Online Appendices

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

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

Company	**Industry**	**Q3** (Conceptual objectives)	**Q4** (Execution Guidance)	**Q5** (Execution Guidance)
Quackers	Retailing	It's a fun brand for kids. Very happy, upbeat and never quit on your dreams. Community and fun.	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.	Duck face a bit like this but with hat and less body visible. (A hyperlink to company website).
Intertwined	Consulting and Professional Services	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.	Image with the company name, or image only. We won't consider text only logos.	None
Rise	Social Media Advertising and Marketing	We are looking for a design that is professional but not too corporate. We want to convey reliability, fun and professionalism.	None.	Not really.

EC.2. Image Comparison Algorithm – SIFT

To classify designers' submissions into "distinct designs" and "variations" in our large-scale data, we employ *Scale-Invariant Feature Transform (SIFT).* SIFT is an algorithm proposed by Lowe (1999) that detects and describes local features in images, and comprises four steps: (1) *Extract SIFT Feature Vectors:* From a pair of images (A and B), descriptors of the key points are extracted by identifying *SIFT feature vectors* in scale space; these vectors are constructed to robustly capture the structural properties of the images. (2) *Match SIFT Feature Vectors:* For each feature vector D_i^A in image A, its shortest Euclidean distance ($d(D_i^A, D_j^B)$) to each of the SIFT feature vectors in image B (D_j^B) is calculated. Feature vectors D_i^A and D_k^B are defined as a matched pair if and only if $\frac{d(D_i^A, D_k^B)}{d(D_i^A, D_j^B)} < 2/3$ for all j. (This is the default threshold in Lowe's paper (1999), essentially the nearest-neighbor approach.) (3) *Compute Similarity Ratio:* Let $\gamma_{A,B} = \frac{N_{A,B}^m}{\min\{N_A, N_B\}}$, where $N_{A,B}^m$ is the number of matched pairs between image A and image B, and N_A (N_B) is the total number of feature vectors extracted from image A (B). (4) *Classify Images Pairs as Similar or Different:* Similarity Ratio $\gamma_{A,B}$ is used to classify images A and B as either similar or different. The higher the ratio, the more similar the two images are (a ratio of 1 means the two images are exactly the same). In our empirical analysis, we classify two submissions as similar if $\gamma_{A,B} \geq 0.4$. If a designer's new submission (a logo image) is very similar to any of her prior submissions (based on the SIFT score), we classify the new submission as a "variation"; otherwise, we consider the new submission a "distinct design".

EC.3. Power Analysis

We use power analyses to evaluate the ability of our empirical study to detect variables characterizing the problem specification that have an impact on the number of participants ($(No.Designers)_q$) and designers' trial efforts ($(No.Submissions)_{i,q}$). Based on the R-squares before and after the inclusion of problem specification-related variables and an alpha level of 0.05 with Bonferroni adjustment, the sample size analysis indicates that we need sample sizes of 174, 182 and 2987 to achieve a power of 0.8 to detect variables characterizing the problem specification in Table 2's Columns (1)(3)(5) respectively. With our current sample sizes, we have enough data to detect any significant variables. Equivalently, we can calculate a post-hoc level of statistical power. With our current sample sizes, we can achieve a power above 0.95 in all regressions, indicating that our tests have adequate statistical power.

EC.4. Additional Empirical Results about the Impact of Problem Specification

Table EC.2 Impact of Different Categories 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	0.177^{*} (0.083)	Yes
Logo Style Dummy	0.101 (0.105)	Yes
Shapes Dummy	0.214^{*} (0.097)	No
Font Dummy	0.029 (0.116)	Yes
Usage Dummy	0.239^{**} (0.078)	Yes
Art Styles Dummy	0.163^{*} (0.077)	No
Resources Dummy	0.132· (0.076)	No
Control Variables		
$(No.Concepts)_q$	0.013 (0.010)	
$Concept\,Similarity$	0.149 (0.479)	
$(No.Designers)_q$	-0.009^{*} (0.004)	
$(No.Updates)_q$	0.204^{***} (0.034)	
DoW, Month, Year Dummies	Yes	
Industry, Creator Dummies	Yes	
Observations	11,757	
R^2 (Adjusted R^2)	0.480 (0.304)	
Residual Std. Error (F Statistic)	3.317 (df = 8790)	
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$	

