

#### 4.5.2 Qualitative Analysis: Results

Through protocol analysis of the transcribed interviews, I identify 3 strategies that describe *how* participants accounted for opponent-specific information (IRR 90%). I 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. Existing literature in decision-making discusses how individuals set goals or targets for themselves while acquiring information [95]. 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. Existing literature acknowledges that resources are an important criteria for information acquisition decisions [96]. Such a criterion is described by the participants. For example, 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. Existing literature in operations research [97] acknowledges that decision makers who recognize improvement in their objectives make decisions to stop a product search and make a purchase. On a similar note, participants are describing such a strategy conditional on opponent-specific information. 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.”*

#### 4.5.3 Hypotheses Formulation

Based on the existing literature and the interview analysis of the participant’s stopping strategies, I hypothesize three stopping strategies as tabulated in Table 4.3. Strategy 1 implies that participants make stopping decisions on the basis of resources they want to expend. Once the expenditure budget is exhausted they decide to stop. Moreover, the value of the budget is influenced based on the opponent-specific



information. Strategy 2 implies that participants make stopping decisions on the basis of the quality of their design solution. Once they achieve a target quality they decide to stop. Moreover, the target quality value is influenced based on the opponent-specific information. Strategy 3 implies that participants make stopping decisions based on the improvement they achieve in their design quality over successive iterations. Once they observe that the quality is not improving enough they decide to stop. Moreover, the amount of improvement is influenced based on the opponent-specific information.

Table 4.3. : Characterizing s-SIADM strategies based on how and when opponent-specific information is utilized to stop the design search.

How	Strategy
<b>Decide Resource Expenditure</b>	Strategy 1: Stop if the cost of information acquisition exceeds a threshold value decided based on the opponent-specific information.
<b>Set Objective Achievement Target</b>	Strategy 2: Stop if the opponent would not be able to achieve the current best design.
<b>Set Objective Improvement Target</b>	Strategy 3: Stop if the amount of improvement one wishes to have in their design objective achievement based on the opponent-specific information is less than a threshold.

## 4.6 Computational Modeling of Hypothesized Stopping Strategies: Quantitative Analysis

In this section, I model the three hypothesized stopping strategies based on the results from the qualitative analysis.

### 4.6.1 Modeling Stopping Decisions

Based on the results of the qualitative analysis, I note that the hypothesized stopping strategies in Table 4.3 are *threshold based*, that is, the decision to stop or not is dependent on the threshold value of a strategy specific criterion. The criteria are

either attributes of the observed history  $\mathcal{H}_t$ , such as the function objective value and the expended resources or they could be derived quantities such as the improvement of objective in successive iterations. Moreover, the threshold value is utilized to make decisions by assessing whether the criteria is satisfied or not. The value of the threshold is dependent on individual specific parameters characterized by the type  $\theta$  of an individual. In my previous work, I introduce computational modeling of threshold based decisions [79, 90]. I leverage such a modeling approach for the hypothesized stopping strategies.

I note that modeling the identified stopping strategies as described by the human subjects falls under the realm of descriptive modeling. The definition of a descriptive decision model involves two activities, (i) formulating a decision strategy as a feature of the observed history, and (ii) modeling the stochasticity of an individual's decision making strategy using a likelihood function. Features are deterministic models that predict decisions for a given decision strategy, while likelihood functions, with their model parameters such as an individual's type  $\theta$ , add a layer of uncertainty around those predictions. The uncertainty modeling acknowledges that designers make decisions subjectively based on their type. Moreover, the assumption of probabilistic decisions assumes the limited cognitive ability of designers to make accurate decisions even though their judgments may be aligned with rational judgments.

Formally, I refer to a mapping between the observed history to some attribute as a feature function. A feature function (or simply feature) incorporates the observed history into the decision models. Given that multiple history attributes may influence decisions, a decision strategy is specified in terms of a weighted sum of multiple independent features. Thus, I model the stopping decision based on whether the weighted sum of features is greater or less than a threshold value. Mathematically, I characterize a particular strategy  $k$  using  $R_k$  independent features denoted by

$g_{k,t,1}(\mathcal{H}_t), \dots, g_{k,t,R}(\mathcal{H}_t)$ , with  $w_{k,1}, \dots, w_{k,R}$  as the weight parameters. Then, I model the stochastic stopping process  $S_{k,t}$  for a strategy  $k$  as follows:

$$S_{k,t} = \begin{cases} 1, & \text{with probability } \text{sigm} \left( \sum_{r=1}^{R_k} w_{k,r} g_{k,t,r}(\mathcal{H}_t) \right) \\ 0, & \text{otherwise,} \end{cases} \quad (4.2)$$

and, the stopping probability is given by,

$$\text{sigm} \left( \sum_{r=1}^{R_k} w_{k,r} g_{k,t,r}(\mathcal{H}_t) \right) = \frac{1}{1 + \exp \left( \sum_{r=1}^{R_k} w_{k,r} g_{k,t,r}(\mathcal{H}_t) \right)} \quad (4.3)$$

where,  $S_{k,t} = 1$  is the observation that an individual using a strategy  $k$  stops at the  $t^{\text{th}}$  time step, type  $\theta = \{w_{k,1:R}\}$  are designer-specific parameters modeled as the weight parameters. The weight parameter  $w_{k,r}$  can be positive or negative depending on whether an increase in  $g_{k,t,r}(\mathcal{H}_t)$ , respectively, increases or decreases the probability of stopping. I take  $g_{k,t,1}(\mathcal{H}_t) = -1$  because in a threshold-based decision model, a constant negative feature function  $g_{k,t,1}(\mathcal{H}_t) = -1$  implies that the *difference* between the weighted sum and a threshold determines the decision strategy.

While it is possible to model multiple history attributes as shown above, I model the stopping decision based on the features identified in the qualitative analysis (refer to Section 4.5.2. From the qualitative analysis, I find that human subjects describe a single feature of history while deciding whether to stop or not. Thus,  $R_k = 2$  for all  $k$ , that is, all the hypothesized strategies. To reflect this, without loss of generality, I model the stochastic process  $S_{k,t}$  as follows:

$$S_{k,t} = \begin{cases} 1, & \text{with probability } \text{sigm} (-\alpha_k (g_{k,t,2}(\mathcal{H}_t) - \beta_k)) \\ 0, & \text{otherwise,} \end{cases} \quad (4.4)$$

and, the stopping probability is given by,

$$\text{sigm}(-\alpha_k(g_{k,t,2}(\mathcal{H}_t) - \beta_k)) = \frac{1}{1 + \exp(-\alpha_k(g_{k,t,2}(\mathcal{H}_t) - \beta_k))} \quad (4.5)$$

where,  $\alpha_k$  and  $\beta_k$  are type  $\theta_k$  (weight) parameters that need to be determined for an individual following a strategy  $k$ .

### **Strategy 1: Decide based on resource expenditure**

According to Strategy 1 ( $k = 1$ ), the total resources expended or the expenditure budget is fixed. I assume that the resources expended in each step is the same. Consequently, I model that the number of steps  $t$  pursued is fixed. Accordingly, the feature function for Equation 4.5 for modeling Strategy 1 is:

$$g_{1,t,2}(\mathcal{H}_t) = t. \quad (4.6)$$

The individual specific parameters  $\theta_1 = (\alpha_1, \beta_1)$  intuitively model an individual's sensitivity to the budget expenditure and their belief about the threshold value for the resources to be expended.

### **Strategy 2: Decide based on objective achievement target value**

According to Strategy 2 ( $k = 2$ ), individuals decide to stop based on a target objective value. Accordingly, the feature function is:

$$g_{2,t,2}(\mathcal{H}_t) = Q_t, \quad (4.7)$$

where,  $Q_t$  is defined in Equation 3.4.

The individual specific parameters  $\theta_2 = (\alpha_2, \beta_2)$  intuitively model an individual's sensitivity to the objective achievement and their belief about the threshold value for the objective achievement target.

### Strategy 3: Decide based on objective improvement threshold

According to Strategy 3 ( $k = 3$ ), individuals decide to stop if the expected improvement of target objective in successive step is small. This strategy fits into Eq. (4.5) by defining the feature function as follows:

$$g_{3,t,2}(\mathcal{H}_t) = \max_{x \in \mathbb{R}} \text{EI}(x; \mathcal{H}_t), \quad (4.8)$$

where, the mathematical definition of EI is given by,

$$\begin{aligned} \text{EI}(x; \mathcal{H}_t) &= \mathbb{E} [\max(0, f(x) - Q_t) | x, \mathcal{H}_t] \\ &= (m_t(x) - Q_t) \Phi(Q_t | m_t(x), c_t(x, x)) + c_t(x, x) \mathcal{N}(Q_t | m_t(x), c_t(x, x)). \end{aligned} \quad (4.9)$$

Refer to Equation 3.4 through Equation 3.12 for the terms used to define EI.

The individual specific parameters  $\theta_3 = (\alpha_3, \beta_3)$  intuitively model an individual's sensitivity to the achievement of the expected improvement in the objective and their belief about the threshold value for the expected improvement.

#### 4.6.2 Inferring an individual's type from experimental observations

The goal of this section is to describe how one can infer the type of an individual  $\theta$  for a strategy  $k$  given a set of experimental history observations

$$h_t = h_{t-1} \cup \{(x_t, y_t, s_t)\}. \quad (4.10)$$

I proceed in a Bayesian way which requires the specification of a prior for  $\theta$ ,  $p(\theta)$ , a likelihood for the features  $g_{k,t,2}(h_t)$  for a strategy  $k$  given  $\theta$ ,  $p(g_{k,t,2}(h_t) | \theta)$ . The posterior state of knowledge about the type  $\theta$  is simply given by Bayes' rule:

$$p(\theta | h_t) \propto p(h_t | \theta) p(\theta), \quad (4.11)$$

and I characterize it approximately via sampling. I now describe each of these steps in detail.

