Divergent Innovation: Directing the Wisdom of Crowd to Tackle Societal Challenges

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Abstract

Crowdsourcing is acknowledged as a promising avenue for addressing societal challenges by drawing on the wisdom of the crowd to offer diverse solutions to complex problems. Advancing a new conceptual framework of 'divergent innovation' which delineates between topic and quality divergence as focal metrics of performance when crowdsourcing for solutions to societal challenges, this study investigates the impacts of four ideation stimuli on divergent innovation. These four stimuli include task description concreteness, resource richness, topic entropy, and judging criteria comprehensiveness. Empirical analysis based on data sourced from an online crowd-ideation platform reveals that task description concreteness negatively affects topic divergence but positively influences quality divergence, whereas resource richness positively affects topic divergence but negatively influences quality divergence. Additionally, the relationship between topic entropy and topic divergence is U-shaped, with no significant impact on quality divergence. These findings contribute to extant literature on crowdsourcing and offer invaluable insights for practitioners.

Keywords: Societal Challenges, Collective Intelligence, Divergent Thinking, Ideation Stimuli, Crowdsourcing

Introduction

The world is continually facing a plethora of societal challenges such as achieving social equality in education, dealing with global epidemic of chronic diseases, eradicating poverty, and reducing carbon emissions. Due to their elusive nature and the fact that they are exceedingly difficult to solve, these societal challenges are commonly referred to as "wicked problems" (Head and Alford 2015) and calls for prompt action to be taken to tackle these challenges. However, there appears to be a dearth of centralized authority spearheading a concerted effort to develop and implement effective solutions (George et al. 2016). Additionally, resolving the aforementioned societal challenges is not a straightforward matter of identifying a singular optimal solution (Gimpel et al. 2020). Rather, societal challenges are inherently complex and intricate problems that cannot be resolved through a single approach (Head and Alford 2015).

Crowdsourcing has garnered significant attention in both research and practice as a promising approach to tackle large-scale societal challenges (Gimpel et al. 2020; Han et al. 2020). The efficacy of crowd-sourced solutions can be attributed to the phenomenon of divergent thinking. This process enables individuals from diverse geographical and cultural backgrounds to generate a wide range of ideas from multiple perspectives, thereby circumventing the aforementioned intricacies of wicked problems. Furthermore, employing crowd-ideation to tackle societal challenges ensures that solutions come from those who will be affected by their implementation. Crowd-ideation platforms like OpenIDEO and InnoCentive allow people from across the world and from all walks of life to submit solutions to societal challenges. With crowdsourcing initiatives in the likes of ideation contests, heterogeneous crowds can be mobilized to contribute valuable insights to the solution of wicked problems.

A societal challenge differs fundamentally from the tasks addressed in previous work on crowdsourcing (Afuah and Tucci 2012; Cao et al. 2022). Prior research has shown that tournament-based crowdsourcing initiatives focused on technical problem solving tend to foster convergent thinking, emphasizing a linear progression towards the identification of an optimal solution (Cao et al. 2022; Dissanayake et al. 2015). In contrast, addressing large-scale societal challenges is typically an open-ended task that requires the crowd to engage in collective divergent thinking to explore a multitude of directions and perspectives in response to a given problem statement. Given the unique and intricate nature of societal challenges, *our first research objective is to develop a new conceptual framework, which we refer to as "divergent innovation", to capture the outcomes of collective divergent thinking in the context of crowd-ideation for tackling societal challenges*. Drawing on extant literature on creativity (Dean et al. 2006; Runco and Jaeger 2012), we propose that divergent innovation in the context of crowd-ideation can be characterized by two critical dimensions: topic divergence and quality divergence. Whereas topic divergence denotes the extent to which the crowd explores a diverse range of topics in response to the ideation contest prompt, quality divergence captures the variability in the quality of ideas generated by the crowd. A trade-off between these two dimensions may arise depending on the contest facilitator's instructions. For instance, if the prompt prioritizes topic diversity over idea quality, the crowd may focus on exploring a broad range of topics at the expense of polishing high-quality ideas, while a focus on idea quality over topic diversity may result in a limited range of ideas but of higher quality.