Common vs. Rare Keywords We measure the keyword usage frequency with Zipf frequency ($ConceptFreq$, which ranges from 0-8, with more frequently used words having large $ConceptFreq$s). (The Zipf frequency of a word is the base-10 logarithm of the number of times it appears per billion words.) For each problem specification, we compute the average and the minimum usage frequency among the manually-coded conceptual objective keywords ($(Avg.ConceptFreq)_q$ and ($(Min.ConceptFreq)_q$). We consider and estimate models in Table EC.3, and find that $(Avg.ConceptFreq)_q$ and $(Min.ConceptFreq)_q$ are both negatively and significantly associated with $(No.Designers)_q$, suggesting that rare conceptual objective keywords are relatively less discouraging for designers participation.

Categories vs. Intensities of Execution Guidance We separately consider the effect of offering more categories of execution guidance ($(No.GuideCats)_q$), and that of offering more detailed guidance in each category, i.e., more keywords per category ($(\frac{No.GuideWords}{No.GuideCats})_q$). We regress $(No.Submissions)_{i,q}$ on both $(No.GuideCats)_q$ and $(\frac{No.GuideWords}{No.GuideCats})_q$, report the results in Table EC.4, and find that $(No.GuideCats)_q$ is significantly positively associated with $(No.Submissions)_{i,q}$, whereas $(\frac{No.GuideWords}{No.GuideCats})_q$ is not.

Table EC.3 Nuance Findings for Conceptual Objectives – Does Frequency of a Keyword in English Affect Participation?

	Dependent variable: $(No.Designers)_q$	
Conceptual Objectives		
$(No.Concepts)_q$	-0.396^{**} (0.137)	-0.604^{***} (0.124)
$Concept\,Similarity$	0.176^{**} (0.064)	0.178^{**} (0.064)
$(Avg.ConceptFreq)_q$	-2.776^{**} (0.887)	
$(Min.ConceptFreq)_q$		-1.316^{**} (0.405)
Execution Guidance		
$(No.GuideWords)_q$	-0.042 (0.104)	-0.040 (0.104)
Control Variables		
$(len_{Q3}/No.Concepts)_q$	0.043 (0.130)	-0.037 (0.130)
$(No.Updates)_q$	0.011 (0.427)	-0.012 (0.427)
DoW, Month, Year, Industry Dummies	Yes	Yes
Observations	441	441
R^2	0.271	0.272
Adjusted R^2	0.198	0.199
Residual Std. Error (df = 400)	9.392	9.383
F Statistic	3.709^{***}	3.735^{***}
Note:		$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table EC.4 Nuance Findings for Nested Structure of Execution Guidance

	Dependent variable: $(No.Submissions)_{i,q}$
Conceptual Objectives	
$(No.Concepts)_q$	0.010 (0.010)
$Concept\,Similarity$	0.002 (0.005)
Execution Guidance	
$(No.GuideCats)_q$	0.172^{***} (0.025)
$(\frac{No.GuideWords}{No.GuideCats})_q$	0.048 (0.052)
Control Variables	
$(No.Designers)_q$	-0.010^{*} (0.004)
$(No.Updates)_q$	0.199^{***} (0.034)
Day-of-Week Fixed Effects	Yes
Month Fixed Effects	Yes
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
Creator Fixed Effects	Yes
Observations	11,509
R^2	0.483
Adjusted R^2	0.306
Residual Std. Error	3.333 (df = 8576)
F Statistic	2.729^{***}
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

EC.5. Additional Tables

Data evidence for problem framing cost increasing with conceptual objectives. Table EC.5 reports the results of the regression of coders' reading time for a problem specification on the characteristics of the 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 only changes with the number of conceptual objectives.

Table EC.5 Regression of Reading Time

		Dependent Variable: $(Reading\,Time)_q$	
$(No.Concepts)_q$		0.071^{***} (0.004)	
$(len_{Q3}/No.Concepts)_q$		0.054^{***} (0.004)	
$(No.GuideWords)_q$		0.001 (0.003)	
Observations	441	R^2 (Adjusted R^2)	0.622 (0.587)
Residual Std. Error	0.304 (df = 403)	F Statistic	17.889^{***}
Note:			$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Robustness checks – alternative measures for designer trial efforts. As we can see from Table EC.6, the two new measures for designer i's trial effort, $(No.DesignStyle)_{i,q}$ and $(Variations/Style)_{i,q}$, are both significantly positively correlated with $(No.GuideWords)_q$, but neither is significantly associated with $(No.Concepts)_q$, which again supports Hypotheses 2a and 2b – more seeker execution guidance leads to more submissions from each designer (both in terms of "distinct designs" and their "variations"), but more conceptual objectives do not.