Following the discussion of the previous section, I associate the type with the vector of parameters  $\theta_k = (\alpha_k, \beta_k) \forall k \in \{1, 2, \text{ or } 3\}$ , all of which have already been defined. From a Bayesian perspective, I describe my prior state of knowledge about  $\theta_k$  by assigning a probability density function to them, i.e.,  $\theta_k$  now becomes a random vector modeling my epistemic uncertainty about the actual type. However, to highlight the distinction between  $\theta_k$  and the random variables I defined in the previous section, I do not capitalize  $\theta_k$ . Specifically, the random variables,  $X_t, Y_t, S_t$ , are associated with the subject's behavior, whereas  $\theta_k$  is associated with my beliefs about the statistics of  $X_t, Y_t, S_t$  assuming a stopping strategy  $k$ .

Having no reason to believe otherwise, I assume that all components are a priori independent, i.e., the prior probability density (PDF) factorizes as:

$$p(\theta_k) = p(\alpha_k)p(\beta_k), \quad (4.12)$$

where,  $\alpha_k$  for all  $k$  are assigned an uninformative Jeffrey's prior, i.e.,  $p(\alpha_k) \propto \frac{1}{\alpha_k}$ , and

$$\begin{aligned} \beta_1 &\sim \mathcal{U}[0, 15] \\ \beta_2 &\sim \mathcal{U}[0, 150] \\ \beta_3 &\sim \mathcal{U}[0, 20] \end{aligned} \quad (4.13)$$

The range of the uniform distribution was chosen based on the design of the experiment. Note that here I have silently introduced a convenient notational convention, namely  $p(v)$ , which is the PDF of the related random variable evaluated at a given point  $v$ .

The second ingredient required for Bayesian inference of the type is the likelihood of the data  $g_{k,t,2}(h_t)$  conditioned on  $\theta_k$ . This was implicitly defined in the previous section. I have:

$$p(h_t|h_0, \theta_k) = \prod_{r=1}^t p(h_r|h_{r-1}, \theta_k), \quad (4.14)$$

since the model is Markovian. For each term within the product I have:

$$p(h_r|h_{r-1}, \theta_k) = [\text{sigm}(-\alpha_k(g_{k,t,2}(h_r) - \beta_k))]^{s_r} [1 - \text{sigm}(-\alpha_k(g_{k,t,2}(h_r) - \beta_k))]^{1-s_r}, \quad (4.15)$$

where  $X_r = x_r, Y_r = y_r, \mathcal{H}_{r-1} = h_{r-1}$  and for  $\alpha_k$  and  $\beta_k$  as in the conditioning  $\theta_k$ . According to my model, the stopping decision fully determined by the features observed thus far.

I sample from the posterior using the No-U-Turn Sampler (NUTS) [69], a self-tuning variant of Hamiltonian Monte Carlo [70] from the PyMC3 [71] Python module. I run the MCMC chain for 10,000 iterations with a *burn-in* period of 500 samples that are discarded. Equation 4.11 is used to estimate the researcher's posterior over  $\theta_k$  for each game play for each individual given their (individual's) search data.

#### 4.6.3 Hypotheses Operationalization

Table 4.4. : Hypotheses and their corresponding operationalization based on the influence of an opponent's past performance on an individual's threshold beliefs for a given stopping strategy.

Hypotheses	Operationalized Hypotheses
H1: Opponent's past performance information influences a participant's threshold for resource expenditure.	<p>H1.1*: The <math>\beta_{1,s}</math> of the individual participants are higher as compared to their <math>\beta_{1,p}</math> values when they are given the information about the opponents.</p> <p>H1.2*: The difference between the <math>\beta_{1,s}</math> and the <math>\beta_{1,p}</math> value of an individual when they are not given the information about their opponents, is zero.</p>
H2: Opponent's past performance information influences a participant's threshold for target objective value.	<p>H2.1*: The <math>\beta_{2,s}</math> of the individual participants are higher as compared to their <math>\beta_{2,p}</math> values when they are given the information about the opponents.</p> <p>H2.2*: The difference between the <math>\beta_{2,s}</math> and the <math>\beta_{2,p}</math> value of an individual when they are not given the information about their opponents, is zero.</p>
H3: Opponent's past performance information influences a participant's threshold for objective improvement.	<p>H3.1*: The <math>\beta_{3,p}</math> of the individual participants are higher as compared to their <math>\beta_{3,s}</math> values when they are given the information about the opponents.</p> <p>H3.2*: The difference between the <math>\beta_{3,s}</math> and the <math>\beta_{3,p}</math> value of an individual when they are not given the information about their opponents, is zero.</p>

I list all the hypotheses and their corresponding operationalization in Table 4.4. I formulate Hypothesis 1 (H1) through Hypothesis 3 (H3) based on Strategy 1 through Strategy 3, respectively. Lets recall the discussion in Section 4.5.3 and reiterate that the opponent-specific information influences participant's decision to stop based on various criteria as listed in Table 4.3. To discuss the operationalization of H1 through H3, I use the model parameters  $\beta_k$  (defined in Section 4.6.1). I define  $\beta_{k,s}$  as  $\beta_k$  for those contests where the opponent has a strong past performance record ( $\mu_{\text{opp}}$  between 95% to 99%) and  $\beta_{k,p}$  as  $\beta_k$  for those contests where the opponent has a poor past performance record ( $\mu_{\text{opp}}$  between 80% to 85%).

Hypothesis 1 is formulated based on Strategy 1 and it is operationalized by considering my computational model as described in Section 4.6.1. I consider that opponent-specific information influences an individual's belief about the threshold value for the resources to be expended ( $\beta_1$ ). I hypothesize (H1.1\*) that an individual's belief  $\beta_{1,s}$  about the threshold value for the resources to be expended will be higher when the opponent has a strong past performance as compared to an opponent with poor past performance  $\beta_{1,p}$ . Based on the protocol analysis, human subjects rationalize that they would have to spend greater resources to compete with a stronger opponent. To further validate the sensitivity of  $\beta_1$  to the information provided to the participants, I hypothesize (H1.2\*) that there is no difference in a participant's belief about the threshold value for the resources to be expended for an unknown opponent irrespective of whether they actually have a strong ( $\beta_{1,s}$ ) or poor ( $\beta_{1,p}$ ) past performance record.

Hypothesis 2 is formulated based Strategy 2 and it is operationalized by considering the computational model as described in Section 4.6.1. I consider that opponent-specific information influences an individual's belief about the threshold value for the objective achievement target value ( $\beta_2$ ). I hypothesize (H2.1\*) that an individual's belief  $\beta_{2,s}$  about the threshold value for the objective achievement target will be higher when the opponent has a strong past performance as compared to an opponent with poor past performance  $\beta_{2,p}$ . Based on the protocol analysis, human subjects rational-



ize that they would have to better achieve the objective to compete with a stronger opponent. To further validate the sensitivity of  $\beta_2$  to the information provided to the participants, I hypothesize (H2.2\*) that there is no difference in a participant's belief about the threshold value for the objective achievement target for an unknown opponent irrespective of whether they actually have a strong  $\beta_{2,s}$  or poor  $\beta_{2,p}$  past performance record.

Hypothesis 3 is formulated based Strategy 3 and it is operationalized by considering the computational model as described in Section 4.6.1. I consider that opponent-specific information influences an individual's belief about the threshold value for the expected improvement in the objective ( $\beta_3$ ). I hypothesize (H3.1\*) that an individual's belief  $\beta_{3,s}$  about the threshold value for the objective improvement will be *smaller* when the opponent has a strong past performance as compared to an opponent with poor past performance  $\beta_{3,p}$ . Based on the protocol analysis, human subjects rationalize that they would have to better achieve the objective to compete with a stronger opponent. Consequently, they would need to observe smaller successive improvements in objective achievement when they decide to stop. To further validate the sensitivity of  $\beta_3$  to the information provided to the participants, I hypothesize (H3.2\*) that there is no difference in a participant's belief about the threshold value for the objective improvement for an unknown opponent irrespective of whether they actually have a strong  $\beta_{3,s}$  or poor  $\beta_{3,p}$  past performance record.

## 4.7 Results and Discussion

The data, collected from the experiment described in Section 4.4, is pooled for every individual. Pooling refers to aggregating the collected data based on a criterion. As there were 36 participants, the experimental data set was pooled into 36 sets. For each set (or every individual) I sample model parameters  $\beta_k$  from the posterior distribution for each experimental treatment (refer to Table 3.2) and test H1.1\* to H3.2\*. Testing the hypotheses based on pooled datasets, helps us identify if any of

the belief parameters  $\beta_k$  are sensitive to the opponent specific information across all the individuals. I then discuss the implications of each of the hypothesis test results.

#### 4.7.1 Hypothesis 1

Mathematically, Hypothesis H1.1\* is considered as:

$$\text{H1.1}^* := \beta_{1,s} > \beta_{1,p}. \quad (4.16)$$

Thus, I calculate the following probability,

$$p(\text{H1.1}^* | h_t, \theta) = \mathbb{E} [\mathbb{I}_{[0,\infty]}(\beta_{1,s} - \beta_{1,p}) | h_t, \theta] \quad (4.17)$$

which is calculated by the average number of times the posterior samples of  $\beta_{1,s}$  are greater than posterior samples of  $\beta_{1,p}$ .

