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The Role of Problem Specification in Crowdsourcing Contests for Design Problems: A Theoretical and Empirical Analysis

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This paper studies the role of seekers' problem specification in crowdsourcing contests for design problems. Platforms hosting design contests offer detailed guidance for seekers to specify their design problems when launching a contest. Yet, problem specification in such crowdsourcing contests is something the theoretical and empirical literature has largely overlooked. We aim to fill this gap by offering an empirically-validated model to generate insights for the provision of information at contest launch. We develop a game-theoretic model featuring different types of information (categorized as "conceptual objectives" or "execution guidelines") conveyed in problem specifications, and assess their impact on design processes. Real-world data is used to empirically test hypotheses generated from the model, and a quasi-natural experiment provides further empirical evidence for our predictions and recommendations. We show theoretically and verify empirically that, with more conceptual objectives disclosed in the problem specification, the number of participants in a contest decreases, but the trial effort provision by each participant does not change; with more execution guidelines disclosed in the problem specification, the trial effort provision by each participant increases, but the number of participants in a contest does not change. With that knowledge, we are able to formulate seekers' optimal decisions on problem specifications. We find that, to maximize the expected quality of the best solution to crowdsourced design problems, seekers should always provide more execution guidelines, and only a moderate number of conceptual objectives.

Key words: crowdsourcing contests, problem specification, design, game theory, empirical analysis

1. Introduction

Online crowdsourcing has become a popular channel for sourcing design (creative) products. A widely used form of organizing the crowdsourced innovation process is the *Crowdsourcing Contest*, used for products ranging from web to interior design. Compared with traditional innovation sourc-

ing approaches, crowdsourcing contests allow seekers to access a large pool of designers, solicit a larger number of solutions from which to choose, and pay for only the most satisfying solutions. A typical crowdsourcing contest starts with a seeker specifying a design problem and associated award(s), based on which designers generate solutions, and compete for the award(s).

We focus on the seeker's problem specification: how the seeker specifies his design problem at the launch of his crowdsourcing contest. In the problem specification, a seeker can state his problem (e.g., he needs a logo for a real estate company), and communicate what he would like the solutions to achieve (e.g., the logo should convey professionalism and reliability; blue color and sharp edges are preferred). The information provided in the problem specification defines what constitutes a "high-quality" solution in the focal contest, which can potentially affect designer behavior and contest outcomes. Hence, it is important to understand the role of problem specifications in crowdsourcing contests.

Yet, the best approach to problem specification is not obvious. At first sight, one may think seekers should specify their problems in the most thorough manner possible. A detailed problem specification clarifies what the seeker is looking for. Without it, designers may miss important points when generating solutions, and they may also face increased uncertainty about how closely their solutions match the seeker's objectives. However, an overly specified problem may backfire, especially when the seeker is not careful about the types of information he provides. By taking a closer look at seekers' problem specifications, we find that problem specifications can contain multiple types of information, which are likely to affect designers' behavior differently. For example, a problem specification with a long list of objectives can overwhelm designers. Designers have to spend more time digesting the list, clarifying design objectives, and creating designs satisfying multiple objectives; consequently, designers may choose to not incorporate all of the design objectives, or even choose not to participate.

In this paper, we aim to address the following research questions: (1) provided with different types of information in a seeker's problem specification, how do designers decide whether to join the contest or not, and if so, how do they reflect information from the problem specification in their design solutions; and (2) how should seekers optimally specify their design problems?

To answer these questions, we first construct a game-theoretical model to capture designers' behavior given a problem specification. Our model distinguishes different types of information provided in problem specifications ("professionalism" and "reliability" can be considered as *conceptual objectives* that the seeker wants design solutions to achieve, whereas "blue color" and "sharp edges" as *execution guidance* that conveys the seeker's instructions for design details). To assess how such information influence decisions in designers' design processes, our model features distinct stages in design processes, which is based upon an established framework in the qualitative *design research*

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literature (e.g., Schön (1984, 1988), Cross (2011)), and explicitly captures the *design problem framing*, *design concept formulating* and *design trials generating* stages designers go through to generate designs. Our theoretical model predicts that the number of participating designers in a contest decreases with more conceptual objectives disclosed in the problem specification, because designers spend more efforts digesting those objectives and creating designs that satisfy those objectives. In addition, participants' trial effort provision increases with more execution guidelines provided in the problem specification, because those guidelines inform designers about certain execution details, which designers need to otherwise spend efforts deciding on.

The theoretical predictions of our model are empirically tested against a dataset of logo design contests collected from a major crowdsourcing platform. In addition, we avail ourselves of a recent "quasi-natural experiment" opportunity that arose on the platform, wherein changes were made to the platform's problem specification template. This further strengthens our empirical results' reliability.

Leveraging our novel, empirically validated game-theoretical model, we offer insight on how seekers can optimize their problem specifications to maximize the quality of the winning design. Our analysis suggests that more execution guidance is always beneficial. However, disclosing more conceptual objectives does not necessarily lead to a better contest outcome, and seekers should not always disclose all their conceptual objectives. The recent update to the problem specification template mentioned above directionally confirms these policy recommendations, and generates additional nuanced insights into the implementation of these recommendations.

Our study makes several contributions. First, it is one of the first papers studying the role of problem specifications in crowdsourcing contests, which holds great practical relevance. Second, we theoretically and empirically distinguish between different types of information contained in problem specifications, i.e., conceptual objectives and execution guidelines, and highlight their differential effects on designers' participation behavior and solution quality. Third, we bring findings from the *design research* field into the study of crowdsourcing innovation contests. In particular, we borrow from the qualitative *design research* literature, and formulate a mathematical model to capture three distinct stages in design processes. The incorporation of the first two stages, the *design problem framing* and *design concept formulating* stages, which are often omitted in theoretical models of crowdsourcing contests, is crucial for capturing a more complete picture of the designers' design process and the impact of information provided in problem specification on this process. Finally, we offer empirical evidence from the field to support the predictions and recommendations from our theoretical model, linking the theoretical and empirical research of crowdsourcing innovation contests.

2. Literature Review

Emerging *crowdsourcing contest*s have attracted increasing academic interest from the operations management community (see Chen et al. (2018) for a summary of the literature). Existing operations management literature on the design of crowdsourcing contests has looked at the impact of award structure (Ales et al. 2017b); competition size and open/closed entry (Boudreau et al. 2011, 2016, Ales et al. 2018); joint decision on award and competition size (Terwiesch and Xu 2008, Körpeoğlu and Cho 2017); contest duration (Korpeoglu et al. 2017); contest stages (simultaneous/sequential) (Hu and Wang 2017); and solvers' choices among coexisting contests (Körpeoğlu et al. 2017) on the outcome of crowdsourcing contests (e.g., the quality and quantity of the crowdsourced solutions). There is also an emerging literature examining the role of *information* in crowdsourcing contests. A few recent studies investigate the impact of the disclosure of intermediate solutions (Boudreau and Lakhani 2015, Wooten and Ulrich, Bockstedt et al. 2016), and interim feedback (Jiang et al. 2016, Gross 2017, Wooten and Ulrich 2017, Bimpikis et al. 2017, Mihm and Schlapp 2018), on contest dynamics and outcomes.

Another important occasion where seekers disclose information to solvers is *problem specification*. The information in a problem specification is a major part of what "defines" the contest, and as such can have a significant impact on participants' behavior and contest outcomes. Our paper contributes to the limited literature on the role of *problem specifications* in crowdsourcing contests. To the best of our knowledge, the only other study that looks at problem specification in crowdsourcing contests is Erat and Krishnan (2012). In that paper, the authors study contests where the seeker starts with a well-defined problem, and solvers choose from a set of known approaches. They focus on how the completeness of problem specifications helps provide a more precise valuation of those approaches, which narrows down the solvers' search by revealing which of the known solutions are more likely to be successful. By contrast, we study open-ended creative contests, where the seeker describes the problem, the "approach(es)" to solving it are generated by each expert designer, and a longer list of specifications may make it more difficult to find a suitable approach. Moreover, we study how different types of information disclosed in the problem specification affect designers' entry, design concept formation and design solution generation behavior. Not surprisingly, with our different model/setting and research focus, we arrive at different managerial insights. Erat and Krishnan (2012) find that the seeker may not want to fully specify their problem, in order to increase ambiguity that in turn increases the breadth of search that the solvers undertake within a set of known solution approaches. By contrast, we model two types of information, and show that the seeker always wants divulge all his execution guidelines, but might not want to divulge all his conceptual objectives because an overly long set of objectives may discourage creators from participating. Furthermore, we use real-world data to empirically test the predictions of our

theoretical model, which not only helps ensure the validity of the theoretical model, but contributes to the empirical literature of crowdsourcing contests.

An innovation in our theoretical model of crowdsourcing contests is that our model borrows from the classic literature in *design research* and explicitly captures various stages of designers' solution generation process. The design research literature (e.g., French et al. (1985), Pahl and Beitz (1988), Hubka (1989), Roozenburg and Cross (1991)) often portrays the design process as a sequence of activities, which can be grouped into phases of *design problem framing* (clarifying objectives), *design concept formulating* (generating and refining design concepts), and *design trial generating* (embodying designs and detailing designs). The last phase, which corresponds to the stage where a designer generates actual solutions, is often the focus of analytical models of crowdsourcing contests in the operations and economics literature. The first two phases are often overlooked, possibly because they are less visible and more abstract. Researchers in design research realize the importance of these two phases in the design process, and call for attention to them (Schön 1984, 1988, Pahl and Beitz 1988, Cross 2011). For example, Schön (1988) suggests that design problems are often "ill-defined", in that "in a design project it is often not at all clear what 'the problem' is"; hence, in order to solve those problems, "the designer must frame a problematic design situation", in which "the goal is set at a high level with clear objectives". Cross (2011) continuous to stress the importance of the *design concept formulating* stage: "a clear concept of how to reach this goal is devised, ... and the solution details then cascade from the concept". In this stage, "designers select features of the problem space to which they choose to attend, and identify areas of the solution space in which they choose to explore" (Cross 2001). The model to be presented in the next section reflects all these important stages of the design process, and captures how information in the problem specification influence designers' decisions in each of these stages.

3. Theoretical Model

In this section, we construct a theoretical model that characterizes seekers' and designers' decisions in a crowdsourcing design contest. Consider a situation where a seeker ("he") wishes to source solutions to a design problem from a group of designers through a crowdsourcing contest. The seeker has some *conceptual objectives* in mind (e.g., the design should convey reliability and helpfulness); each conceptual objective included in a design gives an equal, incremental quality w. (In Online Appendix EC.4.2 we consider an alternative model in which the conceptual objectives have diminishing weights.) Apart from the conceptual objectives, the seeker can also provide *execution guidelines* (e.g. what color or shape is/is not desired, etc.). Unlike conceptual objectives which the designer has to interpret, execution guidelines are more straightforward — e.g., "don't use the color red". (See Online Appendix EC.1 for several examples of conceptual objectives and execution

guidelines in our data.) The sets of all the conceptual objectives and execution guidelines the seeker has in mind are denoted as $\overline{\mathbb{S}}_r$ and $\overline{\mathbb{S}}_g$ respectively, with the size of the two sets being $|\overline{\mathbb{S}}_r| := \overline{S}_r$ and $|\overline{\mathbb{S}}_g| := \overline{S}_g$. Given $\overline{\mathbb{S}}_r$ and $\overline{\mathbb{S}}_g$, the seeker decides which conceptual objectives and execution guidelines to disclose in his problem specification. (Note that we do not study how seekers come up with $\overline{\mathbb{S}}_r$ and $\overline{\mathbb{S}}_g$ in the first place.)

The sequence of events in our crowdsourcing contest model is as follows:

- The seeker posts his design request, in which he announces the award amount (denoted by A) for the contest winner (we consider "single-winner" contests as those are the most common type of contests in our empirical setting), and specifies his design problem. In this problem specification, the seeker can specify some or all of his conceptual objectives and execution guidelines. The sets of disclosed conceptual objectives and execution guidelines are denoted as $\mathbb{S}_r$ ($\subseteq \overline{\mathbb{S}}_r$) and $\mathbb{S}_g$ ($\subseteq \overline{\mathbb{S}}_g$) respectively, with the sizes of the two sets being S_r ($\leq \overline{S}_r$) and S_g ($\leq \overline{S}_g$).

- Given the design request, designers ("she") first decide whether to enter the contest or not, based on their assessment of the expected net payoff they will receive if they join the contest. Those who decide to enter the contest then go through a *design process* (to be explained in Section 3.1) to develop their design submissions, and submit them to the seeker.

- Finally, the seeker evaluates all the submitted designs, claims the best-quality design among those submissions, and gives the award to the designer of the winning design.

As is common in the crowdsourcing literature (Terwiesch and Xu 2008, Erat and Krishnan 2012, Körpeoğlu et al. 2017, Ales et al. 2017b), we model designers simultaneously making participation and other design decisions.

Below we present a mathematical model reflecting a typical *design process*, drawing on the design research literature. Using this model, we analyze designers' behavior in contests in Section 3.2.

3.1. Designers' Three-Stage Design Process

In the design literature, design processes are often considered to consist of several cognitive steps, which can be broadly classified into three stages: *design problem framing*, *design concept formulating* and *design trial generating* (van den Kroonenberg 1986, Cross 2001, 2011). To mathematically represent these three distinct stages, we formulate a stylized model, with simple functional forms, that tractably captures the key features of our setting; simplification by assuming functional forms, to ensure tractability, is an approach widely used in previous theoretical research on crowdsourcing or open innovation contests (Ales et al. 2017b, Korpeoglu et al. 2017, Mihm and Schlapp 2018). Next we provide modeling details for each of the three stages in the design process.

Design Stage (I) — Framing the Design Problem. Design problems are nearly always "not all clear" and "may have been only loosely defined by the client (seeker)" (Cross (2001) p.81). Hence,

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a key aspect of the design process lies in digesting and understanding the conceptual objectives ($\mathbb{S}_r$) in seekers' problem specifications. This stage is referred to as the *design problem framing* stage.