On crowd-ideation platforms, task instructions set forth by contest facilitators are instrumental in encouraging collective divergent thinking toward tackling societal challenges. These instructions are typically communicated through a *request for proposals* (RFP) document (Lüttgens et al. 2014; Pollok et al. 2019), which outlines the societal problem to be solved, evaluation criteria, and other relevant information such as contest timing, prize, and external resource links. However, designing an effective RFP can be challenging, as it should contain sufficient stimuli to trigger collective creativity without leading to tunnel-vision and relatively similar solutions. Inspired by this important yet unsolved problem, *our second research objective is to identify ideation stimuli contained in the RFP that can influence collective divergent thinking and investigate their impacts on divergent innovation*. Through an extensive literature review on crowdsourcing literature (e.g., Gillier et al. 2018; Lüttgens et al. 2014; Pollok et al. 2019; Ward et al. 2004; Yin et al. 2022), we identified four types of ideation stimuli: task description concreteness, resource richness, topic entropy, and judging criteria comprehensiveness. These stimuli can influence the crowd's idea generation and proposal shaping, with judging criteria comprehensiveness acting as a moderator that affects the direct impacts of the other stimuli on divergent innovation.

This study aims to contribute to extant literature in several ways. Firstly, this study distinguishes crowd-ideation for addressing societal challenges from other crowdsourcing initiatives that prioritize convergent thinking. We posit that collective divergent thinking is pivotal to tackling societal challenges and introduce a new framework, divergent innovation, to measure the outcomes of collective divergent thinking in crowd-ideation platforms. Secondly, this study extends research on divergent thinking and creativity by shifting the focus from the individual to the collective level. Thirdly, this study enhances our understanding of the nuanced impacts of different ideation stimuli on divergent innovation. Overall, this study can provide researchers and practitioners with fine-grained insights on how to direct the collective divergent thinking of crowds by delicately formulating RFPs on crowd-ideation platforms to tackle societal challenges.

Theoretical Background and Hypotheses

Crowd Ideation for Societal Challenges

Crowdsourcing for Innovation: An Overview of Extant Literature

Crowdsourcing has emerged as a valuable means of solving complex innovation problems by attracting a large and diverse group of people, including not only experts from within the problem domain but also outsiders such as scientists from other domains, and hobbyists who may have fresh ideas to contribute (Boons and Stam 2019). Information systems (IS) scholars have shown growing interest in this phenomenon, with one stream of research focusing on *tournament-based crowdsourcing* (Afuah and Tucci 2012; Cao et al. 2022; Lüttgens et al. 2014). This approach involves members of the crowd competing to generate the best answer to a given problem, as exemplified by Kaggle, a well-known platform for data scientists to compete and produce the model with the best accuracy. Prior research has demonstrated the effectiveness of this approach in the context of technical problem solving (Lüttgens et al. 2014), and has offered insights into how to improve performance on such platforms (Cao et al. 2022; Dissanayake et al. 2015). Another stream of research has investigated *crowdsourcing communities*, in which members of the crowd interact and collaborate with each other to generate creative outcomes on an ongoing basis (Afuah and Tucci 2012; Bayus 2013), as seen in examples such as Dell's IdeaStorm community or MyStarbucksIdea.com. Research in this line has focused on the motivations of crowds to contribute, the design of the communities, and the dynamics of crowdsourcing outcomes (Acar 2019; Bayus 2013).

However, solving a societal challenge is fundamentally different from the tasks addressed by crowdsourcing initiatives that have been studied in previous research (Afuah and Tucci 2012; Cao et al. 2022). Unlike more specific and well-defined tasks that can be completed by a single individual or a small team, societal challenges are typically complex, multifaceted issues that require input from a diverse range of stakeholders, including experts from various fields, community members, and individuals with lived experience of the challenge at hand (Gimpel et al. 2020). Furthermore, societal challenges often involve issues that affect large groups of people or even entire communities or populations (George et al. 2016), making it critical to involve individuals from different backgrounds and cultures in the problem-solving process to ensure that solutions are equitable and inclusive. The solution to societal challenges is not confined to finding a single "best" solution or formulation, since different stakeholders may not even agree on the nature of the challenge (Head and Alford 2015). Thus, in addressing societal challenges, the imperative lies in generating a greater variety of solutions rather than merely an abundance of similar ones.