The results indicate that  $p(\text{H1.1}^* | h_t, \theta) = 0.71$ . As the value is greater than 50%, it implies that the Strategy 1 can predict stopping behaviors in an SIADM scenario under the influence of competition with a greater than random chance.

To further test the sensitivity of the model parameters, I test H1.2\* using the data where participants do not have information about the opponent. In H1.2\*, I consider no difference between  $\beta_{1,s}$  and  $\beta_{1,p}$ . I define the null hypothesis as follows:

$$\text{H1.2}^*_{\text{null}} := \beta_{1,s} > \beta_{1,p}. \quad (4.18)$$

Thus, I calculate the following probability,

$$p(\text{H1.2}^*_{\text{null}} | h_t, \theta) = \mathbb{E} [\mathbb{I}_{[0,\infty]}(\beta_{1,s} - \beta_{1,p}) | h_t, \theta] \quad (4.19)$$

which is calculated by the average number of times the posterior samples of  $\beta_{1,s}$  are greater than posterior samples of  $\beta_{1,p}$ .

The results indicate that  $p(\text{H1.2}^*_{\text{null}} | h_t, \theta) = 0.48$ . This implies that when the participants do not have information about the opponent, the model for Strategy 1

predicts that participants expend similar efforts for a strong and a poor performing opponent. This result further builds the confidence that the model is able to represent the influence of opponent-specific information on a participant's decision to stop via resource threshold.

#### 4.7.2 Hypothesis 2

Mathematically, Hypothesis H2.1\* can be considered as:

$$\text{H2.1}^* := \beta_{2,s} > \beta_{2,p}. \quad (4.20)$$

Thus, I calculate the following probability,

$$p(\text{H2.1}^* | h_t, \theta) = \mathbb{E} [\mathbb{I}_{[0,\infty]}(\beta_{2,s} - \beta_{2,p}) | h_t, \theta] \quad (4.21)$$

which is calculated by the average number of times the posterior samples of  $\beta_{2,s}$  are greater than posterior samples of  $\beta_{2,p}$ .

The results indicate that  $p(\text{H2.1}^* | h_t, \theta) = 0.62$ . This implies that the probability that Strategy 2 describes the influence of opponent-specific information on a participant's stopping decision is approximately 62%. As the value is greater than 50%, it implies that the Strategy 2 can predict stopping behaviors in an SIADM scenario under the influence of competition with a greater than random chance. However, Strategy 1 is likelier to describe participant behaviors as compared to Strategy 2.

To further test the sensitivity of the model parameters, I test H2.2\* using the data where participants do not have information about the opponent. In H2.2\*, I consider no difference between  $\beta_{2,s}$  and  $\beta_{2,p}$ . Thus, I define the null hypothesis as follows:

$$\text{H2.2}^*_{\text{null}} := \beta_{2,s} > \beta_{2,p}. \quad (4.22)$$

Thus, I calculate the following probability,

$$p(\text{H2.2}^*_{\text{null}} | h_t, \theta) = \mathbb{E} [\mathbb{I}_{[0,\infty]}(\beta_{2,s} - \beta_{2,p}) | h_t, \theta] \quad (4.23)$$

which is calculated by the average number of times the posterior samples of  $\beta_{2,s}$  are greater than posterior samples of  $\beta_{2,p}$ .

The results indicate that  $p(\text{H2.2}^*_{\text{null}}|h_t, \theta) = 0.49$ . This implies that when the participants do not have information about the opponent, the model for Strategy 2 predicts that participants have the same target objective value threshold for a strong and a poor performing opponent. This result further builds the confidence that the model is able to represent the influence of opponent-specific information on a participant's decision to stop via objective threshold.

### 4.7.3 Hypothesis 3

Mathematically, Hypothesis H3.1\* can be considered as:

$$\text{H3.1}^* := \beta_{3,p} > \beta_{3,s}. \quad (4.24)$$

Note that here  $\beta_3$  represents expected improvement which has an inverse relationship with the past performance record of an opponent such that I hypothesize that  $\beta_{3,p} > \beta_{3,s}$ . Thus, I calculate the following probability,

$$p(\text{H3.1}^*|h_t, \theta) = \mathbb{E} [\mathbb{I}_{[0,\infty]}(\beta_{3,p} - \beta_{3,s}) | h_t, \theta] \quad (4.25)$$

which is calculated by the average number of times the posterior samples of  $\beta_{3,p}$  are greater than posterior samples of  $\beta_{3,s}$ .

The results indicate that  $p(\text{H3.1}^*|h_t, \theta) = 0.61$ . This implies that the probability that Strategy 3 describes the influence of opponent-specific information on a participant's stopping decision is approximately 61%. As the value is greater than 50%, it implies that the Strategy 2 can predict stopping behaviors in an SIADM scenario under the influence of competition with a greater than random chance. However, Strategy 1 is likelier to describe participant behaviors as compared to Strategy 3 (and Strategy 2).

To further test the sensitivity of the model parameters, I test H3.2\* using the data where participants do not have information about the opponent. In H3.2\*, I consider no difference between  $\beta_{3,p}$  and  $\beta_{3,s}$ . Thus, I define the null hypothesis as follows:

$$\text{H3.2}^*_{\text{null}} := \beta_{3,p} > \beta_{3,s}. \quad (4.26)$$

Thus, I calculate the following probability,

$$p(\text{H3.2}^*_{\text{null}}|h_t, \theta) = \mathbb{E} [\mathbb{I}_{[0,\infty]}(\beta_{3,p} - \beta_{3,s}) | h_t, \theta] \quad (4.27)$$

which is calculated by the average number of times the posterior samples of  $\beta_{3,p}$  are greater than posterior samples of  $\beta_{3,s}$ .

The results indicate that  $p(\text{H3.2}^*_{\text{null}}|h_t, \theta) = 0.47$ . This implies that when the participants do not have information about the opponent, the model for Strategy 3 predicts that participants have the same expected improvement value threshold for a strong and a poor performing opponent. This result further builds the confidence that the model is able to represent the influence of opponent-specific information on a participant's decision to stop via objective improvement threshold.

#### 4.7.4 Posterior Predictive Checking

To check the fit of the modeled parameters, I conduct posterior predictive checking (PPC). I leverage the posterior distributions  $p(\theta_k|h_t)$  of the model parameters to simulate search history  $h_{t,\text{sim}}$  for each hypothesized strategy.

$$p(h_{t,\text{sim}}|h_t) = \int p(h_{t,\text{sim}}|\theta)p(\theta|h_t)d\theta \quad (4.28)$$

The simulated stopping data  $s_{t,\text{sim}} \subseteq h_{t,\text{sim}}$  for each strategy is utilized to calculate the simulated effort  $t_{\text{sim}}$  against opponents with varying historical information. The number of tries  $t_{\text{sim}}$  by the participants from the simulated stopping data  $s_{t,\text{sim}}$  is given by,

$$t_{\text{sim}} = \{(t) : s_{t,\text{sim}} = 1\}. \quad (4.29)$$

I test for the statistical differences in the simulated efforts  $t_{\text{sim}}$  for each strategy given good and bad opponents to observe systematic discrepancies, if any, across the hypothesized stopping strategies. Based on the observations, I hypothesize that the simulated efforts for each strategy should show that participants expended greater efforts when they knew opponents had a strong past performance record than when they knew opponents had a poor past performance record.

### Simulating Stopping Decisions for Strategy 1

I conduct a two sample t-test with unequal variances to test whether the simulated efforts, based on the resource threshold parameters  $\beta_1$ , are greater when the opponent had a strong past performance record than when the opponents had a poor past performance record. I find a statistically significant difference in the simulated data such that the effort expended is greater when the opponent had a strong past performance record than when the opponents had a poor past performance record.

Table 4.5. : The mean  $\mu$  and standard deviation  $\sigma$  of the simulated number of tries  $T_{\text{sim}}$

Condition	Simulated number of tries $T_{\text{sim}}$ for Strategy 1	
	Mean $\mu$	Standard Deviation $\sigma$
Given $\beta_1$ strong past performance record Sample size=36	$\mu_{T_{\text{sim}}}^G = 4.23$	$\sigma_{T_{\text{sim}}}^G = 2.85$
Given $\beta_1$ poor past performance record Sample size=36	$\mu_{T_{\text{sim}}}^B = 3.70$	$\sigma_{T_{\text{sim}}}^B = 2.10$

Table 4.6. : Summary of the two-sample t-test for posterior predictive check for strategy 1.

	Alternate Hypothesis	t stat.	p-value
PPC1	$\mu_{T_{\text{sim}}}^G > \mu_{T_{\text{sim}}}^B$	-3.33	< 0.01

## Simulating Stopping Decisions for Strategy 2

I conduct a two sample t-test with unequal variances to test whether the simulated efforts, based on the target objective threshold parameters  $\beta_2$ , are greater when the opponent had a strong past performance record than when the opponents had a poor past performance record. I find a statistically significant difference in the simulated data such that the effort expended is greater when the opponent had a strong past performance record than when the opponents had a poor past performance record.