Framing the design problem is effort-consuming (Cross 2001). In reality, conceptual objectives in a problem statement are often embedded in sentences or paragraphs, as seekers endeavor to communicate what they are looking for in a design. Designers need to exert efforts to understand the problem statement text and extract and comprehend the conceptual objectives conveyed. The more conceptual objectives ($\mathbb{S}_r$) are embedded in the problem specification, the higher effort cost a solver has to incur in the design problem framing stage. We model this cost as $c_1 S_r$. Note that we assume the problem framing cost increases only with conceptual objectives but *not* with execution guidelines in problem specifications, as execution guidelines are mostly objective instructions in standardized design terms, and are therefore more straightforward for designers to understand. (Empirical evidence for this assumption is provided in Online Appendix EC.2.)

Design Stage (II) — Formulating the Design Concept. After framing the problem, participating designers "select features of the problem space to which they choose to attend", and then "identify areas in the solution space where they choose to explore" (Cross 2001). We form a mathematical model for these two steps: (1) designer i chooses $\mathbb{D}_{r,i}$ ($\subseteq \mathbb{S}_r$) to incorporate into her design(s), with the number of incorporated objectives being $r_i := |\mathbb{D}_{r,i}|$; (2) designer i searches for a design concept satisfying all conceptual objectives in $\mathbb{D}_{r,i}$.

We model the cost associated with step (2) as follows. Consider a potential design concept to be a "sample" (random draw). The probability that a sampled design concept satisfies any particular conceptual objective is $p \in [0,1]$. Assuming the objectives are independent (we consider an extension capturing the level of overlap across objectives in Online Appendix EC.4.1), the probability of a sampled design concept being "successful", i.e., satisfying all r_i targeted objectives, is p^{r_i}. Hence, in expectation, designer i has to attempt $(\frac{1}{p})^{r_i}$ design concepts until she finds a "successful" one. If the cost associated with each attempt is c_2, the expected cost of the *design concept formulating* stage is $c_2 (\frac{1}{p})^{r_i}$. Note that this cost increases exponentially with the number of objectives designer i incorporates (r_i), which captures the fact that it gets increasingly more challenging to find a design concept that *simultaneously* satisfies more objectives.

Design Stage (III) — Generating Design Trials. In the final stage, based on the design concept identified in Stage II, designers generate design trials, which are submitted to the seeker. (Hereafter, we use submissions, solutions, and trials interchangeably.) We assume designers incur a cost of c_3 to come up with a design trial — in this stage, designers need to figure out the execution details, such as shape, color, font, etc., which is effort-consuming. If the seeker provides execution guidelines, (i.e., recommends designers what fonts, colors, shapes, etc. to use), it will save designers' time and effort in determining such details. Hence, we expect the cost of each design

trial (c_3) decreases with more execution guidelines (S_g). Correspondingly, in our model, we assume $c_3 = h(S_g)$, where $h(\cdot)$ is a decreasing function. (We provide empirical evidence for this assumption in Section 4). Given c_3, designer i who decides to generate m_i design trials incurs a cost of $c_3 m_i$ in the *design trial generating* stage.

For focal designer i, the quality of each trial τ ($= 1, 2, ..., m_i$), denoted as $V_{i\tau}$, is assumed to be the baseline value of designer i's design concept (v_i), plus a quality random shock ($\epsilon_{i\tau}$) (i.e., $V_{i\tau} = v_i + \epsilon_{i\tau}$). The baseline quality of designer i's design concept (v_i) is the sum of weights associated with all its satisfied conceptual objectives, $v_i = wr_i$. The uncertainty captured by $\epsilon_{i\tau}$ may come from seeker taste uncertainty (the perceived quality is often subject to the taste of the seeker) and trial quality shock (the uncertainty associated with the execution of the design concept). Like Dahan and Mendelson (2001) and Terwiesch and Xu (2008), we model trial shocks, $\epsilon_{i\tau}$'s, as Gumbel distributed with mean zero and scale parameter μ, *i.i.d* across design trials.

3.2. Designers' Problem

Combining the three design stages discussed above, when participating designer i incorporates r_i conceptual objectives and generates m_i design trials, her overall expected cost is:

$$C_i(r_i, m_i) = \underbrace{c_1 \cdot S_r}_{\text{Design Stage (I)}} + \underbrace{c_2 \cdot (1/p)^{r_i}}_{\text{Design Stage (II)}} + \underbrace{c_3 \cdot m_i}_{\text{Design Stage (III)}}, \text{ where } c_3 = h(S_g); \tag{1}$$

and the quality of designer i's best design is:

$$V_i(r_i, m_i) = \max_{\tau=1,...,m_i} V_{i\tau} = \max_{\tau=1,...,m_i} (v_i + \epsilon_{i\tau}) = r_i w + \max_{\tau=1,...,m_i} \epsilon_{i\tau}. \tag{2}$$

We are modeling a single-winner contest, where the seeker's utility is determined by the quality of the best design; therefore, if a designer submits multiple designs, only her highest-quality design matters. Note that we do not explicitly consider designers' choices on the amount of execution guidance to follow, because this decision is trivial: designers would always follow all the execution guidance to lower their design trial generation cost. This is captured by setting $c_3 = h(S_g)$.

We now analyze designers' entry decision, design concept formation and trial effort provision in a crowdsourcing contest. Consider a focal designer i facing a contest with award A, S_r conceptual objectives, and S_g execution guidelines. Let $j = 1, ..., N(\neq i)$ index the other designers who would be i's opponents participating in the contest, where r_j is the number of conceptual objectives j will incorporate and m_j is the number of design trials j will generate. Focal designer i makes the following decisions: whether to join the contest or not (i.e., a binary entry decision, denoted by d_i), how many conceptual objectives to incorporate in the *design concept formulating* stage (i.e., a concept formation decision, denoted by r_i), how many trials to generate in the *design trial*

generating stage (i.e., a trial effort decision, denoted by m_i). Designer i makes those decisions to maximize her expected utility (her expected compensation minus her expect costs):

$$\max_{d_i, r_i, m_i} U_i(d_i, r_i, m_i) = \mathbb{I}_{d_i=1} \cdot [\Pr(\text{i wins}) \cdot A - C_i(r_i, m_i)] + \mathbb{I}_{d_i=0} \cdot s,$$

$$\text{where } \Pr(\text{i wins}) = \Pr(V_i > V_{j|j=1,\ldots,N(\neq i)}) = \Pr(V_i(r_i, m_i) > \max\{V_{j|j=1,\ldots,N(\neq i)}(r_j, m_j)\}). \quad (3)$$

If designer i decides not to join ($d_i = 0$), she earns utility s from choosing her outside option. (In other words, we consider s to be the opportunity cost of joining a contest.) If designer i's best design provides the highest value to the seeker (i.e. $V_i > V_j, \forall j \neq i$), she wins the contest and receives the award A; otherwise, she does not receive anything.

3.3. Designer's Equilibrium Behavior

Utilizing Equation (3), we solve for designers' equilibrium behavior. As is common in the crowdsourcing literature (Terwiesch and Xu 2008, Erat and Krishnan 2012, Körpeoğlu et al. 2017, Ales et al. 2017b), we focus on symmetric pure strategy Nash equilibrium throughout the paper. In our analysis, we assume that the number of potential participants is sufficiently large that participants will enter the contest as long as it is profitable to do so. That is, the size of a contest is never limited by a lack of potential participants. (This assumption is natural in crowdsourcing contests — for example, in our dataset, on any given day, the average number of active designers (i.e., potential participants) on the platform is around 300, while the average number of participants in a contest is around 26; see Table 1). Theorem 1 characterizes the equilibrium number of participants (N^*) in a crowdsourcing contest, the equilibrium number of objectives each participating designer incorporates (r^*), and the equilibrium number of design trials each participating designer generates (m^*). See Appendix A for the proof. For simplicity, in our analysis we allow N^*, r^*, and m^* to be non-integer numbers; and to avoid trivial solutions, we confine our attention to problem parameters for which can assume $N^* > 1$, $m^* > 0$, and the seeker is able to induce designers to incorporate all disclosed conceptual objectives by disclosing sufficiently few conceptual objectives in the problem statement (i.e., $r^* = S_r$ if S_r is sufficiently small).

THEOREM 1. *In a crowdsourcing contest, the equilibrium number of participating designers, N^*, decreases with more disclosed conceptual objectives S_r, but does not change with the amount of execution guidance provided S_g. (The exact formula for N^* is provided in Appendix A.)*

The unique symmetric equilibrium for r^* and m^* are as follows. The equilibrium number of objectives a designer incorporates is $r^* = \min\{\bar{r}, S_r\}$, where $\bar{r} = \frac{\ln(\frac{N^*-1}{(N^*)^2} \frac{w}{\mu} \frac{A}{c_2} \frac{1}{\ln(1/p)})}{\ln(1/p)}$, and the equilibrium number of design trials each designer generates is $m^* = \frac{A(N^*-1)}{(N^*)^2 c_3}$, where $c_3 = h(S_g)$.

Theorem 1 suggests that fewer designers will join a contest in which the seeker discloses more conceptual objectives. The intuition is as follows. With more disclosed conceptual objectives, designers

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have to spend more time understanding and digesting the objectives, and more effort searching for design concepts that satisfy those objectives simultaneously, which leads to a higher participation cost (i.e., the total cost a designer incurs throughout the three stages of the design process). This is true even in cases where designers choose to only select a subset of the disclosed objectives to incorporate (i.e., the number of disclosed objectives S_r is larger than the number of objectives designers are willing to incorporate $\bar{r}$), because although designers' design concept formation cost does not increase when S_r exceeds $\bar{r}$, they would still need to spend more time understanding and digesting all disclosed objectives to frame the design problem at the beginning of the design process. Thus, the participation cost always increases with more disclosed conceptual objectives, which leads to a lower equilibrium expected profit under the same level of competition, and correspondingly a smaller number of participants in equilibrium.

Comparing the marginal benefit and cost of incorporating each objective, a participating designer is willing to incorporate at most $\bar{r}$ objectives. When the seeker discloses fewer objectives than what designers are willing to incorporate ($S_r \leq \bar{r}$), designers incorporate all the disclosed objectives, i.e. $r^* = S_r$; otherwise ($S_r > \bar{r}$), designers only incorporate a subset of the disclosed objectives, i.e. $r^* = \bar{r}$. In terms of the trial effort, designers decide on their design trial effort by comparing the marginal benefit against the marginal cost of generating one design trial. Designers' equilibrium trial effort (m^*) increases with a lower cost for the designer to come up with a design trial (c_3). Per Section 3.1, c_3 decreases with more execution guidance (S_g). Hence, with more execution guidance (S_g) and correspondingly a lower trial cost (c_3), designers increase trial effort (m^*). Since designers tailor their equilibrium number of design trials (m^*) to the size of c_3 (or associated S_g), the size of c_3 (or associated S_g) ends up not affecting the designers' entry decision.

3.4. Key Takeaways and Model Extensions

We summarize the key theoretical results as follows.

Takeaway 1: The number of participating designers decreases with the number of disclosed conceptual objectives in the problem specification, but does not change with the amount of execution guidance in the problem specification.

Takeaway 2: Given the equilibrium number of participating designers, more execution guidance leads to a higher level of designer trial effort provision from each participating designer. However, more conceptual objectives will not affect designers' trial effort provision.

We keep our main model parsimonious and focus on capturing a complete picture of designers' design process. The results from this parsimonious model are in fact robust to alternative modeling assumptions and are supported by empirical data. We formally derive theoretical results for two extensions, which we have alluded to in Section 3.1. (Details are provided in Online

Appendix EC.4.) First, we consider overlaps among conceptual objectives (e.g., "friendly" and "welcoming" overlap more than "friendly" and "professional" do). Second, we allow for diminishing weight/importance among conceptual objectives (i.e., some objectives are more important than the others, and objectives are sorted of descending order in importance). In both extensions, the qualitative findings, i.e., Takeaways 1 and 2, remain intact. Next, we specify two sets of hypotheses derived from the theoretical results, and empirically test them in Section 4.

3.5. Hypotheses

Based on the aforementioned predictions of our theoretical model, we develop testable hypotheses. Specifically, we derive Hypothesis 1a and Hypothesis 1b from Takeaway 1, and Hypothesis 2a and Hypothesis 2b from Takeaway 2. We formally specify the hypotheses as follows.

Hypothesis 1a: *The number of participants (N^*) decreases with the number of conceptual objectives (S_r) specified in the problem specification.*

Hypothesis 1b: *The number of participants (N^*) does not change with the amount of execution guidance (S_g) provided in the problem specification.*

Hypothesis 2a: *Given the number of participants (N^*), more execution guidance (S_g) leads to more trial effort provision (m^*) from each participating designer.*

Hypothesis 2b: *Given the number of participants (N^*), the number of conceptual objectives (S_r) does not affect the trial effort provision from each participating designer (m^*).*

4. Data Description and Empirical Analysis

In this section, we empirically test the hypotheses specified in Section 3.5.

4.1. Empirical Context and Data Description

The data we use for the empirical analysis is from crowdsourced creative contests hosted on an online platform. We focus on logo design contests because it is a representative form of open-ended creative contests; it is also the largest category on the platform both in terms of the number of completed contests and the number of designers participating in the category.

A typical logo design contest on this platform proceeds as follows. First, a seeker in need of a design posts a design request. In the posting, he specifies the design problem by answering the following five questions:

- Q1: What name should be in the logo?
- Q2: What is the industry?
- Q3: What are the top 3 things the logo should communicate?
- Q4: What are preferred design styles for the logo?
- Q5: Any other info or links?

The seeker also announces the award structure (e.g., whether the award is guaranteed, the number of winners, and the award(s) for the winner(s)). Based on the seeker specified information, designers on the platform can join the contest and submit design(s). Finally, the seeker picks his favorite submission(s) and gives the pre-announced award to its (their) author(s). Note that, although the platform asks the seeker to list the "top 3 things" (in Q3), there is no hard limit on seekers' answer to this question. As can be seen from the additional examples in Online Appendix EC.1, some seekers specify more than "3 things" in their problem specification. As further evidence of the same, the summary statistics to be shown in Table 1 reveal substantial variation in the length of seekers' answers to Q3 across different contests.

The main advantages of our data include the fact that (i) different types of information, namely, conceptual objectives (Q3) and execution guidelines (Q4 and Q5) are already separated by questions in a seeker's problem specification (the categorization is self-explanatory with how the questions are raised); (ii) the number of submissions made by each designer is available, which allows us to quantify the designers' trial efforts (often-unobserved in other contexts); (iii) the exact problem specification (textual information) provided in each contest is available, from which we can extract conceptual objectives and execution guidelines mentioned in each problem specification using either manual coding or natural language processing.