Robustness checks – sub-sample tests only with contests that did not have updates. The results reported in Table EC.7 are qualitatively the same as those estimated with the full sample (reported in Table 2), indicating that the main findings are not affected by how we control for $(No.Updates)_q$.

Table EC.6 Robustness Checks for Equation (8) (Alternative Measures for Trial Efforts)

	Dependent Variable:	
	$(No.DesignStyle)_{i,q}$	$(Variations/Style)_{i,q}$
Conceptual Objectives		
$(No.Concepts)_q$	0.001 (0.003)	0.010 (0.006)
Concept Similarity	−0.000 (0.001)	−0.000 (0.003)
Execution Guidance		
$(No.GuideWords)_q$	0.006^{**} (0.002)	0.028^{***} (0.005)
Control Variables		
$(len_{Q3}/No.Concepts)_q$	0.001 (0.003)	0.011 (0.006)
$(No.Designers)_q$	−0.0004 (0.001)	-0.006^{**} (0.002)
$(No.Updates)_q$	0.060^{***} (0.009)	0.042^{*} (0.019)
Day-of-Week Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Creator Fixed Effects	Yes	Yes
Observations	11,757	11,757
R^2	0.396	0.403
Adjusted R^2	0.193	0.202
Residual Std. Error (df = 8795)	0.890	1.895
F Statistic (df = 2961; 8795)	1.949^{***}	2.003^{***}
Note:		$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table EC.7 Sub-Sample Tests Containing Only Contests that Did Not Have Updates

	Dependent Variables:		
	$(No.Designers)_q$		$(No.Submissions)_{i,q}$
Conceptual Objectives			
$(No.Concepts)_q$	-0.498^{*} (0.196)	-0.665^{***} (0.173)	0.025 (0.013)
Concept Similarity	$0.173^{\cdot}$ (0.095)	0.163^{*} (0.077)	0.000 (0.006)
Very Short Objectives			
$(No.Concepts)_q * \mathbb{I}_q^{ShortCcpt}$	−5.101 (2.708)		
$\mathbb{I}_q^{ShortCcpt}$	16.513^{*} (7.822)		
Execution Guidance			
$(No.GuideWords)_q$	−0.016 (0.141)	−0.042 (0.141)	0.046^{***} (0.011)
Control Variables			
$(len_{Q3}/No.Concepts)_q$	−0.087 (0.191)	−0.002 (0.184)	0.019 (0.013)
$(No.Designers)_q$			0.002 (0.005)
Day-of-Week Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Creator Fixed Effects	No	No	Yes
Observations	260	260	6,968
R^2	0.325	0.309	0.548
Adjusted R^2	0.201	0.190	0.338
Residual Std. Error	9.505 (df = 219)	9.573 (df = 221)	3.056 (df = 4758)
F Statistic	2.632^{***}	2.595^{***}	2.614^{***}
Note:			$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

EC.6. Properties of $S_r^{\mathbf{gs}}$ and $S_r^{\mathbf{ic}}$

The following lemmas characterize S_r^{gs} and S_r^{ic}.

Lemma 4. *If S_r^{gs} exists, then it is unique and divides the number of conceptual objectives the seeker discloses into two regions. Region 0: when $S_r \le S_r^{gs}$, designers are willing to guess and incorporate more than the disclosed objectives (i.e., $S_r < \overline{r}^g(N_0^*(S_r))$); Region I: when $S_r > S_r^{gs}$, designers do not guess and only incorporate from the disclosed objectives (i.e., $S_r \ge \overline{r}^g(N_0^*(S_r))$).*

Lemma 5. *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 $S_r \le S_r^{ic}$, designers are willing to incorporate all the disclosed objectives (i.e., $S_r \le \overline{r}(N_2^*(S_r))$); Region II: when $S_r > S_r^{ic}$, designers incorporate only a subset of all the disclosed objectives (i.e., $S_r > \overline{r}(N_2^*(S_r))$).*

We prove Lemmas 4-5 by: (A) S_r^{ic} exists, (B) S_r^{ic} is unique, (C) if S_r^{gs} exists, $S_r^{\text{gs}} < S_r^{\text{ic}}$ and S_r^{gs} is unique.