Table 4.7. : The mean  $\mu$  and standard deviation  $\sigma$  of the simulated number of tries  $T_{\text{sim}}$

Condition	Simulated number of tries $T_{\text{sim}}$ for Strategy 2	
	Mean $\mu$	Standard Deviation $\sigma$
Given $\beta_2$ strong past performance record Sample size=36	$\mu_{T_{\text{sim}}}^G = 4.30$	$\sigma_{T_{\text{sim}}}^G = 3.61$
Given $\beta_2$ poor past performance record Sample size=36	$\mu_{T_{\text{sim}}}^B = 3.78$	$\sigma_{T_{\text{sim}}}^B = 2.30$

Table 4.8. : Summary of the two-sample t-test for posterior predictive check for strategy 2.

	Alternate Hypothesis	t stat.	p-value
PPC2	$\mu_{T_{\text{sim}}}^G > \mu_{T_{\text{sim}}}^B$	-3.15	< 0.01

## Simulating Stopping Decisions for Strategy 3

I conduct a two sample t-test with unequal variances to test whether the simulated efforts, based on the expected improvement of the objective threshold parameters  $\beta_3$ , are greater when the opponent had a strong past performance record than when the opponents had a poor past performance record. I do not find a statistically significant difference in the simulated data which implies that I cannot infer whether the effort

expended is greater when the opponent had a strong past performance record than when the opponents had a poor past performance record.

Table 4.9. : The mean  $\mu$  and standard deviation  $\sigma$  of the simulated number of tries  $T_{\text{sim}}$

Condition	Simulated number of tries $T_{\text{sim}}$ for Strategy 3	
	Mean $\mu$	Standard Deviation $\sigma$
Given $\beta_3$ strong past performance record Sample size=36	$\mu_{T_{\text{sim}}}^G = 2.38$	$\sigma_{T_{\text{sim}}}^G = 0.38$
Given $\beta_3$ poor past performance record Sample size=36	$\mu_{T_{\text{sim}}}^B = 2.47$	$\sigma_{T_{\text{sim}}}^B = 0.38$

Table 4.10. : Summary of the two-sample t-test for posterior predictive check for strategy 3.

	Alternate Hypothesis	t stat.	p-value
PPC3	$\mu_{T_{\text{sim}}}^G > \mu_{T_{\text{sim}}}^B$	1.34	0.19

#### 4.7.5 Discussion

I summarize the results of the hypotheses tests as well as the posterior predictive checks in Table 4.11. The results indicate that Strategy 1, that is, stopping based on resource threshold, is the most representative of an individual's stopping strategy under the influence of opponent specific information. While I observe the sensitivity of the threshold parameters across all hypothesized stopping strategies with a probability greater than that of a random chance (0.5).

While specific individuals may adopt different strategies for stopping information acquisition, contest designers would need to analyze behaviors across a group of participants. The result that Strategy 1 is representative of the decision making behaviors across a group of individuals is thus valuable from the perspective of design of engineering design contests. The results contribute to the conditions that



can be facilitated by contest designers, such as, setting target budget expenditures if competition is high such that participants can expend greater efforts.

Table 4.11. : Summary of the Results. ✓ indicates rejection of null and ✗ indicates failure of null rejection.

Hypotheses	Individual-level Results	Posterior Pre-dictive Check
Strategy 1 (H1)	H1.1* : ✓ H1.2* : ✓	✓
Strategy 2 (H2)	H2.1* : ✓ H2.2* : ✓	✓
Strategy 3 (H3)	H3.1* : ✓ H3.2* : ✓	✗

## 4.8 Conclusions

In this study, I illustrate a mixed-methods approach where both interviews and controlled behavioral experimentation are conducted to investigate the influence of opponent-specific information on an individual's stopping decision in a sequential decision making process. I illustrate that the cognitive factors that influence individual's preferences can be investigated using the presented approach.

I find that individuals make decisions to stop acquiring information based on various factors 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. Moreover, the factors are computationally modeled as threshold functions to influence information acquisition via an individual's decision to stop such acquisition. The results of the computational models indicate that an individual's threshold for the expenditure of efforts is influenced the most by the opponent-specific information as compared to the other two thresholds. Thus, we can model individuals' decision to

stop information acquisition activities on the basis of resource expenditure identified as the most sensitive factor influencing the decision.

This study bridges the gap between modeling decision making and account for cognition. I do not claim that all individuals make information acquisition decisions on the basis of resource expenditure. Instead, I suggest that modeling a participant population's decision making on the basis of resource thresholds can provide behavioral insights to contest designers about the population towards making predictions about contest outcomes. By studying the cognitive factors that influence decision making, intervention design decisions can be made to influence behavior change. Moreover, by modeling the influence of such factors, expectations of the behavior change interventions can be set. Such expectations in computational terms would be the predictions about the influence of behavioral change interventions. Further investigations are required to study how the modeled cognitive factors can be leveraged to study contest design for behavior change in the participants and thereby in the contest outcomes.

The triangulation approach utilized in this study was in series (refer to Section 4.3.2). Thus, I acknowledge a potential threat to validity in this study because the experimental population leveraged is the same for both qualitative and quantitative data analysis. While triangulation strengthens validity, if the sample population is the same for both qualitative and quantitative data, existing literature needs to be utilized for establishing whether the results of the qualitative analysis are generalizable. This can be done by analyzing the qualitative findings in light of the behaviors discussed in existing literature. Reference to existing literature is illustrated Section 4.5.2 such that the existing literature on stopping strategies discussed in Section 4.4.2 is leveraged to substantiate the findings from qualitative analysis towards facilitating formulation of hypotheses.

## 5. STUDENTS AS SEQUENTIAL DECISION MAKERS: EDUCATIONAL IMPLICATIONS OF THIS RESEARCH

### 5.1 Chapter Overview

In this chapter, I report the study conducted to investigate students' decision-making during the information gathering activities of a design process. Existing literature in engineering education has shown that students face difficulties while gathering information in various activities of a design process such as brainstorming and CAD modeling. Decision-making is an important aspect of these activities. While gathering information, students make several decisions such as what information to acquire and how to acquire that information. There lies a research gap in understanding how students make decisions while gathering information in a product design process. To address this gap, semi-structured interviews and surveys in a product design course are conducted. I analyze the students' decision-making activities from the lens of the SIADM framework discussed in Chapter 2. I find that the students recognize the need to acquire information about the physics and dynamics of their design artifact during the CAD modeling activity of the product design process. However, they do not acquire such information from their CAD models primarily due to the lack of the project requirements, their ability, and the time to do so. Instead, they acquire such information from the prototyping activity as their physical prototype does not satisfy their design objectives. However, the students do not get the opportunity to iterate their prototype with the given cost and time constraints. Consequently, they rely on improvising during prototyping. Based on the observations, I discuss the need for designing course project activities such that it facilitates students' product design decisions. Thus, this study illustrates the educational implications of

this dissertation work by leveraging the SIADM framework. Parts of this work is published in ASME IDETC/CIE conferences in 2018 [98] and in 2019 [99].

## 5.2 Introduction

Existing literature in engineering education has several studies on students' design behaviors in product design processes [100–103]. Such studies have concluded that students, as novices, face difficulties in the problem scoping and information gathering activities of a design process. They lack the design frames to scope their problem and accordingly gather information [100]. Experts, on the other hand, tend to solve design problems from a domain-specific frame of reference which allows them to quickly converge to meaningful design outcomes [104]. Thus, information gathering activities of students require further investigation in order to understand the specific challenges they face in them in order to enable educators to accordingly design courses and facilitate students' design activities.

One of the lenses to investigate students' information gathering activities is by considering design as a decision-making process [105]. While gathering information, students make several decisions such as what information to acquire and how to acquire that information. There lies a need to investigate such decisions and decision-based design (DBD) frameworks can be utilized to do so [106]. However, the engineering education research community has been dismissive of decision-based design (DBD) frameworks [107]. Dym et al. [107] critique that DBD frameworks provide little guidance on analyzing how students gather information and generate alternatives to make decisions. Moreover, they discuss that DBD frameworks are only considered relevant for making decisions *after* the information required to make such decisions has been acquired [107]. However, I argue that DBD frameworks can be utilized to analyze information acquisition activities of a design process.

In this study, I utilize the SIADM framework, discussed in Chapter 2, to investigate how students make product design decisions. I focus on their information

acquisition decisions such as how to acquire information which ultimately affects their design outcomes. I collect the students' decision-making data through semi-structured interviews and surveys in ME444: Toy Design course offered in the School of Mechanical Engineering at Purdue University.

The investigation results in insights on the specific challenges the students experience while gathering information. I find that they recognize the need to acquire information about the physics and dynamics of their design artifact during the CAD modeling activity of a product design process. However, they do not acquire such information during their CAD modeling activities primarily due to the lack of project requirements, their ability to utilize physics simulation packages, and the time to do so. Instead, they acquire such information from the prototyping activity. With the given cost and time constraints, they do not get the opportunity to iterate their prototype. Consequently, they rely on improvising during prototyping. The study also supports the observation in existing literature that students, as novices, tend to have higher design iterations than expected in product design activities [100–103]. Furthermore, the SIADM framework enables us to understand how information acquisition activities influence students' decision-making behaviors.

The remainder of this chapter is organized as follows. In Section 5.3, I review existing literature on product design processes. The review explores the themes of information gathering, problem framing, and decision-making including my work on the integration of these themes. In Section 5.4, I introduce the course project and its learning objectives. Then, I describe the details of the study including the research methods, data collection, and analyses techniques. In Section 5.5, I report the observations. In Section 5.6, I discuss the need to design courses such that it accounts for students' decision-making and information acquisition behaviors. I provide recommendations for the design of design projects and discuss the limitations of this study.