We use data from logo-design contests on this crowdsourcing platform from March, 2012 to November, 2014. For each contest, we record the seeker's problem specification and participating designers' submission activities. To facilitate the empirical analysis, we focus on 7-day contests where the design seekers promise to award $200 to one and only one final winner. This is because it has been documented (Yang et al. 2009, Liu et al. 2014) that the contest length and award structure can affect designers' behavior and contest outcomes; since the objective of this study is to examine the effect of problem specification and to find the optimal way to specify a design problem, we purposefully minimize the heterogeneity among the contests in these other dimensions. The contests included in our sample are representative contests on the platform — 97% of the contests held on the platform have a single award, 61% have a guaranteed award, and $200 and 7-day are the most common award-level and length among all contests.

The final working sample consists of 463 contests and 11,148 contest-designer combinations. Table 1 reports summary statistics of contest-level characteristics. The first three rows present the summary statistics for the word count for answers to Q3, Q4, and Q5. In our main empirical analysis, we use word count to measure the amount of information provided in the problem specification. That is, a longer answer to Q3 indicates more disclosed conceptual objectives, and longer answers to Q4 and Q5 indicate more execution guidance. We are aware that word count is not a perfect measure. We use it in the main analysis because it is an objective measure and does not suffer from

human or machine coding errors. Later, as robustness checks, we consider alternative measures constructed using textual analysis and manual coding. Specifically, we use textual analysis to count keywords related to each aspect of design execution included in the problem specification (e.g., colors, fonts, shapes, art styles, etc). However, it is challenging to apply this approach (textual analysis based on keywords) to extract conceptual objectives, because conceptual objectives are much less structured and involve a wide range of concepts, which are often embedded in sentences and sometimes implicitly mentioned. Hence, we hire several coders with design backgrounds to read the sampled problem specifications, and manually list down the key conceptual objectives in each problem specification. (See Table EC.1 for summary statistics of these alternative measures.)

Also reported in Table 1 are summary statistics characterizing designers' behavior, including their entry ($No.Designers$) and effort ($Avg.\,Sub\,Per\,Designer$) decisions in each contest. We observe considerable variation in these variables across different contests. Our empirical analysis explores the relationship between characteristics of problem specifications and designers' behavior.

Table 1   Summary Statistics

Variable	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
$Length.\,Q3$	25.205	34.075	0	5	11	33	317
$Length.\,Q4$	20.503	31.053	0	4	9	27.5	442
$Length.\,Q5$	44.216	47.606	0	11	29	63	346
$Avg.\,Sub\,Per\,Designer$	3.551	1.192	1.600	2.759	3.308	3.968	9.429
$No.Designers$	26.305	10.585	7	18	25	33	57
$No.\,Submissions$	71.883	36.484	14	48	65	89	385

4.2.   Empirical Models

Effect of Conceptual Objectives on Number of Participating Designers: To test Hypothesis 1a and Hypothesis 1b, we estimate Equation (4), which characterizes the relationship between different types of information provided in problem specification and designers' entry decisions.

$$(No.Designers)_q = \beta_0 + \overbrace{\beta_1 log(len_{Q3}+1)_q}^{\text{Effect of Conceptual objectives}} + \overbrace{\beta_2 log(len_{Q4}+1)_q + \beta_3 log(len_{Q5}+1)_q}^{\text{Effect of Execution Guidance}} \quad (4)$$
$$+ \alpha_1 (No.Updates)_q + \omega_{Industry} + \phi_{Week\,Day} + \delta_{Month} + \mu_{Year}.$$

In Equation (4), q indexes contests. The number of conceptual objectives contest q's problem specification contains is measured by the logarithm of the word count of the seeker's answer to Q3 ($log(len_{Q3}+1)_q$), and the amount of execution guidance is proxied by the logarithm of the word counts of the seeker's answers to Q4 and Q5 ($log(len_{Q4}+1)_q$ and $log(len_{Q5}+1)_q$). (The log transformation is applied to reduce the skewness of the distribution of the word count of seekers' answers to these questions.) We control for the number of times the seeker updates the problem specification ($(No.Updates)_q$) during contest q. We include the industry fixed effect (i.e., the seeker's answer to Q2) to control for the possibility that different industries might have different

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levels of attractiveness to designers; we also include the year dummies, day-of-week dummies and month fixed effects to control for possible seasonality effects or contemporaneous unobservables.

Effect of Execution Guidelines on Number of Submissions Per Participating Designer: Next, we use Equation (5) to empirically test Hypothesis 2a and Hypothesis 2b. Designer i's trial effort in contest q is proxied by the number of submissions made by designer i to contest q $((No.Submissions)_{i,q})$. Specifically, we regress $(No.Submissions)_{i,q}$ on the amounts of different types of information in the problem specification (proxied by $log(len_{Q3} + 1)_q$, $log(len_{Q4} + 1)_q$ and $log(len_{Q5} + 1)_q$) and the number of designers $(No.Designers_q)$ in contest q. We control for the number of updates $((No.Updates)_q)$, and include industry dummies, day-of-week dummies, month dummies, year fixed effects and designer-specific dummies.

$$
(No.Submissions)_{i,q} = \rho_0 + \overbrace{\rho_1 log(len_{Q3} + 1)_q}^{\substack{\text{Effect of} \\ \text{Conceptual objectives}}} + \overbrace{\rho_2 log(len_{Q4} + 1)_q + \rho_3 log(len_{Q5} + 1)_q}^{\substack{\text{Effect of} \\ \text{Execution Guidance}}} \quad (5)
$$
$$
+ \zeta_1 (No.Updates)_q + \zeta_2 (No.Designers)_q + \upsilon_{Industry} + \chi_{Designer} + \eta_{Week\,Day} + \iota_{Month} + \psi_{Year}.
$$

4.3. Empirical Results

The estimation results for Equation (4) are presented in the first column in Table 2. As can be seen from the table, the number of participating designers in a contest $((No.Designers)_q)$ is significantly negatively associated with the number of conceptual objectives (proxied by $log(len_{Q3} + 1)_q$), which supports Hypothesis 1a. Additionally, the proxies for the amount of seeker execution guidance $(log(len_{Q4} + 1)_q$ and $log(len_{Q5} + 1)_q)$ are not significantly associated with $(No.Designers)_q$, which is consistent with Hypothesis 1b.

The estimation results for Equation (5) are presented in the third column in Table 2. These results show that $(No.Submissions)_{i,q}$ is significantly positively correlated with the amount of seeker execution guidance (measured by $log(len_{Q4} + 1)_q$ and $log(len_{Q5} + 1)_q$). This supports Hypothesis 2a — more seeker execution guidance leads to more submissions per designer. Moreover, $(No.Submissions)_{i,q}$ is not significantly associated with the number of conceptual objectives $(log(len_{Q3} + 1)_q)$, which supports Hypothesis 2b.

Overall, the regression results (for Equations (4)-(5)) are consistent with our theoretical predictions and support our theoretical model. (Negative binomial count models for Equations (4)-(5) yield qualitatively similar results.)

4.4. Robustness Checks

We perform robustness checks to ensure our empirical results are not sensitive to how we measure the numbers of conceptual objectives and execution guidelines. In addition, we use seemingly-unrelated-regression framework to estimate Equations (4)-(5) simultaneously, to account for the

Table 2   Regression Results of Equation (4) and Equation (5) and Corresponding Robustness Checks

	Dependent Variable:			
	$(No.Designers)_q$		$(No.Submissions)_{i,q}$ (per designer)	
Conceptual objectives				
$log(len_{Q3}+1)_q$	-1.707^{***} (0.488)		0.082 (0.049)	
$(No.Concepts)_q$		-0.551^{***} (0.129)		0.013 (0.011)
$(len_{Q3}/No.Concepts)_q$		0.002 (0.134)		
$Concept\ Similarity$		0.259^{***} (0.070)		-0.054 (0.522)
Execution Guidance				
$log(len_{Q4}+1)_q$	-0.416 (0.507)		0.125^{**} (0.038)	
$log(len_{Q5}+1)_q$	-0.127 (0.415)		0.171^{***} (0.031)	
$(No.GuideWords)_q$		0.016 (0.107)		0.061^{***} (0.009)
Control Variables				
$(No.Designers)_q$			-0.008^{*} (0.004)	-0.008^{*} (0.004)
$(No.Updates)_q$	-0.189 (0.421)	-0.110 (0.460)	0.215^{***} (0.032)	0.170^{***} (0.036)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Creator Fixed Effects	No	No	Yes	Yes
Observations	463	463	12,173	12,173
R^2	0.211	0.261	0.479	0.483
Adjusted R^2	0.140	0.188	0.306	0.308
Residual Std. Error	9.818 (df = 424)	9.482 (df = 423)	3.321 (df = 9142)	3.320 (df = 9142)
F Statistic	2.975^{***}	3.383^{***}	2.774^{***}	2.721^{***}

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

possibility that certain contest specific unobservables can affect both designers' entry and trial effort decisions, and show the robustness of our empirical results to this assumption.

Alternative Measure for Number of Conceptual objectives: In our main empirical analyses, we use $log(len_{Q3}+1)_q$ (based on word-count) as a proxy for the number of disclosed conceptual objectives in seekers' problem specifications. One might argue that different seekers can have different writing styles, e.g., some seekers write in a concise way, while others in a more elaborate way. In other words, two problem specifications that contain the same amount of information may have different lengths. To ensure our empirical results are robustness to the measure of conceptual objectives, we consider an alternative measure that involves manual coding. Specifically, we hire several coders with design background and ask each of them to independently read the problem specifications in our dataset, and manually list down the conceptual objectives for each contest. (The complete coding instructions and resulting data are available from the authors upon request.) We take the average across coders and use it as an alternative measure for the number of conceptual objectives $((No.Concepts)_q)$ in each problem specification. The average inter-rater reliability (assessed using Weighted Kappa) is 0.91, which is considered very good (Cohen 1968).

Alternative Measure for Amount of Execution Guidance: In our main empirical analysis, we use $log(len_{Q4}+1)_q$ and $log(len_{Q5}+1)_q$ based on word-count to proxy for the amount of execution guidance. We now consider an alternative measure — we use textual analysis to count keywords related to each aspect of design execution (e.g., colors, fonts, usages, shapes, and styles) in the

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problem specification. For example, we count words such as "green", "red", "round", "shining", etc., and use the total number of such keywords $(No.GuideWords)_q$ as an alternative measure for the amount of execution guidance.

Robustness Checks with These New Measures: With the new measures of the number of conceptual objectives $((No.Concepts)_q)$ and the amount of execution guidance $((No.GuideWords)_q)$, we make the following modifications to Equations (4)-(5). First, we replace the original measure of conceptual objectives $log(len_{Q3} + 1)_q$ with $(No.Concepts)_q$, and replace the original measure of execution guidance $log(len_{Q4} + 1)_q$ & $log(len_{Q5} + 1)_q$ with $(No.GuideWords)_q$. (Note that in these robustness checks, we replace the measures for both conceptual objectives and execution guidance at the same time. The conclusions from robustness checks are the same if we replace the measure for one of them at a time.) Additionally, when measuring conceptual objectives using $(No.Concepts)_q$, we also control for the level of overlap among the coded conceptual objectives. (We compute the semantic similarity of coded objectives based on Wordnet, and use the average pairwise similarity (*Concept Similarity*; on a scale of 1-100) to account for the level of overlap among conceptual objectives.) Finally, in Equation (4), we also add the ratio $(len_{Q3}/No.\text{Concept})_q$, a proxy for in-conciseness, as another control variable.

We estimate the modified Equation (4), and report the estimation results in the second column of Table 2. The results reveal that $(No.Designers)_q$ is significantly negatively associated with the measure of the number of conceptual objectives $(No.Concepts)_q$, but not significantly associated with the amount of execution guidance $(No.GuideWords)_q$, which again supports Hypothesis 1a and Hypothesis 1b. Additionally, after including $(No.Concepts)_q$, $(No.Designers)_q$ is not significantly associated with the in-conciseness $((len_{Q3}/No.Concepts)_q)$, which further verifies that $(No.Designers)_q$ is affected by the number of conceptual objectives (Hypothesis 1a), rather than the conciseness of seekers' expression for each objective. It is also worth noting that $(No.Designers)_q$ is significantly positively associated with *Concept Similarity*, which supports an additional theoretical result from the extension (which we relegate to Online Appendix EC.4.1 to save space) accounting for the overlap across conceptual objectives — the number of participating designers in a contest increases with the overlap across conceptual objectives, everything else equal.

We next estimate the modified Equation (5), and report the estimation results in the last column in Table 2. The results again support Hypothesis 2a and 2b: $(No.Submissions)_{i,q}$ is significantly positively associated with the measure of the amount of execution guidance $(No.GuideWords)_q$, but not significantly associated with the number of conceptual objectives $(No.Concepts)_q$.

Seemingly Unrelated Regression System: We further consider the possibility that certain contest-specific unobservables can affect both designers' entry and trial effort decisions. If this indeed happens, the errors in Equation (4) and those in Equation (5) might be correlated. We

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model and estimate the SUR, and find that the results are almost the same as OLS regression results.

5. Managing the Problem Specification

In the previous sections, we explored how designers' entry, concept formulating and trial effort decisions are influenced by the conceptual objectives and execution guidelines a seeker provides in his problem specification. Based on our empirically validated theoretical model, in this section we analyze how seekers should provide information in their problem specification to maximize their "profit" in crowdsourcing design contests.

A seeker's profit (Π_s) is defined as the expected highest quality among all the designs submitted to his contest, i.e., $\Pi_s = \mathbb{E}_\epsilon \max_i V_i^*$, where V_i^* is the equilibrium quality of designer i's best design, and the expectation is taken over the vector of all participating designers' design trials' quality shocks ϵ. (For simplicity, the "profit" ignores the cost of the award A, as this is a fixed value and we are focusing on how the seeker optimizes the problem specification given an award size A). The seeker maximizes Π_s by choosing *the number of conceptual objectives to disclose (S_r)* and *the amount of execution guidance to provide (S_g)*. We define the seeker's problem as:

$$\max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \Pi_s(S_r, S_g) = \max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \left[\mathbb{E}_\epsilon \max_{i \in N^*} V_i^*(r^*, m^*) \right], \tag{6}$$

where N^* is the equilibrium number of participating designers, and r^* and m^* are the equilibrium design concept formation and trial generation strategies of participating designers. Problem (6) is a joint problem in both S_r and S_g. From Theorem 1, we know the impacts from S_r and S_g can be separated: N^* and r^* are only affected by S_r but not by S_g; and given N^*, m^* is only affected by S_g but not by S_r. So, we can rewrite Problem (6) as the following problem separable in S_r and S_g (see Appendix B for the proof):

LEMMA 1.

$$\max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \Pi_s(S_r, S_g) = \max_{S_r \leq \overline{S}_r} \left[w \cdot r^*(S_r) + \mu \ln A \frac{N^*(S_r)-1}{N^*(S_r)} \right] + \max_{S_g \leq \overline{S}_g} \left[-\mu \ln(h(S_g)) \right]. \tag{7}$$

With the seeker's decisions on S_r and S_g being separable (Problem (7)), we next discuss how the seeker should set S_r and S_g separately.