Divergent Innovation: A New Conceptual Framework

Guilford's seminal work defines divergent thinking as an individual thinking process that involves exploring different directions from an initial problem statement to generate a wide range of diverse ideas, within a context where more than one solution is deemed correct (Guilford 1967). Given the complex and multifaced nature of societal challenges, we posit that collective divergent thinking involving crowd members is key to expanding the exploration of solution space from diverse perspectives. While no established framework currently exists for measuring divergent thinking outcomes at the collective level, previous research on creativity offers valuable insights (Dean et al. 2006). Specifically, researchers have established that idea creativity at the individual level can be defined by two critical dimensions: *novelty* and *quality* (Dean et al. 2006; Runco and Jaeger 2012). Novelty refers to the uncommonness of an idea, while quality captures its relevance, feasibility, and presentation (Dean et al. 2006).

In the context of facilitating collective divergent thinking for the purpose of addressing societal challenges, the primary objective is not centered on producing a single, novel, and high-quality idea. Rather, the emphasis is on fostering the exploration of a diverse array of potential ideas originating from various perspectives. This approach leads to the potential selection of multiple ideas for subsequent implementation. To assess the outcome of this process, a new conceptual framework–*divergent innovation*–is proposed based on the well-established components of individual creativity (i.e., novelty and quality) (Dean et al. 2006). At the collective level, the term "novelty" is redefined as *"topic divergence"*, which reflects the diversity of topics explored by the crowd in a contest. High topic divergence indicates a comprehensive exploration of potential solutions from various perspectives, which is crucial for tackling societal challenges. Moreover, high topic divergence indicates that the idea pool can contain novel and unconventional ideas that may not have been explored before.

We also propose that the term "quality" should be redefined as "*quality divergence*" at the crowd level, which captures the unevenness of quality among the crowd-generated ideas. High quality divergence signifies a wide spectrum of quality levels among the submitted ideas, whereas low quality divergence indicates that idea quality exhibits less variation across the collective submissions. In the context of tackling societal challenges, high quality divergence holds the potential to inadvertently marginalize certain perspectives or stakeholders, particularly when ideas of inferior quality are excluded during the selection process. Conversely, with low quality divergence, most ideas tend to exhibit comparable quality levels, allowing for the consideration of a more extensive pool of ideas for subsequent implementation.

Overall, the new conceptual framework of divergent innovation, with its two sub-dimensions of topic and quality divergence, can provide a deeper understanding of collective creativity and serve as a basis for identifying influential factors for effectively harnessing the power of the crowd to tackle societal challenges.

The Relationship between Ideation Stimulus and Divergent Innovation

Previous research has established the crucial role of stimulus in inspiring individual divergent thinking (Guilford 1967; Luo and Toubia 2015; Wang and Nickerson 2019). For instance, Guilford's Divergent Thinking Test, a classic test of individual divergent thinking, presented participants with various stimuli such as words, pictures, and incomplete drawings to inspire them to generate ideas (Guilford 1967). In the context of crowdsourcing, the ideation stimulus is delivered through the RFP document, which contains information on the problem statement, task description, evaluation criteria, contest timing, prize, and external resource links (Lüttgens et al. 2014; Pollok et al. 2019). Despite the potentially influential impact of stimulus in RFPs on the crowd's divergent thinking process, there is a lack understanding of whether and how specific stimulus can exert its impact.

In this study, we propose that the crowd's collective divergent thinking is affected by the stimulus provided in the RFP document. To identify potential stimulus in RFP document, we conducted a comprehensive literature review on crowdsourcing literature regarding task instructions. Based on the thorough literature review, we consolidated four elements that the RFP typically involve: task description, resource provided, topic entropy, and judging criteria (see Table 1).