### 5.3 Literature Review: Problem Framing, Information Gathering, and Decision-making

Problem framing is recognized as that activity of the design process that deals with the identification of problems, setting the design goals, requirements, and stating the assumptions and/or limitations [100]. Several studies have acknowledged the importance of problem framing [102,108]. While studying expert designers, the authors [104] observed that the experts engaged in problem framing activities that motivated them to innovate. Studies that focus on expert-novice differences have found that experts spend more time in problem framing activities than novices [100,109,110]. Studies on students, as novices, have also shown that students tend to be more effective as designers if they spend greater amounts of time in problem framing activities [111].

Information gathering is an essential part of problem framing activities. Studies have suggested how information gathering is observed in effective team's design behaviors [111]. It is also shown that information gathering as a part of design activities is more meaningful than the act of gathering information in itself [112]. Students who just focused on information gathering got stuck in the early stages of design rather than progressing to generate design outcomes. The authors [112] observe that effective students quickly learn to integrate acquired information within the frame of their problem.

Problem framing and information gathering culminate into decision-making activities [10,105]. Consequently, decision-based design research has emerged as an important research area built on the foundations of mathematical principles and decision theory [105,113]. Existing research has focused on characteristics of decision-making activities such as preference analysis [12], decision-making under uncertainty [114], and deviation from rationality [115]. Thus, decision-making motivates the formulation of important learning objectives in engineering design education [116].

Using the foundations of decision theory has been recognized as a means to improve engineering design education [117]. However, DBD frameworks in engineering education are considered relevant purely from a pedagogical standpoint [107]. From a research standpoint, it is argued that DBD frameworks provide little guidance on analyzing how students gather information and generate alternatives to make decisions [107]. Such a belief in the engineering education research community is not unfounded. Historically, DBD research has primarily emphasized on making artifact decisions using a specified state of information [68]. However, efforts are being made towards utilizing descriptive theory, i.e., understanding how humans make decisions within the design process [106, 118, 119]. In the previous chapter (refer to Chapter 2) I present an SIADM framework that integrates information gathering and decision-making activities which is utilized as a lens to analyze the information acquisition activities of students in a product design process.

## 5.4 The Study

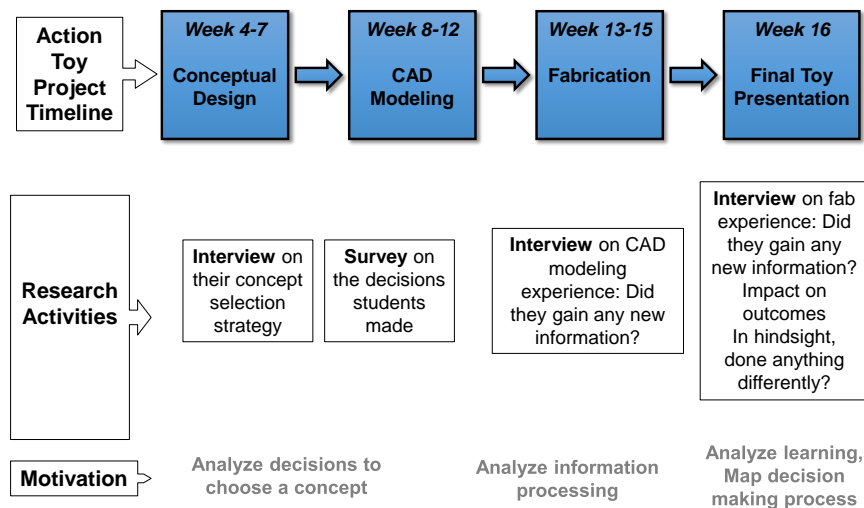


Figure 5.1. : Overview of the design process activities and the research activities during the action toy project in ME444 Toy Design course.

I observe the students' decision-making in ME444: Toy Design course offered as an elective undergraduate course in the School of Mechanical Engineering at Purdue University. The learning objectives of the course include integrating CAD knowledge with rapid prototyping techniques such as 3D printing and laser cutting. For the achievement of the learning objectives, the students are required to work on two projects, a guided design project and an action toy project. The guided project's emphasis is on CAD modeling and rapid prototyping activities only. In the guided project, they are required to model a car chassis in CAD software and create a prototype. They are provided with all the information required to do so. Thus, they do not engage in information gathering activities. For the action toy project, they are required to design a toy following a typical product design process involving brainstorming, conceptual design, CAD modeling, and prototyping activities. In the action toy project, they experience information gathering and decision-making in various activities of a typical product design process. Thus, the study only focused on the students' decision-making in the action toy project. However, I account for the fact that they gain experience in rapid prototyping techniques via the guided project. Such a design of the course projects was deliberate such that the students have prior experience for the CAD modeling and prototyping activities in the action toy project. The course had a total of 44 upper-level undergraduate students divided into 12 teams. The students work in teams of 3 or 4 who are randomly assigned at the beginning of the semester.

The overview of the activities of the action toy project is illustrated in Figure 5.1. The students were required to brainstorm toy ideas and then submit a proposal document with detailed design, assembly, prototyping, and purchase plans for two toy design concepts. The project required a "non-trivial motion" and they could make purchase decisions for electronic components such as motors and batteries, if required, with the given cost constraints. The students received feedback on their proposal document from the instructor and the teaching assistants. Each team had to then decide which idea to choose. I consider these activities and decisions as a part



of the conceptual design activities for the toy. After the conceptual design activities, the students were required to model the details of their chosen toy in CAD and create the toy assembly. I consider these activities as a part of the CAD modeling activities for the toy. Then, the students had to utilize rapid prototyping techniques namely laser cutting and 3D printing to physically fabricate their toy. They were given size and volume constraints for the same. The students were required to assemble their fabricated parts along with their purchased parts to create the toy prototype. I consider these activities as a part of the prototyping activities for the toy. Finally, they had to present their toy prototype via a group presentation.

#### **5.4.1 Data Collection**

I conducted one survey and three semi-structured interviews over the course of the toy design project as shown in Figure 5.1. The survey was conducted during the conceptual design activities and focused on the students having to list the decisions they were making during these activities. The semi-structured interviews were designed to investigate how and why the students made decisions in the conceptual design, CAD modeling, and prototyping activities. The students were incentivized for participating in the survey and interviews. They were provided with a 2% participation bonus to their overall grade.

The interviews were audio recorded and then transcribed. The first and second interviews were conducted one-on-one with the students. This was done in order to document the decisions made by every team member as well as verify decisions across team members. These interviews lasted for an average of 5 minutes. The final interviews (interview 3) were conducted with the entire team due to time constraints and lack of the students' availability after the end of the course. The final interviews lasted for an average of 12 minutes.

## Conceptual Design Activities

In the conceptual design activities, I focused on investigating the students' concept elimination and concept selection strategy. By the term 'strategy', I refer to their motivations and preferences for eliminating and selecting their reported concepts. I distinguish between concept elimination and selection strategy as follows. I label the students' reported preferences to choose two concepts from the several ideas they were brainstorming as their concept elimination strategy. The students received feedback on their proposed concepts. Then, based on the feedback and their team preferences, they were required to select a toy concept as their toy project. I label the students' reported preferences to choose a concept from their proposal as their concept selection strategy.

The students were asked to complete an online survey and report the decisions they were making, various alternatives they were considering, and the alternative they chose. I use the survey data to report the decisions the students made during the conceptual design activities. During interview 1, the students were interrogated on their strategies to eliminate and select concepts.

I acknowledge that the conceptual design activities are worthy of extensive research on their own. There are several activities that occur at a cognitive level such as students recollecting their experiences from memories which allows them to exploit various known toy concepts as well as students utilizing various sources of information to explore further concepts. However, in this study, for the conceptual design activities, I only focus on the students' decision-making strategy for concept selection and elimination.

## CAD Modeling Activities

For the action toy project, the students spent the majority of their time on the CAD modeling activities. Therefore, I investigate these activities in detail. From the lens of the SIADM framework, I consider that CAD modeling acts as an information

processing as well as an information acquisition activity. CAD modeling enables students to visualize their conceptual design and therefore helps them process the information they acquired during the conceptual design activities. CAD also results in information acquisition as students can experiment with various dimensions of the toy parts and consequently process information about how various parts will work together as an assembly.

To understand the impact of CAD activities on the students' decision-making, I formulate interviews 1 and 2 as follows. First, I wanted to know what the students believe about CAD as a part of the product design activity *before* entering into the CAD modeling activities. Since interview 1 was conducted prior to the beginning of CAD modeling activities, it was utilized to elicit their beliefs. By the term beliefs, I refer to their motivations for CAD modeling such as CAD as an information acquisition activity and as an activity to create STL files to facilitate 3D printing. During the CAD modeling activities, the students were making detailed design decisions such as what dimensions to choose for each toy part. Interview 2 was conducted at the end of these activities. From interview 2, I investigated the students' experience with CAD *after* the activity. I wanted to investigate whether the students acquired additional information, what decisions they made, and if they encountered anything unexpected from the CAD modeling activities.

### **Prototyping Activities**

During the prototyping activities, the students assembled the physical prototype of their toy. They had received their parts from the laser cutting and 3D printing workshops as well as the electronic parts they had ordered. Their decisions of tolerance selections for dimensions as well as choosing the fabricating techniques were made during the CAD modeling activities. The students were interrogated during interview 2 regarding their tolerance decisions and their motivation to choose proto-

typing techniques for their toy parts. During the prototyping activities, they gained information regarding the outcomes of the decisions made in CAD modeling activities.