Seeker's Decision on Number of Conceptual Objectives to Disclose. We first consider the problem associated with the seeker's optimal choice of S_r, the number of conceptual objectives to disclose in the problem specification. The seeker's objective is to choose a S_r that maximizes the expected quality of the best design sourced from the contest under any fixed amount of execution guidance provided (S_g), i.e., $\max_{S_r \leq \overline{S}_r} \Pi_s(S_r; S_g)$.

PROPOSITION 1. $\Pi_s(S_r; S_g)$ *decreases in* S_r *once* S_r *becomes sufficiently large, and thus for sufficiently large* $\bar{S}_r$, *we have* $S_r^* < \bar{S}_r$. *Details are in Appendix C.*

The seeker's profit Π_s is first increasing and eventually decreasing with S_r. The intuition is as follows. Disclosing more conceptual objectives has two countervailing effects. On the one hand, with more conceptual objectives being disclosed, designers are aware of and thus can incorporate more objectives, which leads to a higher expected quality of each design generated, positively affecting the best design quality $\Pi_s(S_r)$. We call this effect the *"quality effect"*. On the other hand, with more disclosed objectives, the designers' total participating cost increases (higher costs in the *design problem framing* and *design concept formulating* stages), leading to fewer designers participating in the contest. We call this the *"competition effect"*. This *competition effect* negatively affects the best design quality $\Pi_s(S_r)$, because $\Pi_s(S_r)$ is an extreme value of qualities of all design submissions, which will decrease if there are fewer participating designers.

As the seeker discloses more and more conceptual objectives (a larger S_r), the negative *competition effect* increases and eventually dominates the *quality effect*, because (i) design concept formation cost grows exponentially with S_r, hence the number of designers decreases quickly, (ii) with only a handful of designers in the contest, a small decrease in the number of participating designers would have a severe impact on the extreme value $\Pi_s(S_r)$. As a result, $\Pi_s(S_r)$ will decrease when the seeker discloses too many conceptual objectives. Therefore, the seeker should not always disclose all the conceptual objectives he cares about. For reasonable parameter ranges, simulation results suggest that the optimal S_r^* is relatively small (from 2 to 5); see Appendix C.

Seeker's Decision on Number of Execution Guidelines to Provide. Next, we consider the seeker's problem of choosing a S_g that maximizes the expected quality of the best design sourced from the contest under any fixed level of conceptual objectives provided (S_r), i.e., $\max_{S_g \leq \bar{S}_g} \Pi_s(S_g; S_r)$. This problem is trivial, since providing more execution guidelines (S_g) always increases best design quality. Intuitively, as the seeker provides more execution guidelines (a larger S_g), it is easier for designers to come up with design trials (a lower trial cost c_3), because the execution guidelines give directions for different aspects of design execution (such as color, shape, etc.), which designers otherwise need to spend effort figuring out and deciding on. Hence, with the lowered cost to generate each design trial, designers will come up with more trials (a larger m^*), which then in turn leads to a higher extreme value in submission quality (a higher Π_s). Therefore, the seeker should disclose all his execution guidelines (i.e., $S_g^* = \bar{S}_g$).

6. Further Evidence from the Field

In this section, we discuss a recent change to the crowdsourcing platform we collect data from: the template for seekers' problem specifications was updated. This update, as to be shown below,

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not only validates our earlier suggestions on how seekers should provide information in problem specifications, but also introduces an exogenous shock to seeker problem specification behavior on the platform and thus provides an opportunity for us to further identify the effects of disclosing conceptual objectives and execution guidelines on designers' behavior.

The update took place in summer 2017. The update involves two major adjustments. First, the platform provided an example when prompting the seeker to specify conceptual objectives (i.e., "top 3 things to communicate"). This example only includes three sample keywords. Potentially, this short three-keyword example can lead seekers to shorten their list of conceptual objectives. Second, the updated template changed the way the seeker provides execution guidelines. Instead of providing a short text answer to the "what logo styles do you prefer" question in a text box, seekers are asked to answer four multiple choice questions, including logo usage (e.g. screen/digital, clothing), preferred logo style (e.g. image+text, image only), preferred fonts (e.g. sans-serif, mono), colors to explore (e.g. aqua, green). The multiple choice question format can potentially reduce the cost for seekers to provide execution guidelines. (In our model, we concluded that the seeker should provide all his execution guidelines but we did not include a cost of doing so. One can easily imagine that, if there are costs associated with the seeker coming up with or disclosing execution guidelines, the seeker will stop providing more when the marginal cost of providing an additional guideline exceeds the marginal benefit from doing so.) The multiple choice question format can also remind them to provide guidelines on each of these four aspects of logo designs. But at the same time, it limits the guidelines the seeker can provide — the seeker is not expected to provide guidelines on other logo features beyond usage, style, font and color. Therefore, the direction of the effect of this second adjustment is not very clear.

Since this update does not affect how seekers answer Question 5 (Q5) much, we do not consider Q5 in the following analysis. Besides the two main changes described above, we also observe that the platform added a new area called "vision" in the template. This new area is located below the "top 3 things" box, providing additional space for the seeker to elaborate what message he envisions a logo to convey. We find that most of the time, content provided in the "vision" area does not involve introducing *additional* conceptual objectives. In the manual coding of conceptual objectives for contests that took place after the website update, we incorporate the occasional additional objectives that are mentioned in the "vision" area but do not appear in the "top 3 things" box.

This update shows that the platform recognizes problem specification as a crucial design element for crowdsourcing design contests, and distinguishes among different types of information conveyed through the problem specification, i.e., conceptual objectives and execution guidelines.

Moreover, the example the platform provides for specifying the "top 3 things" is also aligned with our recommendation not to specify too many conceptual objectives.

In addition, the website update provides an exogenous shock to how seekers specify their problems. In the empirical analysis presented in Section 4, the identification of the effects of the number of disclosed conceptual objectives and the number of execution guidelines relies on cross-contest variations in the amounts of these two types of information provided under the same website layout. One may argue that these variations could be driven by seekers' unobserved idiosyncratic characteristics, and if those seeker characteristics can also affect designers' participation behavior, then the regression models presented earlier may suffer from an endogeneity problem. The update to the problem specification template imposes an exogenous shock on the number of conceptual objectives and execution guidelines, which is unlikely to be correlated with seekers' idiosyncratic characteristics, allowing us to better identify the effects of conceptual objectives and execution guidelines on designers' participation behavior.

Specifically, we collect additional data on all logo design contests that took place on the platform three months before and three months after the update. As in the empirical analysis presented in Section 4, we focus on contests where the design seekers promise to give a $200 award to one and only one winner. (However, we include contests that are not only 7-days long to increase the statistical power of the test.) The contests that took place during the transition of the platform website (i.e., 10 days before and after August 31, 2017) are excluded. This new sample consists of 214 contests (6,070 contest-designer combinations). Below, we first establish how the template update affects the numbers of conceptual objectives and execution guidelines seekers provide in their problem specification, and then study how these changes in seekers' problem specification affect designers' entry and trial effort decisions.

Conceptual objectives: We first test whether the number of conceptual objectives decreases, as expected, after the website update. Specifically, we compare how many words there are in seekers' answers to Q3 (i.e., using the seeker's answer to the "top 3 things" question as a proxy for the number of conceptual objectives) before and after the template update — the average word-count for Q3 before the update $(Len(Q3)_q^{\mathrm{pre}})$ is 30.02, and the average word-count after the update $(Len(Q3)_q^{\mathrm{post}})$ is 8.75, and the difference is statistically significant (p-value<0.001; details of T-tests are in Appendix D). We also compare the number of manually coded conceptual objectives before and after the update, and the results are similar — the average number of conceptual keywords before the update $((No.\,\mathrm{Concept})_q^{\mathrm{pre}})$ is 5.72, and the number after the update $((No.\,\mathrm{Concept})_q^{\mathrm{post}})$ is 3.81, and the difference is also statistically significant (p-value<0.001). In the manual coding process, the coders report the total number of conceptual keywords mentioned in both the "top

3 things" and "vision" areas. These results suggest that seekers indeed provide fewer conceptual objectives after the update.

Next we examine how fewer disclosed conceptual objectives affect designer behaviors. Specifically, we regress the number of designers in each contest on the the dummy variable $\mathbb{I}(\text{post-update})_q$, which indicates whether the focal contest took place after the website update. We include contest duration, and Day-of-Week dummies in the regression as control variables. Additionally, we include "Week Slope" in the regression model, to control for any time trend that may exist prior to the website update. The estimation results for this regression are shown in the first column of Table 3. The estimated coefficient of the dummy variable $\mathbb{I}(\text{post-update})_q$ is positive and significant, indicating that after the update, the number of participating designers increases. This result, combined with the finding that after the website update, seekers disclose fewer conceptual objectives, again supports Hypothesis 1a, which hypothesizes that the number of participating designers decreases with the number of disclosed conceptual objectives. (In a robustness check, we test and verify that the increase in $(No.Designers)_q$ is indeed due to the decrease in the number of disclosed objectives, but not other concurrent changes to the platform resulting from this update. Details are provided in Appendix D.)

Table 3   Regression Results for the Update's Impacts on Contests' Outcomes

	$(No.Designers)_q$	$(NO\,Submission)_{i,q}$	
		Dependent Variable:	
$\mathbb{I}(\text{post-update})_q$	10.579** (3.779)	−0.872** (0.313)	
$\mathbb{I}(\text{short Q4})_q * \mathbb{I}(\text{pre-update})_q$			0.772 (0.384)
$\mathbb{I}(\text{long Q4})_q * \mathbb{I}(\text{pre-update})_q$			1.213*** (0.354)
Control Variables			
$(No.Designers)_q$		−0.004 (0.004)	−0.004 (0.004)
$Duration_q$	0.650** (0.195)	0.035** (0.011)	0.028* (0.011)
Week Slope	Yes	Yes	Yes
$No.Updates$	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Designer Fixed Effects	No	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes
Observations	214	6,070	6,070
R^2	0.323	0.316	0.318
Adjusted R^2	0.199	0.211	0.213
Residual Std. Error	12.136 (df = 180)	3.337 (df = 5262)	3.333 (df = 5261)
F Statistic	2.604***	3.011***	3.033***

Note: *p<0.05; **p<0.01; ***p<0.001

Execution Guidelines: Since the platform updated the form of execution guidelines from open-ended descriptions to multiple choice questions, we cannot directly measure the change in the number of execution guidelines; however, we notice some changes in the information provided. Prior to the update, the number of guidelines provided varies a lot from seeker to seeker — some seekers provide extremely detailed execution guidelines, including suggestions for shape, color, and pattern (e.g., "*Please use variations of red, black, silver and gold (matte, not shiny). Make sure*

that the logo doesn't rely on silver and gold effects, need a color palette that is easily translatable to web. Please do not use green, blue or maroon."), whereas others provide very brief guidelines (e.g., *"image+text"*). After the update, this seeker heterogeneity no longer exists, because all seekers are now required to answer the exact same set of multiple-choice questions.

We regress the number of submissions per designer on the post-update dummy, controlling for the number of designers in the same contest, contest duration, Day-of-Week dummies and week slope. The regression results are reported in the second column of Table 3. Quite surprisingly, the coefficient of $\mathbb{I}(\text{post-update})_q$ turns out to be negative and significant, suggesting that on average each designer submits *fewer* designs after the update. Why is this the case? One possible explanation is that, as mentioned previously, the template update removes seeker heterogeneity in execution guideline provision. Prior to the update, some seekers are willing to provide detailed guidelines, and others are not. For seekers who would provide few execution guidelines in the open-ended Q4 template, the switch to the standardized questionnaire may have increased the number of guidelines they provide; whereas for seekers who would provide detailed guidelines in the open-ended Q4 template, the switch in fact limits the amount of execution guidance they can provide. An average negative effect reflected in the negative estimated coefficient of $\mathbb{I}(\text{post-update})_q$ seems to suggest that more seekers suffer the negative effect of the switch to the standardized questionnaire format than those who benefit from it.

To test whether this explanation is supported by the data, we use $\mathbb{I}(\text{short Q4})_q * \mathbb{I}(\text{pre-update})_q$ and $\mathbb{I}(\text{long Q4})_q * \mathbb{I}(\text{pre-update})_q$ to substitute for the $\mathbb{I}(\text{post-update})_q$ dummy variable in the regression of the number of submissions per designer described above, with $\mathbb{I}(\text{short Q4})_q$ ($\mathbb{I}(\text{long Q4})_q$) indicating the focal contest having less (more) than 15 words in the Q4 answer. In doing so, we treat the post-update contests as the baseline group, and separately evaluate the difference in the number of submissions per designer between the post-update contests and pre-update contests with short ($\mathbb{I}(\text{short Q4})_q$) v.s. long ($\mathbb{I}(\text{long Q4})_q$) execution guidelines. The results of the regression are presented in the third column of Table 3. The coefficient of the interaction term $\mathbb{I}(\text{short Q4})_q * \mathbb{I}(\text{pre-update})_q$ is insignificant, whereas the coefficient of the interaction term $\mathbb{I}(\text{long Q4})_q * \mathbb{I}(\text{pre-update})_q$ is significant and positive. These results align with our conjecture: pre-update seekers who provide a lot of execution guidelines on average receive more submissions from each participating designer, compared with seekers using the new multiple-choice format; seekers using the new multiple-choice format can only achieve a similar number of submissions per participant as pre-update seekers who provide few execution guidelines.