(A) Existence of $S_r^{\mathbf{ic}}$. We prove S_r^{ic} exists by showing:

Lemma 6. *(1) $\exists S_r \to 0$ s.t. $\overline{r}(N_2^*(S_r)) \ge S_r$, and (2) $\exists S_r > 0$ s.t. $\overline{r}(N_2^*(S_r)) < S_r$.*

We now provide proofs for (1) and (2) in Lemma 6. (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. $\overline{r}(N_2^*(S_r)) \ge S_r$. (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 increases, N^* decreases (shown in Appendix A). On the other hand, when S_r becomes extremely large, the number of participating designers approaches zero: $\lim\limits_{S_r \to \infty} N^*(S_r) = 0$ (both $\lim\limits_{S_r \to \infty} N_1^*(S_r) = 0$, and $\lim\limits_{S_r \to \infty} N_2^*(S_r) = \lim\limits_{S_r \to \infty} \frac{\sqrt{4Y(X+1)+X^2}-X}{2Y} = 0$ (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 $\lim\limits_{S_r \to S_{r,N=1}} \overline{r}(N^*(S_r)) = \lim\limits_{S_r \to S_{r,N=1}} \overline{r}(N^*{=}1) = -\infty$, which implies $\overline{r}(N^*(S_r)) < S_r$, and thus the number of participating designers in the equilibrium is N_2^*. Hence, $\exists S_r$ s.t. $\overline{r}(N_2^*(S_r)) < S_r$.

(B) Uniqueness of $S_r^{\mathbf{ic}}$. If there are multiple S_r^{ic}'s s.t. $S_r^{\text{ic}} = \overline{r}(N_2^*(S_r^{\text{ic}}))$, call the smallest one among them $S_r^{\text{ic}(1)}$. Lemma 6 implies that $\frac{\partial \overline{r}(N_2^*(S_r))}{\partial S_r}|_{S_r^{\text{ic}(1)}} \le 1$. Next, at any point S_r, we can compare the left and right limits of $\frac{\partial \overline{r}(N_2^*(S_r))}{\partial S_r}$, namely left limit $\lim\limits_{S_r \to S_r^-} \frac{\Delta \overline{r}(N_2^*(S_r))^-}{\Delta S_r} = \frac{\overline{r}(N_2^*(S_r)) - \overline{r}(N_2^*(S_r\text{-}\Delta S_r))}{\Delta S_r}$, and right limit $\lim\limits_{S_r \to S_r^+} \frac{\Delta \overline{r}(N_2^*(S_r))^+}{\Delta S_r} = \frac{\overline{r}(N_2^*(S_r+\Delta S_r)) - \overline{r}(N_2^*(S_r))}{\Delta S_r}$. Note that $\overline{r}(N_2^*(S_r))$ 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.6) 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 $\overline{r}(N_2^*)$, we can write $\Delta \overline{r}$ as a function of ΔN_2^*: $\Delta \overline{r} = \left(\frac{N_2^{*-}|\Delta N_2^*|-1)(N_2^*)^2}{(N_2^{*-}|\Delta N_2^*|)^2(N_2^*-1)} \right) / (\ln \frac{1}{p})$. Now, we can compare $\lim\limits_{S_r \to S_r^-} \frac{\Delta \overline{r}^-}{\Delta S_r}$ and $\lim\limits_{S_r \to S_r^+} \frac{\Delta \overline{r}^+}{\Delta S_r}$:

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

The assessment of the left and right limits indicates that, $\frac{\partial \overline{r}}{\partial S_r}$ is either decreasing or negative. Therefore, we have that $\forall S_r > S_r^{\text{ic}(1)}$, and $\frac{\partial \overline{r}}{\partial S_r}|_{S_r} < 1$. This suggests $S_r^{\text{ic}(1)}$ is the only S_r, s.t. $\overline{r}(N_2^*(S_r)) = S_r$. This result, combined with Lemma 6, suggests that S_r^{ic} divides the number of conceptual objectives the seeker discloses S_r into two regions: Region I, when $S_r \le S_r^{\text{ic}}$, $S_r \le \overline{r}(N_2^*(S_r))$; Region II, when $S_r > S_r^{\text{ic}}$, $S_r > \overline{r}(N_2^*(S_r))$.