During interview 3, the students were asked whether they believed that the nature of their design process was iterative and they were asked to elaborate on the specific aspects of what they found iterative in nature. The motivation for such a question was to investigate the sequence of their decision-making process. The students were also engaged in a hypothetical scenario where they were asked if they had added 4 weeks of time, what steps they would have taken. The purpose of such a question was to understand what the students learned from their design prototype and their tendency to move further along the product design process.

Table 5.1. : Concept Selection and Elimination Preferences Coding Scheme

Preference Criterion	Details	Coded Example
Constraint Satisfaction (CS)	Satisfying constraints based on criteria provided in the project description such as complexity requirement, manufacturing techniques, cost requirement, volume constraints, mechanical motion, and complexity.	<i>“we want to do something with the mechanisms and the ideas that are not feasible with 3d printing and laser cutting [were eliminated]”</i>
Team’s Ability (AB)	Ability to think and execute detailed design for an idea.	<i>“we all agreed that we wanted to make a mechanism that’s simple and it’s not outside our ability so the first step was to make sure that everything was doable.”</i>
Team’s Interest/Fun (FN)	Whether the concept was fun to pursue.	<i>“We all picked one idea that we liked that was fun project to make”</i>
Originality (OG)	Whether the idea was original and innovative.	<i>“we also wanted our idea to be original and so couple of our ideas weren’t original”</i>
User Centered Design (UC)	Whether the idea was fun for children.	<i>“we kind of eliminated ideas based on what was the most interesting to kids.”</i>
Fixation (FX)	Selecting an idea because the team was fixated on it.	<i>“we went and thought about other ideas but since we were most passionate about the first idea we kind of like knew kind of in the beginning that we would go through that one ”</i>
Prior Knowledge (PK)	Whether team members had prior experience to deal with the detailed design.	<i>“[we] just kinda came up with creative ideas on our own based on the things we’ve done in our lives ”</i>

### 5.4.2 Data Analysis

I analyze teams' decision-making activity from all the interviews as well as the submitted proposal document. These documents were analyzed through content analysis [93] to code words and sentences as 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 5.2. The characterized decisions were then analyzed from the lens of the SIADM framework to characterize information acquisition, information processing, and decision-making activities.

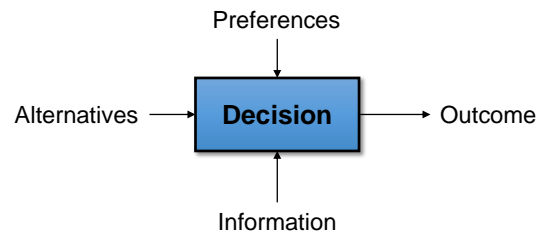


Figure 5.2. : Characteristics of a decision.

Using the SIADM framework as shown in Figure 2.1, I characterize the students' decision-making activity by investigating the information they required to make the decisions, their recognition of whether they possessed the information, their decision to acquire information if needed, and their decision based on the information they acquired. For example, transcripts with words such as “what”, “how”, “choose”, “decide”, and “when” typically resulted in identification of decisions. The interviews were semi-structured. Therefore, follow up questions were asked to further investigate how such decisions were made by investigating the characteristics of a decision as described in Figure 5.2. Various decisions reported by individual students were then pooled to their respective teams to get a clearer picture of their decisions across conceptual design, CAD modeling, and prototyping activities. The decisions in each of these activities are reported in Section 5.5. I report the common and critical decisions

for each team in Section 5.5.4. In Section 5.5.4, I also analyze the hypothetical decisions they reported that they would've made from the final interview (interview 3).

For the conceptual design activities, I utilized content analysis [93] to elicit the students' preferences for eliminating and selecting concepts. Through such analysis, I marked words and phrases into various preference categories that represent the conditions on the basis of which the students eliminated and selected concepts. For example, when a student mentioned "we wanted to select an idea that was doable" I considered the statement as a part of their elimination strategy and labeled such a preference criterion as a part of the team's ability category. Table 5.1 lists all the categorized preference criteria. Such criteria were then utilized to label their concept selection and elimination strategy discussion from interview 1. The transcribed text from Interview 1 was analyzed several times over to count the number of instances that belong to each of these criteria. We sum the frequencies of instances of each of these criteria across interviews. We also sum these frequencies from individual interviews according to the teams to which the individuals' data belonged. Multiple coders analyzed the frequencies to ensure the reliability of the results. The inter-rater reliability (IRR) was calculated by taking the ratio of the number of agreements amongst coders for labeling each instance to the overall sum of agreements and disagreements [94].

$$IRR\% = \frac{Agreements}{Agreements + Disagreements} * 100\% \quad (5.1)$$

We also utilized the content analysis to analyze the teams' submitted proposals for their decisions and proposed ideas. The results of the content analysis are presented in Section 5.5.1. Additionally, the content analysis aided us in understanding the students' beliefs about CAD modeling activity. Such beliefs about CAD modeling are summarized in Section 5.5.2.

## 5.5 Results

I present the results of the observations on the students' decision-making activities in the order of the conceptual design, CAD modeling, and prototyping activities of the product design process as described in Figure 5.1. I also report the observations from analyzing decisions across individual students as well as the teams.

### 5.5.1 Conceptual Design Activities

Out of the 44 students, 34 were available for interview 1. In other words, 7 out of 12 teams had all the members who reported for interview 1. I find that ( $IRR\% = 80$ ) on average the students eliminated ideas predominantly based on constraint satisfaction (CS), i.e., whether the idea satisfied the design constraints provided in the project description. In order to select the final idea, I find that ( $IRR\% = 79$ ) the students not only selected the idea that satisfied constraints (CS) but also selected it based on their team's interest (FN) to pursue the idea. These results are also applicable on a team-level analysis to the 7 teams where all the members reported for interview 1. Table 5.2 illustrates the frequency count of preference criteria codes for all the teams for concept elimination strategy.

I also find that each team reported two decisions, namely, the decision to propose two ideas, and the decision to select the final idea. However, only two students reported additional decisions related to assembly, prototyping, and purchasing. These decisions were expected to be made while submitting their conceptual design proposal. I observe the students' assembly, prototyping, and purchasing decisions in the submitted proposal document. However, they do not report these decisions in the interviews during the conceptual design activities. Instead, I observe the discussion of such decisions during the specific activities for which the decisions were made, namely, during the CAD modeling and prototyping activities.

An interesting observation ( $IRR\% = 100$ ) is that 8 out 12 teams had one of their toy proposal idea similar to the car design guided project conducted earlier in the

Table 5.2. : Frequency Count Data for Concept Elimination Coding

Preference Criteria	Frequency of Instances											
	Team 1	Team 2	Team 3*	Team 4*	Team 5	Team 6*	Team 7*	Team8	Team 9*	Team 10*	Team 11*	Team 12*
Sum												
CS	0	2	6	16	0	15	7	1	7	3	8	10
AB	3	3	2	7	4	0	2	0	2	1	4	5
FN	0	4	2	5	1	5	3	2	3	2	1	3
OG	0	2	0	1	0	4	1	0	0	0	0	3
UC	0	0	0	3	0	0	0	0	3	0	0	0
FX	2	2	0	0	0	0	1	0	2	0	0	0
PK	0	0	0	1	0	0	0	0	0	0	0	1
	** indicates those teams where all the members were available for interview 1											
Sum												



semester. The idea was modified to accommodate the project requirements, however, it was observed that the students strategize idea proposal such that one of the ideas was an outcome of the brainstorming activity which the team wanted to pursue based on interest. The other idea involved the guided project's car design concepts. This observation is an example of design fixation [120] during the conceptual design activities. However, it can also be argued that the students' design behaviors are rational given the project time constraints such that their prior experience from the guided toy project is being judiciously utilized.

### 5.5.2 CAD Modeling

Out of the 44 students, 36 were available for interview 2. I find that 10 out of 12 teams believe that the course content improved their CAD modeling ability as well as their ability to use Creo which is a CAD modeling software. The remaining two teams reported that the course did not improve their CAD knowledge as they already had prior experience. All the students reported that they believe that CAD as an activity is important for the visualization of their design concepts.

I find that ( $IRR\% = 100$ ) 9 out of 12 teams recognize the need to model the physics of their toy including aspects such as springs, hydraulic actuators, and gravity. For example, helical springs in Creo can be modeled if one knows how to utilize helical sweeps as well as provide the geometric information required by Creo to do so. However, all the 9 teams reported that they did not acquire such information during CAD modeling activities as the project requirement did not explicitly state the need to do so, the students did not have the appropriate knowledge to utilize various modeling functionalities and simulation packages in CAD, and the students had limited time to fabricate their toy. This resulted in the students encountering prototyping problems as their physical toy prototype did not function as intended. The students also did not have enough resources in terms of budget and time to iterate their prototype. Such setbacks resulted in the students having to improvise modifications for their physical

prototype. Table 5.3 provides examples of instances when the students reported their lack of information acquisition in CAD.

Table 5.3. : Examples of instances when the students could not acquire information in CAD.