To fully understand the mechanism driving the difference in outcome between long- and short-guideline contests, we perform a textual analysis to understand the exact change in the content of the execution guidelines seekers provide before and after the update. In particular, we first classify

seeker-provided execution guidelines into seven categories (colors, logo styles, shapes, font, usage, art styles, and resources). For each problem specification in the sample (to increase the statistical power we include all single-guaranteed-award contests from March 2012 to November 2014, and control for the award amount and contest duration), we note down whether the seeker provides any information in each of these seven categories. Then we regress the number of submissions made by each participating designer on the seven dummy variables indicating whether the seeker provides guidelines in the corresponding categories, as well as a similar set of control variables as those appearing in Table 3. The results of this regression (reported in Table D.3 in Appendix D to save space in the body), provides several interesting observations. (1) Providing guidelines for "color" and "logo style", two of the four categories included in the new multiple-choice format, is not very helpful in increasing the number of submissions made by each designer. (2) Providing guidelines for "shape" and "art style", information categories that are not included in the new multiple-choice format, has a significant positive effect on the number of submissions per participating designer. (3) The multiple-choice format limits the amount of information the seeker can provide for each category. Consider "usage" as an example. After the update, the seeker can only choose from the five options provided (outdoor, clothing, screen/digital, print, signature); whereas, prior to the update, seekers could, and in fact did provide more detailed information about logo usage (e.g. embroidery, building, banner, sticker, letterhead, device, t-shirt, vest, uniform, hat, etc). All these results suggest that the new multiple-choice format appears to be less effective for execution guideline provision than the old open-ended format, and therefore, this change may have increased designers trial cost (c_3 in our analytical model), which then leads to the decrease in the number of submissions per participant we observe in the data. This result further supports Hypothesis 2a.

To sum up, the recent website update discussed above underscores the importance of managing the problem specification, especially the seeker's provision of conceptual objectives and executive guidelines. The update related to the conceptual objective provision is successful — as discussed in Section 5, disclosing fewer conceptual objectives may increase the number of participants, which is beneficial to the seeker. On the other hand, the update related to the execution guideline provision is not very effective. The convenient multiple-choice format is intended to encourage seekers to provide more execution guidelines; however, empirical data suggest that this new format may have limited the amount and the variety of execution guidance the seeker can provide, and consequently, has a negative effect on the number of submissions made by each participating designer, especially in contests where seekers are willing to provide detailed execution guidance if possible.

7. Conclusion

Crowdsourcing contests are an increasingly popular way to source solutions to design problems (creative problems). How to optimally specify problems for such contests is an important question facing seekers, as the information provided in the problem specification can affect how many

designers their contests can attract, how much effort participating designers are willing to exert, and how good the solutions sourced from the contests will be. In this paper, we combine analytical and empirical methods to examine the effects of different types of information provided in seekers' problem specifications — namely, conceptual objectives and execution guidance — on designers' participation behavior, and prescribe recommendations for optimal information provision in problem specifications.

Our study provides the following novel insights. First, our theoretical analysis suggests — and our empirical analysis confirms — that the number of participating designers in a contest decreases with more conceptual objectives provided in the problem specification, and that the trial effort provision increases with more execution guidance provided in the problem specification. Based on the empirically validated theoretical model, we then solve the seeker's problem of the numbers of conceptual objectives and execution guidelines to provide in the problem specification. Our analysis suggests that, while providing more execution guidelines always benefits the seeker, the seeker should not always disclose all the conceptual objectives he cares about. Further, we exploit a "quasi-natural experiment" (involving an update to the platform's problem specification template) to strengthen the reliability of our empirical results. In addition, the update made by the crowdsourcing platform directionally supports our recommendations for seekers' problem specifications, and our detailed textual analysis provides further insights into what types of execution guidelines are more helpful in reducing designers' cost to come up with design trials.

Like any research, our study has a few limitations. First, our empirical analyses are based on data collected from a single crowdsourcing platform. Although we believe that contests on this platform are representative, further empirical analysis of data collected from other crowdsourcing platforms would be helpful in establishing the external validity of our findings. Second, we focus on how the initial problem specification affects the contest outcome, and do not consider the updates to the problem specification that might take place during the contest period. Such updates are relatively rare in our data, but in other settings where updates to problem specifications are more prevalent, the effects of the problem specification updates may require special attention. Third, because analyzing a model with both the agent's output uncertainty and heterogeneity is considered intractable in the innovation-contest literature (e.g., Terwiesch and Xu (2008), Ales et al. (2017a), Korpeoglu et al. (2017)), we assume homogeneous designers and focus on the impact of the designers' solution uncertainty.

Despite these limitations, our study offers rich empirical evidence from the field to support the predictions and recommendations from our theoretical model, linking the theoretical and empirical research of crowdsourcing contests. This study also proposes a novel theoretical model building upon the design literature to characterize designers' design process, which allows us to examine

the role of information in distinct stages of this design process and its impact on contest outcome. This theoretical modeling framework can be used to study other design problems in the context of open design/creative contests. As one of the first papers studying problem specification in crowdsourcing contests, this study contributes to the academic literature of crowdsourcing contests. It also provides rich managerial implications, especially for individuals or organizations that are using crowdsourcing contests to source creative solutions or products (i.e., seekers in crowdsourcing creative contests). We hope that this study inspires further work that analytically and/or empirically investigates problems in crowdsourcing contests.

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Appendices

A. Proofs for Theorem 1 — Designers' Equilibrium Decisions

To solve designers' problem (Equation (3)), we first solve for designers' equilibrium choices of the number of conceptual objectives to incorporate ($r^*(N)$) and the number of design trials to generate ($m^*(N)$), given a number of participating designers (N). Then we solve for the equilibrium number of participating designers (N^*). As a preparation, we exploit the Gumbel distribution's property (recall that Vs in Equation (2) follow a Gumbel distribution), and compute designer i's probability of winning, given i's choices (r_i and m_i), and all other competing designers' choices (r and m):

$$\Pr(i \text{ wins}) = \frac{m_i \exp(v(r_i)/\mu)}{m_i \exp(v(r_i)/\mu) + (N-1)m \exp(v(r)/\mu)}. \tag{A.1}$$

We analyze the symmetric pure strategy Nash equilibrium, where every designer chooses the same r^* and m^*. Such equilibrium exists in our game, according to Theorem 1.2 in Fudenberg and Tirole (2000).

Equilibrium r^*: Designer i's first-order condition (F.O.C.) with respect to concept formation decision r_i (in Equation (3)) is $\frac{\partial U_i}{\partial r_i} = 0$. Substituting $\Pr(i \text{ wins})$ from Equation (A.1), and using symmetry ($m = m_i = m^*$ and $r = r_i = r^*$), we can simplify the marginal change in the winning chance with respect to r_i as $\frac{\partial \Pr\{i \text{ wins}\}}{\partial r_i} = \frac{w}{\mu} \frac{N-1}{N^2}$. With that, we solve the F.O.C. and obtain a unique symmetric solution: $\bar{r} = \frac{\ln(\frac{N-1}{N^2} \frac{w}{\mu} \frac{A}{c_2} \frac{1}{\ln(1/p)})}{\ln(1/p)}$. Note that, by definition, designers cannot incorporate more conceptual objectives than the total disclosed ones (i.e., $r_i \leq S_r$); therefore,

$$r^*(N) = \min(S_r, \bar{r}) \text{ , where } \bar{r} = \frac{\ln(\frac{N-1}{N^2} \frac{w}{\mu} \frac{A}{c_2} \frac{1}{\ln(1/p)})}{\ln(1/p)}. \tag{A.2}$$

Equilibrium m^*: Designer i's F.O.C. with respect to trial effort decision m_i (in Equation (3)) is $\frac{\partial U_i}{\partial m_i} = 0$. Substituting $\Pr(i \text{ wins})$ from Equation (A.1) into the F.O.C., and using symmetry ($m = m_i = m^*$ and $r = r_i = r^*$), the F.O.C. reduces to $A \frac{(N-1)m^*}{(m^* N)^2} - c_3 = 0$, which has a unique solution:

$$m^*(N) = \frac{A(N-1)}{N^2 c_3}. \tag{A.3}$$

Equilibrium N^*: Having derived participating designers' equilibrium choices ($r^*(N)$ and $m^*(N)$) under a given number of participants N, we compute the equilibrium number of participating designers (N^*). We add a subscript to N^* to help distinguish N^* in two scenarios: N_1^* stands for N^* when $r_i \leq S_r$ is binding (i.e., designers decide to incorporate all the disclosed conceptual objectives); N_2^* stands for N^* when $r_i \leq S_r$ is not binding (i.e., designers decide to incorporate a subset of all disclosed conceptual objectives).

- Region I: In this region, designers are willing to incorporate all disclosed conceptual objectives. Equilibrium conditions imply that designers are indifferent between participating or not, i.e., $\Pr(i \text{ wins}) \cdot A - C_i(r_i = S_r, m_i = m^*) = s$. In a symmetric equilibrium, $\Pr(i \text{ wins}) = 1/N$. We can simplify and solve for the equilibrium number of participating designers as

$$N^* = N_1^* = \sqrt{\frac{A}{s + c_1 \cdot S_r + c_2 \cdot (1/p)^{S_r}}}. \tag{A.4}$$

- Region II: In this region, designers incorporate a subset of all disclosed conceptual objectives. Again, designers are indifferent between participating or not, i.e., $\Pr(i \text{ wins}) \cdot A - C_i(r_i = \bar{r}, m_i = m^*) = s$. In a symmetric equilibrium, $\Pr(i \text{ wins}) = 1/N$. After substituting $\bar{r}$ (see Equation (A.2)), we can rearrange and solve for the equilibrium number of participating designers as:

$$N^* = N_2^* = \frac{\sqrt{4Y(X+1)+X^2} - X}{2Y} \text{ , where } X = \frac{w}{\mu \ln(1/p)} \text{ and } Y = \frac{s + c_1 \cdot S_r}{A}. \tag{A.5}$$

1

Next, we show that, the two regions are located on either side of a threshold S_r^{ic} such that $S_r^{\text{ic}} = \bar{r}(N_2^*(S_r^{\text{ic}}))$ (where $\bar{r}$ is from Equation (A.2), and N_2^* is from Equation (A.5)). In words, S_r^{ic} is the number of conceptual objectives the seeker discloses, under which designers are willing to incorporate exactly what are disclosed. The following Lemma characterizes S_r^{ic}.

LEMMA 2. *There exists a unique S_r^{ic}. S_r^{ic} divides the number of conceptual objectives the seeker discloses into two regions. Region I: when $S_r \leq S_r^{ic}$, designers are willing to incorporate all the disclosed objectives (i.e., $S_r \leq \bar{r}(N_2^*(S_r))$); Region II: when $S_r > S_r^{ic}$, designers incorporate only a subset of all the disclosed objectives (i.e., $S_r > \bar{r}(N_2^*(S_r))$).*

Lemma 2 (proved in Online Appendix EC.3) suggests we can discuss N_1^* and N_2^* separately in Region I and Region II defined in Lemma 2; the two regions are self-contiguous and do not overlap.

The Number of Participants Decreases with More Disclosed Conceptual objectives. It is obvious that in Region I, the number of participating designers (N_1^*) decreases with more disclosed conceptual objectives (S_r). In Region II, we have, $\frac{\partial N_2^*}{\partial S_r} = \frac{\partial N_2^*}{\partial Y} \cdot \frac{\partial Y}{\partial S_r} = -\frac{-X\sqrt{X^2+4XY+4Y}+X^2+2XY+2Y}{2Y^2\sqrt{X^2+4XY+4Y}} \cdot \frac{c_1}{A} \leq 0$. That is, the number of participating designers (N_2^*) also decreases with more disclosed conceptual objectives (S_r) in Region II. Moreover, N^* is continuous with S_r. Therefore, the number of participating designers always decreases with more disclosed conceptual objectives.

Lastly, we can substitute N^* (Equations (A.4)-(A.5)) into Equations (A.2)-(A.3), and get m^* and r^* under the equilibrium number of participating designers.

B. Proof for Lemma 1

$\max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \Pi_s(S_r, S_g)$

$$
\begin{aligned}
&= \max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \left[\mathbb{E}_\epsilon \max_{i \in N^*} V_i^*(r^*, m^*) \right], \text{ (from Problem (6))} \\
&= \max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \left[\mathbb{E}_\epsilon \max_{i \in N^*(S_r)} V_i^*(r^*(S_r), m^*(S_g, N^*(S_r))) \right], \text{ (according to Theorem 1)} \\
&= \max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \left[v(r^*(S_r)) + \mu \ln (m^*(S_g, N^*(S_r)) \cdot N^*(S_r)) \right], \text{ (Gumbel distribution's property)} \\
&= \max_{S_r \leq \overline{S}_r, S_g \leq \overline{S}_g} \left[w \cdot r^*(S_r) + \mu \ln \frac{A(N^*(S_r)-1)}{N^*(S_r)} - \mu \ln(h(S_g)) \right], \\
&= \max_{S_r \leq \overline{S}_r} \left[w \cdot r^*(S_r) + \mu \ln A \frac{N^*(S_r)-1)}{N^*(S_r)} \right] + \max_{S_g \leq \overline{S}_g} \left[-\mu \ln(h(S_g)) \right].
\end{aligned}
$$

(B.6)

C. Details for Proposition 1

We provide a detailed discussion on the characteristics of seekers' optimal number of conceptual objectives to disclose ($S_r^* := \arg\max \Pi_s(S_r; S_g)$), including its theoretical properties and simulated comparative statics.

Theoretical Properties of S_r^*. We separately discuss the optimal number of conceptual objectives to disclose (S_r^*) under two scenarios: In Scenario 1, we assume that N^* follows Equation (A.4), m^* follows Equation (A.2), and $r^* = S_r$ regardless of the size of S_r. In Scenario 2, we assume that N^* follows Equation (A.5), m^* follows Equation (A.2), and $r^* = \bar{r}$ regardless of the size of S_r. In words, in Scenario 1 (2) we assume that the equilibrium formulas of Region I (II) will prevail regardless of the size of S_r. We define S_r^{1*} and S_r^{2*} as the optimal numbers of conceptual objectives the seeker should disclose in Scenario 1 and 2 under $\overline{S}_r = \infty$, and show their properties in Lemmas 3 and 4, respectively.