(C) $S_r^{\mathrm{gs}} < S_r^{\mathrm{ic}}$, and S_r^{gs} is unique. If S_r^{gs} exists, $S_r^{\mathrm{gs}} < S_r^{\mathrm{ic}}$, since for any $N^* = N$, $\bar{r}^g(N) < \bar{r}(N)$. We prove that S_r^{gs} is unique by contradiction. Suppose there are multiple S_r^{gs}s, among which the very first one is $S_r^{\mathrm{gs},1}$ (i.e., $\bar{r}^g(N_0^*(S_r^{\mathrm{gs},1})) = S_r^{\mathrm{gs},1}$). Then there should be $S_r' > S_r^{\mathrm{gs},1}$, under which designers "guess". However, $\bar{r}^g(N_0^*(S_r')) < \bar{r}^g(N_0^*(S_r^{\mathrm{gs},1})) = S_r^{\mathrm{gs},1} < S_r'$, which suggests that designers cannot be "guessing" under S_r'. Note the first inequality is from the following facts. We know that $S_r' > S_r^{\mathrm{gs},1}$ and under both points designers "guess", and we also know that when designers "guess", N_0^* increases with S_r; hence, $N_0^*(S_r') > N_0^*(S_r^{\mathrm{gs},1})$. We further know that $\bar{r}^g$ is a decreasing function of N_0^*, hence, we get the first inequality.

EC.7. 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.7.1. 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 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 7. *In a crowdsourcing contest, where the equilibrium number of participating designers equals* $N^{\alpha,*}$*, the unique symmetric equilibrium for* $r^{\alpha,*}$ *and* $m^{\alpha,*}$ *are as follows. The equilibrium number of objectives a designer incorporates is* $r^{\alpha,*} = \begin{cases} \overline{r}^{\alpha,g} & \text{if } S_r < \overline{r}^{\alpha,g} \\ S_r & \text{if } \overline{r}^{\alpha,g} \leq S_r \leq \overline{r} \\ \overline{r}^{\alpha} & \text{if } S_r > \overline{r}^{\alpha} \end{cases}$*, where* $\overline{r}^{\alpha,g} = \frac{ln(\frac{N^{\alpha,*}-1}{(N^{\alpha,*})^2} \cdot \frac{\nu w}{\mu} \cdot \frac{A}{c_2} \cdot \frac{1}{\ln 1/p} \cdot p^{1-\alpha} - \frac{c_g}{c_2} \frac{1}{\ln(1/p)} \cdot p^{1-\alpha})}{\alpha \ln \frac{1}{p}}$ *and* $\overline{r}^{\alpha} = \frac{ln(\frac{N^{\alpha,*}-1}{(N^{\alpha,*})^2} \cdot \frac{w}{\mu} \cdot \frac{A}{c_2} \cdot \frac{1}{\ln 1/p} \cdot p^{1-\alpha})}{\alpha \ln \frac{1}{p}}$*; and the equilibrium number of design trials each designer generates is* $m^{\alpha,*} = \frac{A(N^{\alpha,*}-1)}{(N^{\alpha,*})^2 c_3}$*, where* $c_3 = h(S_g)$*. The equilibrium number of participating designers* ($N^{\alpha,*}$) *first increases (when* $S_r < \overline{r}^{\alpha,g}$*) and then decreases (when* $S_r \geq \overline{r}^{\alpha,g}$*) with more disclosed conceptual objectives* S_r*; but* $N^{\alpha,*}$ *does not change with the amount of execution guidance* S_g*.*

Lemma 7 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 Takeaways 1-2 also remain intact. Note that this extension provides an additional insight: when the number of disclosed conceptual objectives is moderate or large (designers do not guess and incorporate undisclosed conceptual objectives), 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 (3) 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 (hence Takeaway 3 remain intact). The proofs are straight-forward generalization of proofs in Appendices A and C, omitted to save space.