Team Number	Instance of lack of information acquisition during CAD
Team 6	<i>“Our design process is definitely iterative because we had to rebuild stuff in cad multiple times and I built 6-7 tracks none of them ending up working the cad model”</i>
Team 8	<i>“the physical model was quite different and we had to add multiple batteries and that wasn’t accounted for... If we had a way to model k value of springs etc it would’ve been better ”</i>
Team 9	<i>“the charge system is very tolerance dependent it was difficult to model in cad with motion. our design use a lot of spring based mechanism but its hard to estimate the friction from 3d printed parts ”</i>
Team 12	<i>“[we] have gravity to worry about and just there is going to be a few problems with how everything comes together”</i>

I also find that the students report that they execute several design iterations for achieving the volume constraints in CAD. The students experiment with different dimensions of their CAD parts and report this activity as an iterative procedure towards *satisficing* the volume constraint provided for the material utilized for fabrication activities. For example, one of the students reported as follows, *“Our [CAD] design process is definitely iterative because we had to rebuild stuff in cad multiple times”*.

### 5.5.3 Prototyping

All the 44 students were available for the final interview. I find that the teams’ decision to choose dimensions for a toy part was influenced by the prototyping technique chosen for the fabrication of that part. This behavior is consistent with the learning objective of the course where the students are required to learn how to de-

sign for manufacturability. I also find that teams who faced difficulty in anticipating potential roadblocks, while translating their CAD model to a physical prototype, relied on trial and error to improve the assembly of their prototype. For example, a member of team 10 reported the following. *“after printing [from] the SLA printer we figured out there was warping ’coz of the print direction. We definitely learnt a lot about improving our design.”* .

During the prototyping activities, the students acquired information about the physics of their prototypes such as friction between parts, tolerance limits for 3d printing and laser cutting techniques, the strength of the parts such as springs, and an understanding of the actuation power required for a successful motion of the toy. The students also did not account for the impact of using spray paints to improve the aesthetics of the toy. The spray paint added an additional layer of coating over the parts which resulted in dimension tolerance mismatch and jamming of parts. Such lack of information during the CAD modeling activities resulted in the students reporting the need to have additional iterations during the prototyping activities.

#### 5.5.4 Decisions

By analyzing decisions across the teams, I tabulated decisions that were common across all teams in Table 5.4. I also report the decisions that critically affected the design outcome of each team in Table 5.5. I find that the teams that reported a greater number of detailed design decisions in CAD such as what fasteners to choose, what material to choose, and what parts to order, typically had a functioning prototype. For example, Team 3 reported a total of 16 detailed design decisions and had the best functioning prototype (according to the instructor) whereas Team 5 reported a total of 6 detailed design decisions and their prototype was jamming and did not have a smooth output motion.

During the final interview, all the teams discussed the need to improve their prototype. The students considered the outcome of their design process of the design

project as a first iteration of the many required for design prototyping. I also asked them to hypothetically discuss their next set of decisions assuming that they achieved their objectives for all the design activities of their design process. They recognized the need to evaluate the market potential of their product and ultimately discussed the economic decisions required to be made to maximize revenue generation for their product.

It is also noticed that the SIADM framework is formulated in [68] on the assumption that decision-makers optimize for design objectives. However, the students are observed to make decisions that satisfy the design requirements rather than optimize them. For example, when the students are asked why they chose certain dimensions, they typically rationalize their decisions on the basis of satisfying volume constraints. They do not report their decision objective that is to minimize the use of the material. Such an observation is consistent with existing literature on decision-making between experts and novices [121]. In Section 5.6, I discuss the potential reasons why I observe such a difference between the theoretical SIADM framework and the students' decision-making process.

Table 5.4. : Common decisions across teams.

Number	Decision
1	What two concepts to choose?
2	What final idea to choose?
3	How to add functionality?
4	What assembly part to focus on the most in CAD?
5	What manufacturing technique to use for which part?
6	What dimensions to choose?
7	How much volume to assign to each part?
8	How to assemble in real?
9	What material to choose?
10	Which parts to order?
11	How to account for constraints from parts that are ordered?
12	What tolerance limit to choose?
13	How to add the electronics?
14	How to select the best fab model?
15	How to make aesthetic improvements?

Table 5.5. : Critical decisions made by each team.

Team	Critical Decisions Teams Faced
Team 1	How to reduce weight and friction? How many linkages to choose to ensure functionality?
Team 2	How many mechanisms to choose?
Team 3	How to improve strength, usability, functionality?
Team 4	How to simulate hydraulics?
Team 5	How to ensure the complexity required in the project?
Team 6	How to model wires in CAD?
Team 7	–did not report–
Team 8	How to reduce the complexity and sustainability of the design?
Team 9	How to simulate springs?
Team 10	What information to acquire from CAD?
Team 11	How to utilize electronics knowledge?
Team 12	How to ensure innovation requirements?

## 5.6 Summary and Discussion

In this study, I utilize a decision-making framework to analyze students' information acquisition and decision-making activities in a product design scenario. The results of this study paint the following collective picture of how upper-level undergraduate students make product design decisions. I find that during the brainstorming of design ideas, students frame potential ideas on the basis of their prior knowledge and skills acquired in the course, based on design fixation, and on the basis of their domain-specific interests. During the CAD modeling activities of a product design process, I find that the students recognize the need to acquire information about the physics and dynamics of their design artifact. However, they do not acquire such information during these activities. The factors that contribute to the failure of information acquired during the CAD modeling activity are the lack of i) explicit learning objectives in the project specifications, ii) the students' lack of knowledge to do so, and iii) the time constraints for project completion. Instead, they acquire such information from the prototyping activity as their toy does not satisfy the design objectives and work as intended. Such information acquisition results in the students wanting to have more number of iterations for prototyping activities to improve the achievement of their design objectives. With the given cost and time constraints, the

students do not get the opportunity to iterate their prototype. Consequently, the students rely on improvising during prototyping.

Existing literature has shown that the design of an environment affects user behavior [122, 123]. Students are no different. In the ME444 course, I observed that the resource constraints were a budget limit of \$60 and a 15 cubic inch constraint on the volume of material that could be 3D printed. Such constraints in effect implied that the students get one shot to prototype. Thus, the design project essentially abstracted a design scenario where physical experimentation is cost intensive and virtual experimentation is cheap. Consequently, the students' design behavior was observed to be rational where they wanted to gain maximum information from the cheapest information source that is their CAD model and through simulations. Instructors need to anticipate such design behaviors and account for them while formulating design project constraints in the design projects. From a course design standpoint, there lies a need to recognize what aspect of reality is represented by the given design constraints in a design project.

On interviewing the instructor, it was found that they did want to encourage iterations while prototyping. However, due to the lack of additional time to prototype the students could not do so. Instead, the students improvised improvements to their prototype to make them functional without having to fabricate the parts again. Existing studies in design have highlighted the importance of improvisation in product design processes [124]. However, the instructor did not account for such design behaviors. The project was assessed based on innovation, the quality of CAD models and prototypes, their final presentation, and design portfolio. There was a lack of assessment on the team's improvisation to their prototype. By understanding students' design behaviors while acquiring information, assessments of design teams can be improved. Additional studies are required to understand how improvisation in design can be assessed as well as encouraged. I hypothesize that design scenarios where the cost of physical experimentation is high will result in students improvising their design prototypes as observed in this course.

Based on the observations, I recommend formulating design projects such that it guides students towards appropriate information sources as well as accounts for their ability to process the required information. In this study, I find that the course should have been designed such that the students could have the opportunity as well as incentives to gain more information from CAD models, if they wanted to, by teaching them simulation packages or giving enough time in the course for them to develop their domain-specific skills and apply it in CAD modeling activities. However, there was no incentive for the teams who recognized the need to acquire information about the physics and dynamics of their model during CAD activities. Assessments for design projects should account for such recognition of decisions in order to incentivize teams to critically analyze their design. For example, I notice that the students tend to satisfice their volume constraint requirement for 3d printing as opposed to optimize the use of the material. I believe that the students did not have the incentive to optimize such objectives. If the students were given a higher evaluation of their design prototypes if they utilized lesser resources I hypothesize that students would tend to optimize their design objectives as formulated in the SIADM framework.

It is acknowledged that in practice, it is unreasonable to assume that instructors should possess a “know-it-all” book about all the information students need. Moreover, it should not be encouraged. However, the intent of this research study is to enable instructors to *predict* what information students would need as well as how students would use such information based on their state of knowledge such that design courses can be deliberately designed to encourage information acquisition behaviors.

While existing studies in engineering education highlight that students encounter roadblocks in information gathering activities [100–103], DBD frameworks have not been utilized to analyze their information acquisition decisions. This study illustrates the use of a decision-based design framework for investigating the information acquisition and decision-making activities of students. I highlight the need to integrate information acquisition and decision-making activities. The potential of such an integrated view of these activities can enable us to investigate the factors that

influence students' design behaviors. I encourage the engineering education research community to explore DBD research specifically the work on descriptive theories to understand how humans make design process decisions.

Finally, I acknowledge the limitations of the research methods. In this study, I rely on self-reported data from the students obtained through interviews and surveys. In order to verify the decisions reported by the students, I cross-check the reported decisions across individuals from the same team. Students may have self-reporting bias where the rationale for decisions may have been formulated a posteriori. However, the researchers ensured that interviews and surveys were conducted at appropriate instances during the students' product design activities for facilitating recollection of their design activities. For example, I asked the students for their decision-making strategy for concept selection and elimination during their proposal submission to ensure they would be able to recollect their rationale for the elimination and selection strategies. While multiple coders analyzed interviews, a single researcher conducted the interviews. Due to the semi-structured nature of such interviews, I acknowledge that additional data could have been collected if different researchers had variations in follow up questions. Also, although the students were incentivized to participate, the research data is dependent on the amount of information students provide from the interviews and surveys.