2

LEMMA 3. *In Scenario 1, the seeker's profit* Π_s *is first increasing and eventually decreasing with* S_r. *When* $c_1 = 0$ *(i.e., no designers' problem framing cost),* $\Pi_s(S_r)$ *is a concave function maximized at* $S_{r,c_1=0}^{1*} = \frac{\ln\left(2[\sqrt{A(A+s(\frac{\mu}{w})^2 \ln^2 \frac{1}{p} + 2s\frac{\mu}{w}\ln\frac{1}{p})} + (A-2s) - s\frac{\mu}{w}\ln\frac{1}{p}]\right) - \ln\left(c_2(\frac{\mu}{w}\ln\frac{1}{p}+2)^2\right)}{\ln(1/p)}$. *When* $c_1 \geq 0$, $\Pi_s(S_r)$ *is maximized at* S_r^{1*}, *and* $S_r^{1*} \leq S_{r,c_1=0}^{1*}$.

LEMMA 4. *In Scenario 2, the seeker's profit* Π_s *decreases with* S_r.

The proofs for Lemmas 3 and 4 are provided in Online Appendices EC.5 and EC.6, respectively. Note that Scenario 1 corresponds to Region I in Lemma 2 when $S_r \leq S_r^{\text{ic}}$; Scenario 2 corresponds to Region II in Lemma 2 when $S_r > S_r^{\text{ic}}$. With this observation and the continuity of $\Pi_s(S_r)$, Lemmas 3 and 4 imply that the optimal number of conceptual objectives to disclose is $S_r^* \leq \min\{\overline{S}_r, S_r^{1*}, S_r^{\text{ic}}\}$. Therefore, the seeker should not always disclose all the conceptual objectives he cares about.

Comparative Statics of S_r^*. Next, we examine how the optimal number of conceptual objectives to disclose (S_r^*) changes with the nature of the design problem. Specifically, we simulate S_r^* at different values of the model primitives, including: cost of digesting each conceptual objective (in the "design problem framing" stage) (c_1); unit cost of each design concept formulating attempt (c_2); opportunity cost (s); concept formulating difficulty ($1/p$); award level (A); and relative problem uncertainty ($\lambda := \mu/w$). Figure C.1 illustrates the simulation results. The relationships between S_r^* and each of those model primitives are consistent with intuition. To save space, detailed discussion of the results are provided in Online Appendix EC.7.
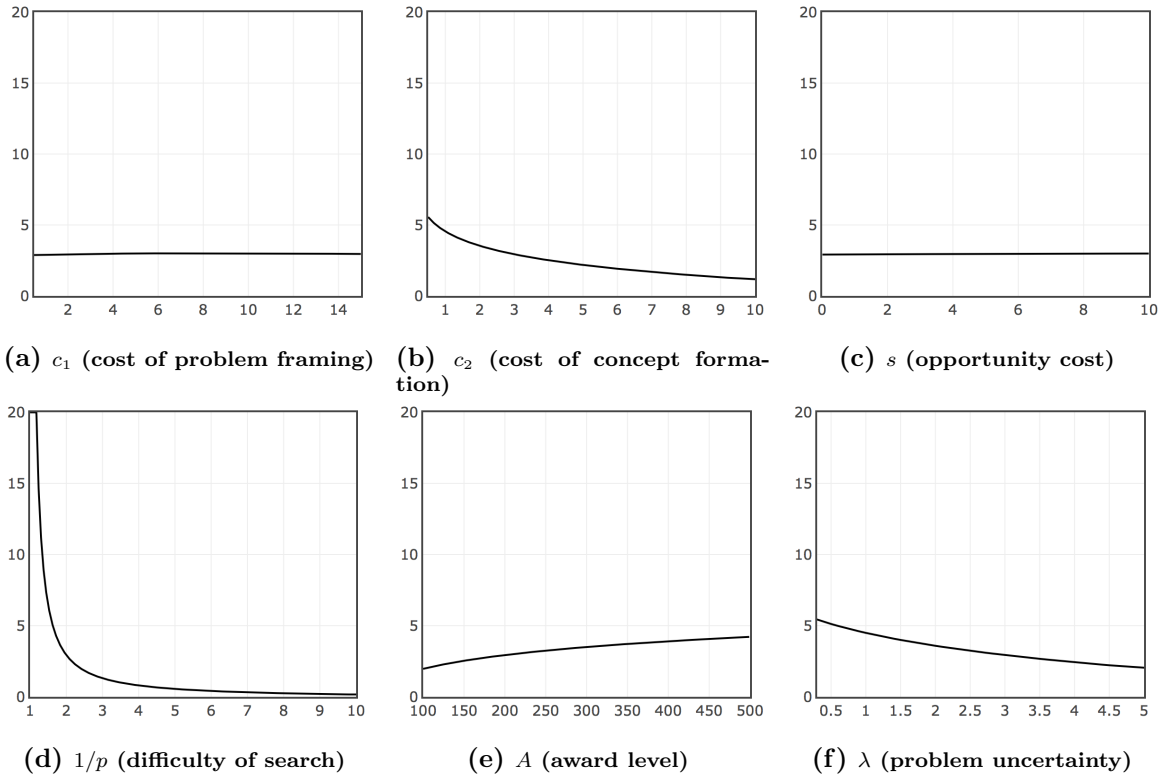

(a) c_1 **(cost of problem framing)**   **(b)** c_2 **(cost of concept formation)**   **(c)** s **(opportunity cost)**

(d) $1/p$ **(difficulty of search)**   **(e)** A **(award level)**   **(f)** λ **(problem uncertainty)**

Figure C.1   Optimal Number of Conceptual Objectives to Disclose, S_r^*

(when $A = 200$, $s = 2$, $p = 0.5$, $c_2 = 3$, $\mu = 6$, $w = 2$, $c_1 = 2$**).**

3

D. Changes in Problem Specification Before and After the Platform Update

Table D.1 **Measured by the Word-Count**

	$Len(Q3)_q^{\text{post}}$	$Len(Q3)_q^{\text{pre}}$
Mean	8.745	30.025
Variance	102.114	3706.703
Observations	51	163
H_0	$Len(Q3)_q^{\text{post}} = Len(Q3)_q^{\text{pre}}$	
df	187	
t Stat	-4.278	
P(T≤t) two-tail	3.007E-05	

Table D.2 **Measured by the Number of Manually Coded Keywords (Including "Top-3 Things" and "Vision" Boxes)**

	$(No.\,\text{Concept})_q^{\text{post}}$	$(No.\,\text{Concept})_q^{\text{pre}}$
Mean	3.810	5.718
Variance	2.577	14.401
Observations	51	163
H_0	$(No.\,\text{Concept})_q^{\text{post}} = (No.\,\text{Concept})_q^{\text{pre}}$	
df	187	
t Stat	-5.234	
P(T≤t) two-tail	3.957E-07	

Table D.3 **Impact of Different Elements of Execution Guidelines on No.Submissions Per Designer**

	Dependent Variable: $(NO\,Submission)_{i,q}$	In Post-Update Multiple-Choice Questions?
Elements of Execution Guidance		
Colors Dummy	−0.041 (0.035)	Yes
Logo Style Dummy	0.046 (0.029)	Yes
Shapes Dummy	0.063 (0.040)	No
Font Dummy	0.174*** (0.046)	Yes
Usage Dummy	0.088** (0.031)	Yes
Art Styles Dummy	0.154*** (0.029)	No
Resources Dummy	0.100** (0.031)	No
Control Variables		
$log(len_{Q3}+1)_q$	−0.005 (0.010)	
$Duration_q$	0.015*** (0.001)	
$Award_q$	0.001*** (0.0001)	
$(No.Designers)_q$	−0.001** (0.0003)	
Fixed Effects	Start-Date, Industry, Creator	
Observations	124,183	
R² (Adjusted R²)	0.247 (0.214)	
Residual Std. Error (F Statistic)	3.381 (7.467***, df = 118960)	

Note: *p<0.05; **p<0.01; ***p<0.001

Robustness check for the impact of platform update on $(\textbf{No.Designers})_{\textbf{q}}$. To make sure the increase in $(No.Designers)_q$ after the website update is indeed due to the decrease in the number of disclosed conceptual objectives, but not other concurrent changes to the platform, we conduct the following robustness check. We regress the number of participants in each contest on not only $\mathbb{I}(\text{post-update})_q$, but also $log(len_{Q3}+1)_q$ and $\mathbb{I}(\text{post-update})_q * log(len_{Q3}+1)_q$. (We include the same set of control variables as those shown in Table 3.) The estimation results are reported in the second column of Table D.4. After controlling for $log(len_{Q3}+1)_q$, the dummy $\mathbb{I}(\text{post-update})_q$ no longer correlates with $(No.Designers)_q$, indicating that the increase in $(No.Designers)_q$ is explained by the change in the number of disclosed objectives ($log(len_{Q3}+1)_q$); after considering $log(len_{Q3}+1)_q$, $\mathbb{I}(\text{post-update})_q$ does not explain the change in $(No.Designers)_q$. In addition, the interaction term $\mathbb{I}(\text{post-update})_q * log(len_{Q3}+1)_q$ is not significantly associated with $(No.Designers)_q$, suggesting that the effect of conceptual objectives on participation is not significantly different before and after the platform update.

Table D.4 **Robustness Check on Platform Update's Impact**

	Dependent Variable: $(No.Designers)_q$	
	(main test)	(robustness)
$\mathbb{I}(\text{post-update})_q$	10.579** (3.779)	−1.615 (7.344)
$log(len_{Q3}+1)_q$		−1.794** (0.680)
$\mathbb{I}(\text{post-update})_q * log(len_{Q3}+1)_q$		3.238 (3.500)
Control Variables	$No.Updates_q$, $Duration_q$, Week Slope, Day-of-Week, Industry Fixed Effects	
Observations	214	214
R² (Adjusted R²)	0.323 (0.199)	0.329 (0.201)
Residual Std. Error (F Statistic)	12.136 (2.604***; df = 180)	12.118 (2.580***; df = 179)

Note: *p<0.05; **p<0.01; ***p<0.001

4

Online Appendices

EC.1. Examples of the Types of Information in Problem Specifications in the Data

Example-1

Company Name: ███████.

Industry: Retailing.

Q3 (Conceptual objectives): It's a fun brand for kids. Very happy, upbeat and never quit on your dreams. Community and fun.

Q4 (Execution Guidance): Image only. A cartoon duck with a sailor hat - not too much like Donald Duck. The hat should be green, the duck bill should be yellow. The duck should be white.

Q5 (Execution Guidance): Duck face a bit like this (link) but with hat and less body visible.

Example-2

Company Name: ████████.

Industry: Consulting and Professional Services.

Q3 (Conceptual objectives): We want to generate a sense of progress to our customers, as well as communicate that we are a professional organization. We're here to help our clients cut through industry baggage to help them really focus on what will help them do business well.

Q4 (Execution Guidance): Image with the company name, or image only. We won't consider text only logos.

Q5 (Execution Guidance): None.

Example-3

Company Name: ████.

Industry: Social Media Advertising and Marketing.

Q3 (Conceptual objectives): We are looking for a design that is professional but not too corporate. We want to convey reliability, fun and professionalism.

Q4 (Execution Guidance): None.

Q5 (Execution Guidance): Not really.

EC.2. Additional Tables

Additional summary statistics. In Table EC.1, we report the summary statistics of alternative measures number of conceptual objectives and the amount of execution guidance per problem specification.

Table EC.1   Summary Statistics for Alternative Measures of Conceptual Objectives and Execution Guidance

Variable	Notation	Mean	Std. Dev.	Min	Pctl(25)	Med	Pctl(75)	Max
Number of Conceptual objectives	$(No.Concepts)_q$	5.759	3.857	1	3	4	7	30
Word-count per objectives	$(len_{Q3}/No.\,\text{Concept})_q$	3.529	3.654	0.63	1.25	2.03	4.11	28.91
Semantic Similarity Among objectives	$Concept\,Similarity$	18.3	7	0	14	17	21	51
Number of Execution Guidelines	$(No.GuideWords)_q$	6.482	4.560	0	3	5	9	26

Data evidence for problem framing cost increasing with conceptual objectives. Table EC.2 reports the results of the regression of coders' reading time for a problem specification on the characteristics of the

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problem specification. The results suggest that the coders spend more time reading problem specifications with more conceptual objectives, but not on those with more execution guidelines. This supports our modeling assumption that the problem-framing cost increases with the number of conceptual objectives, but not with the number of execution guidelines.

Table EC.2   Regression of Reading Time

	Dependent Variable: $(Reading\,Time)_q$
$(No.Concepts)_q$	0.074^{***} (0.004)
$(len_{Q3}/No.Concepts)_q$	0.054^{***} (0.004)
$log(len_{Q4}+1)_q$	-0.004 (0.016)
$log(len_{Q5}+1)_q$	-0.014 (0.013)
$Constant$	-0.395^{***} (0.112)
Observations	463
R^2	0.647
Adjusted R^2	0.612
Residual Std. Error (F Statistic)	0.292 $(18.536^{***};$ df $= 424)$

Note: *p<0.05; **p<0.01; ***p<0.001

Robustness checks related to the "quasi-natural experiment". As a robustness check for the platform update's impact on the number of submissions per designer, we experimented with alternative cutoffs for the short- and long-execution-guideline problem specifications. The results of this robustness check, which are reported in Table EC.3, show that the qualitative results of the regression are not affected by the choice of the cutoff value.

Table EC.3   Alternative Cutoffs for Short v.s. Long Execution Guidelines

	Dependent Variable: $(NO\,Submission)_{i,q}$		
Cutoff for Short v.s. Long Q4	10	15 (main analysis)	20
$\mathbb{I}(\text{short Q4})_q * \mathbb{I}(\text{pre-update})_q$	0.762 (0.374)	0.772 (0.384)	0.699 (0.366)
$\mathbb{I}(\text{long Q4})_q * \mathbb{I}(\text{pre-update})_q$	1.174^{***} (0.353)	1.213^{***} (0.354)	1.150^{**} (0.350)
Control Variables			
$(No.Designers)_q$	-0.003 (0.004)	-0.004 (0.004)	-0.004 (0.004)
$Duration_q$	0.029^{*} (0.011)	0.028^{*} (0.011)	0.028^{*} (0.011)
Additional Controls	$No.Updates_q$, Week Slope, Day-of-Week, Industry, Designer Fixed Effects		
Observations	6,070	6,070	6,070
R^2 (Adjusted R^2)	0.317 (0.213)	0.318 (0.213)	0.318 (0.213)
Residual Std. Error (df = 5261)	3.333 (3.029^{***})	3.333 (3.033^{***})	3.333 $(3.033^{***}$)

Note: *p<0.05; **p<0.01; ***p<0.001

EC.3.   Proof for Lemma 2

Below, we first show that S_r^{ic} exists and is unique. Recall that S_r^{ic} is the point where designers are willing to incorporate the exact number of conceptual objectives disclosed by the seeker, i.e., $S_r^{\text{ic}} = \bar{r}(N_2^*(S_r^{\text{ic}}))$. N_2^* is the equilibrium number of participating designers when $r^* \geq S_r$ is not binding.