EC.7.2. 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 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} 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 8. *In a crowdsourcing contest, where the equilibrium number of participating designers equals* $N^{\Phi,*}$*, the unique symmetric equilibrium for* $r^{\Phi,*}$ *and* $m^{\Phi,*}$ *are as follows. The equilibrium number of objectives a designer incorporates is* $r^{\Phi,*} = \begin{cases} \overline{r}^{\Phi,g} & \text{if } S_r < \overline{r}^{\Phi,g} \\ S_r & \text{if } \overline{r}^{\Phi,g} \le S_r \le \overline{r} \\ \overline{r}^{\Phi} & \text{if } S_r > \overline{r}^{\Phi} \end{cases}$*, where* $\overline{r}^{\Phi,g} = \frac{ln\left(\frac{N^{\Phi,*}-1}{(N^{\Phi,*})^2} \cdot \frac{\nu w}{\mu(1-\Phi)} \cdot \frac{A}{c_2} \cdot \frac{\ln 1/\Phi}{\ln 1/p} - \frac{c_g}{c_2} \cdot \frac{\ln 1/\Phi}{\ln 1/p}\right)}{\ln \frac{1}{p\Phi}}$ *and* $\overline{r}^{\Phi} = \frac{ln\left(\frac{N^{\Phi,*}-1}{(N^{\Phi,*})^2} \cdot \frac{w}{\mu(1-\Phi)} \cdot \frac{A}{c_2} \cdot \frac{\ln 1/\Phi}{\ln 1/p}\right)}{\ln \frac{1}{p\Phi}}$*; and the equilibrium number of design trials each designer generates is* $m^{\Phi,*} = \frac{A(N^{\Phi,*}-1)}{(N^{\Phi,*})^2 c_3}$*, where* $c_3 = h(S_g)$*. The equilibrium number of participating designers (*$N^{\Phi,*}$*) first increases (when* $S_r < \overline{r}^{\Phi,g}$*) and then decreases (when* $S_r \ge \overline{r}^{\Phi,g}$*) with more disclosed conceptual objectives* S_r*; but* $N^{\Phi,*}$ *does not change with the amount of execution guidance* S_g*.*

Lemma 8 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 Takeaways 1-2 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 (hence Takeaway 3 remain intact). 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.8. Proof for Lemma 2

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:

$$\max_{S_r \le \bar{S}_r} \Pi_s^1(S_r; S_g) = \max_{S_r \le \bar{S}_r} w \cdot S_r + \mu \ln A(1 - \tfrac{1}{N_1^*(S_r)}) - \mu \ln(h(S_g)), \text{ where } N_1^* \text{ is from Equation (A.5).} \quad \text{(EC.1)}$$

EC.8.1. 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 $[x \ln \frac{1}{p} c_2 \mu + 2w(s + x c_2)]^2 = 4w^2 A(s + x c_2)$, where $x := (\frac{1}{p})^{S_r}$. The roots for this quadratic function are:

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

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.8.2. 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, $S_r \le S_r^{\text{ic}}$, 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 $\frac{\partial \frac{\partial \Pi_s^1(S_r;S_g)}{\partial S_r}}{\partial c_1} = -\mu \ln'(1\text{-}\frac{1}{N_1^*}) \frac{\partial \frac{1/N_1^*}{\partial S_r}}{\partial c_1} < 0$, suggesting

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

Recall that, $\Pi_s^1(S_r;S_g|c_1 = 0)$ is concave and maximized at $S_{r,c_1=0}^{1*}$; thus, $\frac{\partial \Pi_s^1(S_r;S_g|c_1=0)}{\partial S_r}|_{S_r > S_{r,c_1=0}^{1*}} < 0$. Combining this with Equation (EC.4), we have $\frac{\partial \Pi_s^1(S_r;S_g|c_1 \geq 0)}{\partial S_r}|_{S_r > S_{r,c_1=0}^{1*}} \leq \frac{\partial \Pi_s^1(S_r;S_g|c_1=0)}{\partial S_r}|_{S_r > S_{r,c_1=0}^{1*}} < 0$. 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, suggesting that the maximum $S_{r,c_1>0}^{1*}$ is relatively close to $S_{r,c_1=0}^{1*}$.

EC.9. Proof of Lemma 3

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:

$$\max_{S_r \leq \bar{S}_r} \Pi_s^2(S_r;S_g) = \max_{S_r \leq \bar{S}_r} [w \cdot \overline{r}(N_2^*(S_r)) + \mu \ln(m^*(S_g, N_2^*(S_r)) \cdot N_2^*(S_r))],$$
$$\text{where } N_2^* \text{ is from Equation (A.6), and } m^* \text{ and } \overline{r} \text{ are from Theorem 1.} \tag{EC.5}$$

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.6), 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.