## 6. CONCLUSIONS

In this dissertation, I have illustrated that by conducting controlled behavioral experiments we can acquire data of contestant behaviors that can be utilized to develop and calibrate computational models of contestants' sequential decision-making behaviors, thereby, enabling predictions about the outcomes of design contests. To that end, I have answered the following research questions (RQs):

1. RQ1: How can we quantify the impact of a designer's domain knowledge and problem framing on their information acquisition decisions and the corresponding design outcomes?
2. RQ2: How can we quantify the influence of providing information about historical contests on a participant's information acquisition decisions in a design contest?
3. RQ3: How can we study a designer's cognitive processes that influence their decision to stop acquiring information under the influence of competition?

The results indicate that,

1. designers better understand problem constraints and generate more feasible design solutions when a design problem is framed in a domain-specific context as compared to a domain-independent framing of the problem.
2. contestants' efforts to acquire information about a design artefact to make design improvements are significantly affected by the information provided to them about their opponent who is competing to achieve the same objectives. Specifically, designers expend higher efforts when they know that their opponent has a history of generating good quality design solutions as compared to when their opponent has a poor performance history.

3. contestants make information acquisition decisions such as when to stop acquiring information, based on various criteria such as the amount of resources they have, the target objective value they want to achieve, and the amount of improvement in their design quality in successive iterations. Moreover, the threshold values of such criteria are influenced by the information the contestants have about their opponent.
4. individual's decisions to stop acquiring information is influenced by opponent specific information through the mediating factor of resource expenditures. This implies that when competition is high individuals tend to expend more resources and effort than when competition is low.
5. the Bayesian SIADM model is able to capture the influence of problem framing on an individual's knowledge about the problem constraints as well as their performance.
6. the SIADM framework enables us to understand how individuals sequentially acquire information and make decisions in a design context. Using the framework, we can study the impact of factors, such as problem framing and an individual's lack of domain knowledge, on the SIADM outcomes of a design search problem with constraints.
7. the Strategic SIADM model is able to account for the influence of opponent-specific specific information on an individual's information acquisition decisions such as when to stop.
8. by combining protocol analysis and controlled behavioral experimentation we can study cognitive factors that influence individual's decision making process.

Moreover, in the context of engineering education, I have investigated students' sequential information acquisition and decision making behaviors in product design processes via ERQ1. I find that the students recognize the need to acquire information about the physics and dynamics of their design artifact. However, they do not

acquire such information during the design process. The factors that contribute to the failure of information acquired during the product design activity are the lack of (i) explicit learning objectives in the project specifications, (ii) the students' lack of knowledge to do so, and (iii) the time constraints for project completion. Instead, they acquire such information from the prototyping activity as their toy does not satisfy the design objectives and work as intended. Such information acquisition results in the students wanting to have more number of iterations for prototyping activities to improve the achievement of their design objectives. With the given cost and time constraints, the students do not get the opportunity to iterate their prototype. Consequently, the students rely on improvising during prototyping.

## 6.1 Contributions

The dissertation provides theoretical, experimental, methodological, and educational contributions of the descriptive investigations of sequential information acquisition and decision making in engineering design. Theoretically, the SIADM (Chapter 2) and the S-SIADM (Chapter 3) frameworks provide a foundation for the analysis of the factors that influence designer behaviors and the outcomes of sequential decision making process. Experimentally, the dissertation illustrates the need to conduct controlled behavioral experimentation. The research studies illustrate the need to identify the dependent, independent, and the confounding variables in order to make causal inferences while mitigating the effect of human biases. Methodologically, I illustrate a mixed-methods approach (Chapter 4) that combines protocol analysis and computational modeling of behaviors towards understanding designer behaviors and developing behavioral theories for design studies. Furthermore, the educational impact of investigating sequential decision making by understanding students' behaviors towards providing formative feedback is also discussed (Chapter 5).

## 6.2 Future Work

The avenues for further research based on the work in this dissertation include investigations of 1) sociotechnical influences in manufacturing and transportation industries, 2) design for behavioral change in educational contexts, 3) human-like artificial intelligence through embedding cognition, that is, the theory of mind, and 4) plan recognition using behavioral design theories and artificial intelligence. Sociotechnical design implies a deliberate and purposeful influence on people's interaction through technical environments. By leveraging behavioral theories that quantify the influences of behaviors in conjunction with the sequential decision making framework discussed in this dissertation, future research could investigate sociotechnical design. For manufacturing systems, this would mean designing systems to purposefully influence operator decisions in manufacturing processes, thereby, influencing the quality of products and their throughput. Similarly, in transportation systems, sociotechnical design would imply designing autonomous cars that recognize and influence driver decisions. In educational context, theoretical foundations of SIADM can be leveraged for an understanding of how students acquire and process information which can enable provision of formative feedback through predictive analysis of students' progress trajectories. Within AI literature, Plan Recognition (PR) [125, 126] is an active area of research that aims to understand a person's plans from their low-level action streams. However, the limitations of scalability and a lack of human-interpretability in complex environments of PR techniques curtails its benefits to areas such as sociotechnical design [127–129]. Future research could leverage the SIADM framework to enable AI to computationally infer cognition to facilitate sociotechnical design.

I reiterate the issue of validity as discussed in Chapter 2 in Section 2.6.2. The advantage of the controlled experiments is high internal validity which enables theory building. While external validity is equally important in establishing the impact of the developed theories, it is important to focus on right aspects of a behavioral design study for establishing external validity. For example, the proposed frameworks

such as SIADM and S-SIADM are highly general and can be leveraged in sequential decision making problems. However, the domain-specific contextualizations in the computational models are specific to the research studies that focus on a class of design optimization problems. Moreover, multiple research studies across varying levels of complexity and contexts are required to establish external validity.

Another aspect of validity that needs to be acknowledged are the human subjects recruited in the behavioral experiments for this dissertation. The subject population comprised of engineering students. Since the population to which the generalizability of information acquisition and decision making is being sought is in the context of engineering design, I argue that leveraging engineering student population makes it possible to identify factorial influences of contest design elements on the decision making behaviors. Thus, I draw on the parallelism of the engineering design population and the engineering students that would be a part of the future population of the engineering design community.

This dissertation alone cannot claim to have established a generalized theory of sequential decision making in design contests. Instead, this dissertation illustrates how the design community would need to collectively establish the protocols for investigating designer behaviors such as decision making for strengthening the foundations of theory-driven design research.

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## PEER REVIEWED PUBLICATIONS

- J1 **Shergadwala, M.**, Bilonis, I., and Panchal, J. H., 2020. “Sequential Design Decision-making Under the Influence of Competition: A Mixed-methods Approach.” *ASME Journal of Mechanical Design*. (under preparation) [\[link\]](#)
- J2 **Shergadwala, M.**, Bilonis, I., and Panchal, J. H., 2020. “Quantifying the Influence of Information Sharing About Competitor’s Performance on a Participant’s Sequential Design Behaviors in Design Contests.” *ASME Journal of Mechanical Design*. (under preparation) [\[link\]](#)
- J3 **Shergadwala, M.**, Forbes, H., Schaefer, D., and Panchal, J. H., 2019. “Challenges and Research Directions in Crowdsourcing for Engineering Design: An Interview Study with Industry Professionals.” *IEEE Transactions on Engineering Management*. (pp. accepted) [\[link\]](#)
- J4 **Shergadwala, M.**, Bilonis, I., Kannan, K. N., and Panchal, J. H., 2018. “Quantifying the impact of domain knowledge and problem framing on sequential decisions in engineering design.” *ASME Journal of Mechanical Design*. 2018; 140(10):101402-101402-13. [\[link\]](#)
- C1 Forbes, H., **Shergadwala, M.**, Schaefer, D., and Panchal, J. H., 2020. “Investigating the Implication of Organization Size on Crowdsourcing for Engineering Design.” In *ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. accepted). American Society of Mechanical Engineers. [\[link\]](#)
- C2 **Shergadwala, M.**, and Panchal, J. H., 2020. “Human Inductive Biases in Design Decision Making.” In *ASME 2020 International Design Engineering Tech-*

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- C3 **Shergadwala, M.**, and Panchal, J. H., 2020. “Sequential Design Decision Making Under the Influence of Competition: A Protocol Analysis.” *In ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. accepted). American Society of Mechanical Engineers. [\[link\]](#)
- C4 **Shergadwala, M.**, Panchal, J. H., and Ramani, K., 2019. “Students’ decision-making in a Product Design Process: An Observational Study.” *In ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 3: 21st International Conference on Advanced Vehicle Technologies; 16th International Conference on Design Education.* (pp. V003T04A016-V003T04A016). American Society of Mechanical Engineers. [\[link\]](#)
- C5 **Shergadwala, M.**, Bilonis, I., and Panchal, J. H., 2018. “Students as Sequential Decision-Makers: Quantifying the Impact of Problem Knowledge and Process Deviation on the Achievement of their Design Problem Objective.” *In ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. V003T04A011-V003T04A011). American Society of Mechanical Engineers. [\[link\]](#)
- C6 **Shergadwala, M.**, Kannan, K. N., and Panchal, J. H., 2016. “Understanding the Impact of Expertise on Design Outcome: An Approach Based on Concept Inventories and Item Response Theory.” *In ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. V003T04A016 - V003T04A016). American Society of Mechanical Engineers. **(Best Paper)** [\[link\]](#)
- C7 Bi, Y., **Shergadwala, M.**, Reid, T., and Panchal, J. H. (2015, August). “Understanding the utilization of information stimuli in design decision-making using

eye gaze data.” *In Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. V02AT03A017 - V02AT03A017). [\[link\]](#)