Existence. We prove S_r^{ic} exists by showing:

LEMMA 5. *(1)* $\exists S_r \to 0$ *s.t.* $\bar{r}(N_2^*(S_r)) \geq S_r$, *and (2)* $\exists S_r > 0$ *s.t.* $\bar{r}(N_2^*(S_r)) < S_r$.

We now provide proofs for (1) and (2) in Lemma 5.

(1) By assumption, $r^* = S_r$ if S_r is sufficiently small (see Section 3.3), hence we know that $\exists S_r \to 0$ s.t. $\bar{r}(N_2^*(S_r)) \geq S_r$.

(2) We are interested in studying contests where $N^* > 1$ (see Section 3.3); hence, under the problem parameters we focus on, $\exists S_r$ s.t. $N^*(S_r) > 1$. This implies when S_r is sufficiently small, $N^* > 1$, since when S_r

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increases, N^* decreases (shown in Appendix A). On the other hand, when S_r becomes extremely large, the number of participating designers is approaching zero: $\lim_{S_r \to \infty} N^*(S_r) = 0$ (both $\lim_{S_r \to \infty} N_1^*(S_r) = 0$, and $\lim_{S_r \to \infty} N_2^*(S_r) = \lim_{S_r \to \infty} \frac{\sqrt{4Y(X+1)+X^2}-X}{2Y} = 0$ (by L'Hopital's Rule)). Hence, given continuity of $N^*(S_r)$, $\exists S_r > 0$ s.t. $N^*(S_r) = 1$ (denoted as $S_{r,N=1}$). If the seeker discloses $S_{r,N=1}$ conceptual objectives, the number of objectives designers are willing to incorporate is $\lim_{S_r \to S_{r,N=1}} \bar{r}(N^*(S_r)) = \lim_{S_r \to S_{r,N=1}} \bar{r}(N^*=1) = -\infty$, which implies $\bar{r}(N^*(S_r)) < S_r$, and thus the number of participating designers in the equilibrium is N_2^*. Hence, $\exists S_r$ s.t. $\bar{r}(N_2^*(S_r)) < S_r$.

Uniqueness. If there are multiple S_r^{ic}'s s.t. $S_r^{\text{ic}} = \bar{r}(N_2^*(S_r^{\text{ic}}))$, call the smallest one among them $S_r^{\text{ic}(1)}$. Lemma 5 implies that $\frac{\partial \bar{r}(N_2^*(S_r))}{\partial S_r}\big|_{S_r^{\text{ic}(1)}} \leq 1$. Next, at any point S_r, we can compare the left and right limits of $\frac{\partial \bar{r}(N_2^*(S_r))}{\partial S_r}$, namely left limit $\lim_{S_r \to S_r^-} \frac{\Delta \bar{r}(N_2^*(S_r))^-}{\Delta S_r} = \frac{\bar{r}(N_2^*(S_r)) - \bar{r}(N_2^*(S_r - \Delta S_r))}{\Delta S_r}$, and right limit $\lim_{S_r \to S_r^+} \frac{\Delta \bar{r}(N_2^*(S_r))^+}{\Delta S_r} = \frac{\bar{r}(N_2^*(S_r + \Delta S_r)) - \bar{r}(N_2^*(S_r))}{\Delta S_r}$. Note that $\bar{r}(N_2^*(S_r))$ is a function of S_r through the equilibrium number of participating designers (N_2^*). Hence, corresponding to the left and right limits, we can define the changes in N_2^* as ΔN_2^{*-} and ΔN_2^{*+} respectively. Algebra based on Equation (A.5) implies that, $\frac{\partial N_2^*}{\partial S_r} < 0$ and $\frac{\partial^2 N_2^*}{\partial S_r^2} > 0$, from which we know $|\Delta N_2^{*+}| < |\Delta N_2^{*-}|$ (i.e., the number of participants decreases with S_r at a decreasing speed). Based on the formula for $\bar{r}(N_2^*)$, we can write $\Delta \bar{r}$ as a function of ΔN_2^*: $\Delta \bar{r} = \left(\frac{N_2^{*-}|\Delta N_2^*|-1)(N_2^*)^2}{(N_2^{*-}|\Delta N_2^*|)^2(N_2^*-1)} \right) / (\ln \frac{1}{p})$. Now, we can compare $\lim_{S_r \to S_r^-} \frac{\Delta \bar{r}^-}{\Delta S_r}$ and $\lim_{S_r \to S_r^+} \frac{\Delta \bar{r}^+}{\Delta S_r}$:

- When $N_2^* > 2$: $\frac{\partial \Delta \bar{r}}{\partial |\Delta N_2^*|} > 0$. In this case, $\Delta \bar{r}^+ < \Delta \bar{r}^-$ since $|\Delta N_2^{*+}| < |\Delta N_2^{*-}|$. Hence, $\lim_{S_r \to S_r^+} \frac{\Delta \bar{r}^+}{\Delta S_r} < \lim_{S_r \to S_r^-} \frac{\Delta \bar{r}^-}{\Delta S_r}$.
- When $N_2^* < 2$: $\bar{r}$ increases with N_2^*, so decreases with S_r ($\Delta \bar{r}^- < 0$, $\Delta \bar{r}^+ < 0$). So $\lim_{S_r \to S_r^-} \frac{\Delta \bar{r}^-}{\Delta S_r} < 0$, $\lim_{S_r \to S_r^+} \frac{\Delta \bar{r}^+}{\Delta S_r} < 0$.

The assessment of the left and right limits indicates that, $\frac{\partial \bar{r}}{\partial S_r}$ is either decreasing or negative. Therefore, we have that $\forall S_r > S_r^{\text{ic}(1)}$, and $\frac{\partial \bar{r}}{\partial S_r}\big|_{S_r} < 1$. This suggests $S_r^{\text{ic}(1)}$ is the only S_r, s.t. $\bar{r}(N_2^*(S_r)) = S_r$. This result, combined with Lemma 5, suggests that S_r^{ic} divides the number of conceptual objectives the seeker discloses S_r into two regions: Region I, when $S_r \leq S_r^{\text{ic}}$, $S_r \leq \bar{r}(N_2^*(S_r))$; Region II, when $S_r > S_r^{\text{ic}}$, $S_r > \bar{r}(N_2^*(S_r))$.

EC.4. Extensions

We extend our main model to allow for the following possibilities: (1) overlap/similarity across conceptual objectives; (2) diminishing weights/importance among conceptual objectives. We are able to show in both cases, the qualitative results from the model, hypotheses derived from the model predictions, and the managerial implications (the optimal way of providing problem specifications) remain intact.

EC.4.1. Extension (I): Overlap Across Conceptual objectives

We extend our main model to consider the level of overlap across conceptual objectives. For example, designers might consider "friendly" and "welcoming" more overlapping than "friendly" and "professional". Intuitively, satisfying multiple conceptual objectives with a large overlap is likely to be easier than satisfying the same number of objectives with a small overlap; on the other hand, if a design already satisfies one objective, satisfying another objective that overlaps a lot with the first one might only generate limited marginal improvement to the design's quality. To capture these effects, we make the following adjustments to the main model. Given the level of overlap (denoted as $1 - \alpha$ where $\alpha \in [0,1]$, i.e., when α is smaller, objectives overlap significantly), we assume that conditional on one objective being satisfied, (1) the probability

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that another objective is satisfied by a random design concept generated is p^α (when objectives are more overlapping, p^α is closer to 1); (2) the weight carried by any additional objective is αw (when objectives are more overlapping, αw is closer to 0). Correspondingly, when a designer incorporates r objectives, her cost of concept formulation is $(1/p)^{1+\alpha(r-1)}$; and the base quality of her designs is $w(1+\alpha(r-1))$. Another way to think about this is that the number of "orthogonal" objectives is $1+\alpha(r-1)$ (when objectives are almost completely overlapping, the number of "orthogonal" objectives approaches 1; on the other extreme, as the level of overlap goes to zero, the number approaches r). We solve for designers' equilibrium behavior, given the seeker's problem specification (S_r, S_g, and α):

LEMMA 6. *In a crowdsourcing contest, the equilibrium number of entrants, $N^{\alpha,*}$, is decreasing with more disclosed conceptual objectives S_r, but does not change with the amount of execution guidance provided S_g. Specifically, let $S_r^{\alpha,ic}$ be the threshold number in extension I (its analog in the main model is S_r^{ic} defined in Lemma 2). When $S_r \leq S_r^{\alpha,ic}$, $N^{\alpha,*} = N_1^{\alpha,*} = \sqrt{\frac{A}{s+c_1 \cdot S_r + c_2 \cdot (1/p)^{1+\alpha(S_r-1)}}}$; when $S_r > S_r^{\alpha,ic}$, $N^{\alpha,*} = N_2^{\alpha,*} = \frac{\sqrt{4Y(X+1)+X^2}-X}{2Y}$, where $X = \frac{w}{\mu \ln(1/p)}$ and $Y = \frac{s+c_1 \cdot S_r}{A}$.*

The unique symmetric equilibrium for $r^{\alpha,*}$ and $m^{\alpha,*}$ is as follows. The equilibrium number of objectives a designer incorporates is $r^{\alpha,*} = \min\{\bar{r}^\alpha, S_r\}$, where $\bar{r}^\alpha = \frac{ln\left(\frac{N^{\alpha,*}-1}{(N^{\alpha,*})^2} \cdot \frac{w}{\mu} \cdot \frac{A}{c_2} \cdot \frac{1}{\ln 1/p} \cdot p^{1-\alpha}\right)}{\alpha \ln \frac{1}{p}}$, and the equilibrium number of design trials each designer generates is $m^{\alpha,*} = \frac{A(N^{\alpha,*}-1)}{(N^{\alpha,*})^2 c_3}$, where $c_3 = h(S_g)$.

Lemma 6 generalizes Theorem 1, and considers the level of overlap among conceptual objectives. This lemma has the same intuition as Theorem 1 — the direction of the relationship between designers' equilibrium behaviors and the number of conceptual objectives and execution guidelines in seekers' problem specification remains unchanged; and Hypotheses 1a-b and 2a-b also remain intact. Note that this extension provides an additional insight: as α decreases (i.e., the level of overlap increases), the number of participating designers increases (first strictly increases, and then stays the same). We in fact find empirical support for this additional insight: the number of participating designers in a contest increases with the semantic similarity (*Concept Similarity* on a scale of 1-100) among the manually coded keywords for conceptual objectives (see Table 2 Column 2 for the detailed regression results). Furthermore, our recommendation that seekers should disclose as much execution guidance as possible, but disclose conceptual objectives only up to a certain level stays the same. The proofs are straight-forward generalization of proofs in Appendix A and Appendix C, which we omit here given the limited space.

EC.4.2. Extension (II): Descending Weights Among Conceptual Objectives

We extend our main model to consider the possibility that conceptual objectives could carry different weights/importance to the seeker. Each conceptual objective (denoted as s_r) carries a weight of w_{s_r}, which represents the importance of this objective, or the quality improvement of a design if this additional objective s_r is satisfied. The seeker's objectives ($s_r = 1, ..., \bar{S}_r$) are sorted in descending importance, with smaller s_r indicating more important objectives (i.e., w_{s_r} is decreasing with s_r). We assume $w_{s_r} = w\Phi^{s_r-1}$, where $\Phi \in [0,1]$. The parameter Φ captures how "skewed" the distribution of w_{s_r} is, i.e., when Φ is large, all the objectives are very similar in terms of their importance to the seeker; whereas when Φ is small, the importance drops quickly with s_r, and only a small number of objectives are important. We assume that w_{s_r}

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is common knowledge. As objectives are equally difficult to achieve but of different importance, the seeker would always want to disclose objectives in the order of decreasing importance (i.e., from the most important to the least important). Given the seeker's problem specification (S_r, S_g, and Φ) we solve for designers' equilibrium behavior:

LEMMA 7. *In a crowdsourcing contest, the equilibrium number of entrants, $N^{\Phi,*}$, is decreasing with more disclosed conceptual objectives S_r, but does not change with the amount of execution guidance provided S_g.*

The unique symmetric equilibrium for $r^{\Phi,*}$ and $m^{\Phi,*}$ is as follows. The equilibrium number of objectives a designer incorporates is $r^{\Phi,*} = \min\{\bar{r}^\Phi, S_r\}$, where $\bar{r}^\Phi = \frac{ln(\frac{N^{\Phi,*}-1}{(N^{\Phi,*})^2} \cdot \frac{w}{\mu(1-\Phi)} \cdot \frac{A}{c_2} \cdot \frac{\ln 1/\Phi}{\ln 1/p})}{\ln \frac{1}{p^\Phi}}$, and the equilibrium number of design trials each designer generates is $m^{\Phi,*} = \frac{A(N^{\Phi,*}-1)}{(N^{\Phi,*})^2 c_3}$, where $c_3 = h(S_g)$.

Lemma 7 generalizes Theorem 1, and considers the possible descending weights/importance among conceptual objectives. It has the same intuition as Theorem 1: the direction of the relationship between designers' equilibrium behaviors and the numbers of conceptual objectives and execution guidelines in the seeker's problem specification remains unchanged; and Hypotheses 1a-b and 2a-b remain intact. Furthermore, our recommendation that it is optimal for seekers to disclose as much execution guidance as possible stays the same, and our suggestion that seekers should only disclose conceptual objectives up to a certain level becomes even more salient. Intuitively, as the importance of the conceptual objectives decreases with s_r, the quality improvement from incorporating an additional objective is smaller (a lower "quality effect"). Yet, the negative "competition effect" from disclosing more conceptual objectives remains (a higher cost for designers to digest and incorporate disclosed conceptual objectives, which lowers the number of participating designers). The proofs are straightforward generalization of proofs in Appendix A and Appendix C, which we omit here given the limited space.

EC.5.   Proof for Lemma 3

We denote Π_s in Scenario 1 (defined in Appendix C) as Π_s^1. In Scenario 1, all designers incorporate all the disclosed objectives (S_r). In this case, the seeker solves the following optimization problem:

$$\max_{S_r \leq \bar{S}_r} \Pi_s^1(S_r; S_g) = \max_{S_r \leq \bar{S}_r} w \cdot S_r + \mu \ln A(1 - \frac{1}{N_1^*(S_r)}) - \mu \ln(h(S_g)), \text{ where } N_1^* \text{ is from Equation (A.4).} \quad \text{(EC.1)}$$

EC.5.1.   With Zero Cost for Designers to Digest Each Conceptual objective (i.e., $c_1 = 0$)

We calculate the second derivative of $\Pi_s^1(S_r; S_g | c_1 = 0)$ with respect to S_r as follows:

$$\frac{\partial^2 \Pi_s^1(S_r; S_g | c_1 = 0)}{\partial S_r^2} = -\frac{\mu c_2^2 \ln^2 \frac{1}{p} (\frac{1}{p})^{S_r} [c_2(\frac{1}{p})^{S_r} + 2s(1-B)]}{4A^2 B^3 (B-1)^2} < 0, \text{ where } B = \sqrt{\frac{c_2(\frac{1}{p})^{S_r} + s}{A}} = \frac{1}{N^*} \in (0,1], \quad \text{(EC.2)}$$

which shows $\Pi_s^1(S_r; S_g | c_1 = 0)$ is a concave function w.r.t S_r.

Maximum of $\Pi_s^1(S_r; S_g | c_1 = 0)$: For a concave function $\Pi_s^1(S_r; S_g | c_1 = 0)$, the global maximum is reached when $\frac{\partial \Pi_s^1(S_r; S_g | c_1 = 0)}{\partial S_r} = 0$. We can write this F.O.C. as $[x \ln \frac{1}{p} c_2 \mu + 2w(s + xc_2)]^2 = 4w^2 A(s + xc_2)$, where $x := (\frac{1}{p})^{S_r}$. The roots for this quadratic function are:

$$\begin{cases} x_1 = \frac{2[-\sqrt{c_2^2 A w^2 (Aw^2 + s\mu^2 \ln^2 \frac{1}{p} + 2s\mu w \ln \frac{1}{p})} + (c_2 w^2(A-2s) - c_2 s\mu w \ln \frac{1}{p})]}{c_2^2 (\mu \ln \frac{1}{p} + 2w)^2}; \\ x_2 = \frac{2[\sqrt{c_2^2 A w^2 (Aw^2 + s\mu^2 \ln^2 \frac{1}{p} + 2s\mu w \ln \frac{1}{p})} + (c_2 w^2(A-2s) - c_2 s\mu w \ln \frac{1}{p})]}{c_2^2 (\mu \ln \frac{1}{p} + 2w)^2}. \end{cases} \quad \text{(EC.3)}$$

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Because $c_2{}^2 A w^2 (A w^2 + s\mu^2 \ln^2 \frac{1}{p} + 2s\mu w \ln \frac{1}{p}) - (c_2 w^2 (A - 2s) - c_2 s\mu w \ln \frac{1}{p})^2 = c_2{}^2 s w^2 (A - s)(\mu \ln \frac{1}{p} - 2w)^2 > 0$, we know that $x_1 < 0$, $x_2 > 0$. Hence, x_2 is the unique maximum (by definition, $x = (\frac{1}{p})^{S_r}$ is positive). Therefore, the optimal number of conceptual objectives to disclose is $S_{r,c_1=0}^{1*} = \min\{\overline{S}_r, \frac{\ln x_2}{\ln(1/p)}\}$, where x_2 is from Equation (EC.3).

EC.5.2. With Positive Cost for Designers to Digest Each Conceptual Objective (i.e., $c_1 > 0$) The Seeker's Profit Π_s^1 is Eventually Decreasing with S_r. As mentioned in Section 3.3, we are interested in studying contests where $N^* > 1$; hence, under the problem parameters we focus on, $\exists S_r$ s.t. $N^*(S_r) > 1$. This implies when S_r is sufficiently small, $N^* > 1$, since when S_r increases, N^* further decreases (shown in Appendix A). Also, when S_r is sufficiently small, specifically, $S_r \leq S_r^{\mathrm{ic}}$, the equilibrium number of participating designers is N_1^*, and thus $N_1^* > 1$. On the other hand, when S_r becomes extremely large, N_1^* is approaching zero: $\lim_{S_r \to \infty} N_1^*(S_r) = 0$. Hence, given continuity of $N_1^*(S_r)$, $\exists S_r > 0$ s.t. $N_1^*(S_r) = 1$ (we denote it as $S_{r,N_1^*=1}$).

While S_r increases and approaches $S_{r,N_1^*=1}$, the seeker's profit is approaching to negative infinity, i.e., $\lim_{S_r \to S_{r,N_1^*=1}} \Pi_s^1(S_r; S_g) = \lim_{S_r \to S_{r,N_1^*=1}} w \cdot S_r + \mu \ln A(1 - \frac{1}{N_1^*(S_r)}) - \mu \ln(h(S_g)) = -\infty$. Therefore, the seeker profit Π_s^1 is eventually decreasing with a high enough S_r, which suggests $S_r^{1*} < \infty$, i.e., the seeker should not always disclose all of his conceptual objectives in Scenario 1 (i.e., even if designers are "required" to incorporate all the disclosed conceptual objectives).

Optimal Number of Conceptual Objectives to Disclose (S_r^{1*}) is Bounded Above by $S_{r,c_1=0}^{1*}$. We first show that the seeker's profit always decreases with the unit cost for designers to frame the design problem (i.e., a higher c_1). $\frac{\partial \Pi_s^1(S_r; S_g)}{\partial c_1} = \frac{\partial \Pi_s^1(S_r; S_g)}{\partial N_1^*} \frac{\partial N_1^*}{\partial c_1} < 0$ (according to Equation (EC.1)). Hence, $\Pi_s^1(S_r; S_g | c_1 > 0) < \Pi_s^1(S_r; S_g | c_1 = 0)$, i.e., the seeker's profit is always lower when there is positive cost for designers to frame the design problem. In addition, based on algebra, we have $\frac{\partial \frac{\partial \Pi_s^1(S_r; S_g)}{\partial S_r}}{\partial c_1} = -\mu \ln'(1 - \frac{1}{N_1^*}) \frac{\partial \frac{1/N_1^*}{\partial S_r}}{\partial c_1} < 0$, which suggests

$$\frac{\partial \Pi_s^1(S_r; S_g | c_1 \geq 0)}{\partial S_r} \leq \frac{\partial \Pi_s^1(S_r; S_g | c_1 = 0)}{\partial S_r}. \tag{EC.4}$$

Recall that, $\Pi_s^1(S_r; S_g | c_1 = 0)$ is concave and maximized at $S_{r,c_1=0}^{1*}$; thus, $\frac{\partial \Pi_s^1(S_r; S_g | c_1 = 0)}{\partial S_r}\big|_{S_r > S_{r,c_1=0}^{1*}} < 0$. Combining this with Equation (EC.4), we have $\frac{\partial \Pi_s^1(S_r; S_g | c_1 \geq 0)}{\partial S_r}\big|_{S_r > S_{r,c_1=0}^{1*}} \leq \frac{\partial \Pi_s^1(S_r; S_g | c_1 = 0)}{\partial S_r}\big|_{S_r > S_{r,c_1=0}^{1*}} < 0$. In other words, when S_r is greater than $S_{r,c_1=0}^{1*}$, the seeker's profit is always decreasing with S_r. Hence, the global maximum of $\Pi_s^1(S_r; S_g)$ is bounded above by $S_{r,c_1=0}^{1*}$. Furthermore, based on simulations in Appendix C, we find that S_r^{1*} is not very sensitive to c_1, which suggests that, the maximum $S_{r,c_1>0}^{1*}$ is relatively close to $S_{r,c_1=0}^{1*}$.

EC.6. Proof of Lemma 4

We denote Π_s in Scenario 2 (defined in Appendix C) as Π_s^2. In Scenario 2, designers incorporate the equilibrium subset ($\overline{r}$) of all the disclosed objectives. In this case, the seeker solves the following optimization problem:

$$\max_{S_r \leq \overline{S}_r} \Pi_s^2(S_r; S_g) = \max_{S_r \leq \overline{S}_r} [w \cdot \overline{r}(N_2^*(S_r)) + \mu \ln(m^*(S_g, N_2^*(S_r)) \cdot N_2^*(S_r))], \tag{EC.5}$$

where N_2^* is from Equation (A.5), and m^* and $\overline{r}$ are from Theorem 1.

Now we show $\frac{\partial \Pi_s^2}{\partial S_r} < 0$, i.e., $\Pi_s^2(S_r; S_g)$ is monotonically decreasing w.r.t S_r. Note that, $\Pi_s^2(S_r; S_g)$ is a function of S_r only through N_2^*; hence, we can write

$$\frac{\partial \Pi_s^2}{\partial S_r} = \frac{\partial \Pi_s^2}{\partial N_2^*} \cdot \frac{\partial N_2^*(S_r)}{\partial S_r}, \tag{EC.6}$$

in which we know that $\frac{\partial N_2^*(S_r)}{\partial S_r} \leq 0$ (see the proof in Appendix A). Now we show $\frac{\partial \Pi_s^2}{\partial N_2^*} > 0$:

$$\frac{\partial \Pi_s^2}{\partial N_2^*} = w\frac{\partial \bar{r}(N_2^*)}{\partial N_2^*} + \mu \frac{1}{(N_2^*)^2 - N_2^*} = \frac{1}{(N_2^*)^2 - N_2^*} \cdot \frac{w}{\ln(1/p)} \cdot (\frac{\mu \ln(1/p)}{w} + 2 - N_2^*). \tag{EC.7}$$

Based on Equation (A.5), the last term in Equation (EC.7) can be re-written as $\frac{\mu \ln(1/p)}{w} + 2 - N_2^* = \frac{1}{X} + 2 - \frac{\sqrt{4Y(X+1)+X^2}-X}{2Y}$, which can be shown to be positive using algebra. With all the terms in Equation (EC.7) being positive (by assumption, $N_2^* > 1$), $\frac{\partial \Pi_s^2}{\partial N_2^*} \geq 0$. Combining $\frac{\partial N_2^*(S_r)}{\partial S_r} \leq 0$ and $\frac{\partial \Pi_s^2}{\partial N_2^*} \geq 0$, we have $\frac{\partial \Pi_s^2}{\partial S_r} \leq 0$ (Equation (EC.6)). That is, the seeker profit is monotonically decreasing with respect to the number of disclosed objectives in the problem specification in Scenario 2.

EC.7. Intuition for Comparative Statics in Figure C.1

It is optimal for the seeker to disclose more conceptual objectives (a higher S_r^*), when the unit cost of concept formation is lower (a smaller c_2), or the conceptual objectives are easier to satisfy (a larger p, or equivalently, a smaller $1/p$). This is intuitive – when it is less costly or less difficult to find a design concept satisfying each disclosed conceptual objective, designers are willing to incorporate more conceptual objectives and the seeker benefits from disclosing more objectives with a lower *competition effect*. Note that neither the unit cost of problem framing (c_1), nor the opportunity cost (s) has a large impact on the optimal number of disclosed conceptual objectives (S_r^*). This is because the opportunity cost and the "problem framing" cost are fixed for every participating designer, and those fixed costs do not significantly affect the seeker's trade-off between the *quality effect* and the *competition effect*, given designers' decision on the number of conceptual objectives to incorporate is not significantly affected by those fixed costs (Theorem 1).

We also observe that, if the seeker can afford a larger award amount, the optimal number of disclosed conceptual objectives increases. The reasons are as follows. When the award level is high, everything else equal, (1) designers are willing to incorporate more conceptual objectives; (2) a higher possible award balances with the increased participation cost, which alleviates the negative *competition effect*.

Another observation worth mentioning is that, when the problem is more uncertain (a larger $\lambda := \mu/w$, meaning the quality uncertainty is on a larger scale in comparison with the weights of the conceptual objectives), the optimal number of conceptual objectives to disclose is smaller. When uncertainty in design quality is relatively high, it is crucial for the seeker to attract more designers to the contest — more participating designers allow more random draws from the distribution of quality shocks (ϵ's); when the scale of the quality shock is larger, the contribution of each additional participant and her submissions (or, additional random quality draws) to the expected extreme (highest) quality value (i.e., the seeker's profit) is also larger. In this case, the *competition effect*, which drives the number of participating designers down, has a very strong negative effect. Therefore, the seeker will be better-off disclosing fewer conceptual objectives to reduce the *competition effect*.

In terms of the sensitivity of the optimal number of conceptual objectives to disclose (S_r^*) to these model parameters, somewhat surprisingly, we find that S_r^* is not sensitive to most parameters, including unit cost

of problem framing (c_1), unit cost of concept formulating (c_2), opportunity cost (s), award level (A), and relative problem uncertainty ($\lambda := \mu/w$). This is because in our model, the "design concept formulating" cost rises very fast (exponentially) with the number of conceptual objectives designers incorporate. We believe this aligns with the reality that it becomes increasingly difficult for a designer to satisfy and fit in multiple objectives in a single design solution simultaneously. In particular, based on our numerical examples (Figure C.1 in Appendix C), the optimal number S_r^* is always around 2–5, regardless of how we adjust the set of model parameters discussed above. This result has important managerial implications, as it suggests that different contests may share a similar optimal number of conceptual objectives to disclose, and the platform does not need to adjust the recommended number of disclosed conceptual objectives for different seekers or different contests. The only parameter to which S_r^* is sensitive is the concept formation difficulty, $1/p$. The concept formation difficulty is more related to the nature of the design problem the seeker has. For example, in crowdsourcing industrial design contests with straightforward conceptual objectives that are less challenging to achieve ($1/p$ is smaller; e.g., for a helmet design, the objectives can be: protective, lightweight, adjustable fit system, and with cost-effective material), the platform should recommend the seeker to disclose more conceptual objectives he wants the designs to achieve. In contrast, in crowdsourcing fashion design contests with less straightforward conceptual objectives (e.g., a bag design that symbolizes excellence, elegance, and supremacy), the seeker may want to highlight only a few important conceptual objectives, because those objectives tend to be relatively more abstract, ambiguous, and thus, more challenging to achieve ($1/p$ is larger).