Author (year)	Design Elements of Task Instruction	Nature of Elements	Method
Yin et al. (2022)	✓ Requirement-oriented instruction writing strategy ✓ Reward-oriented instruction writing strategy	Task description	Quantitative (Secondary data)
Karahan et al. (2020)	✓ Abstract problem formulation ✓ Technical problem formulation ✓ Metaphorical formulation	Task description	Experiment
Gillier et al. (2018)	✓ Unbounded task instructions ✓ Suggestive task instructions ✓ Prohibitive task instructions	Task description	Quantitative (Secondary data)
Stetler and Magnusson (2015)	✓ Task clarity	Task description	Quantitative (Survey)

Ward et al. (2004)	✓ Specific task formulation ✓ Abstract task formation	Task description	Experiment
Luo and Toubia (2015)	✓ Stimulus ideas ✓ Problem decomposition	Task description, Resource provided	Experiment
Wang and Nickerson (2019)	✓ Stimuli relatedness	Resource provided	Experiment
Koh (2019)	✓ Exemplar specificity ✓ Exemplar quantity ✓ Exemplar variability	Resource provided	Experiment
Koh and Cheung (2021)	✓ Problem-related exemplar ✓ Problem-unrelated exemplar	Resource provided	Experiment
Cui and Liu (2020)	✓ /	Topic entropy	Quantitative (Secondary data)
Pollok et al. (2019)	✓ Problem-seeker knowledge distance ✓ Number of solution criteria and technical requirements	Task description, Judging criteria formulation	Quantitative (Secondary data)
Lüttgens et al. (2014)	✓ Judging criteria formulation	Judging criteria formulation	Longitudinal study

Table 1. Summary of Crowdsourcing Task Instructions Investigated in Extant Literature

We categorized these ideation stimuli into pre-ideation stimulus and post-ideation stimulus based on their effect on the ideation process. While pre-ideation stimulus influences how the crowd generates ideas, post-ideation stimulus influences how the crowd shapes their ideas. In this section, we will introduce these potential ideation stimuli and discuss their impact on divergent innovation in detail. Our research model is presented in Figure 1.

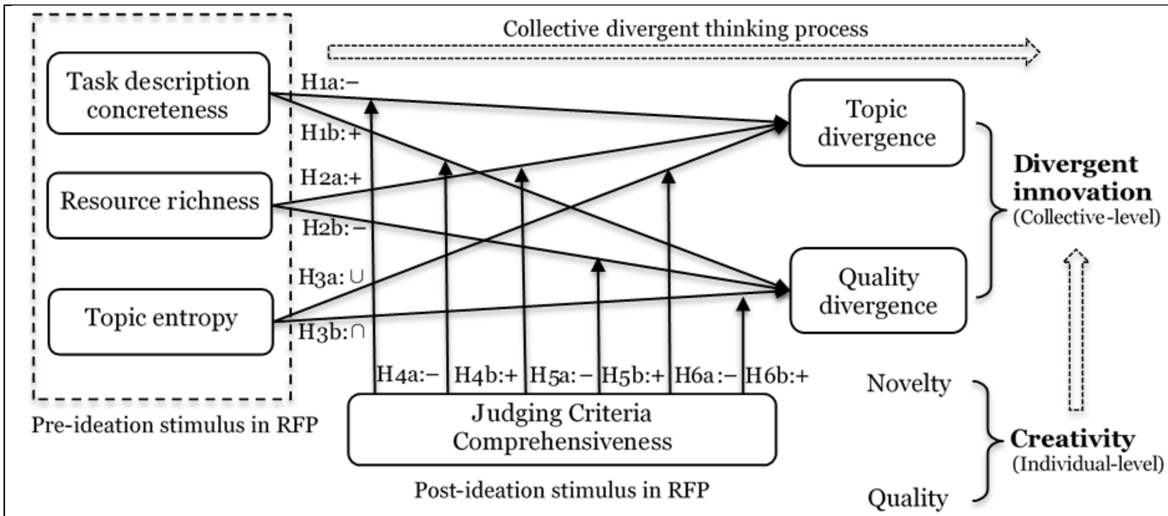

Figure 1. Research Model

Pre-ideation Stimulus

Task description concreteness refers to the degree of specificity and clarity in the task statement in each RFP provided to the crowd. When a task description shown in RFP is highly concrete, it provides clear and well-defined guidelines for tackling a societal challenge. However, this precision may not leave much room for collective divergent thinking, as potential ideas generated by the crowd are more likely to fall within the given task instructions and constrains (Stetler and Magnusson 2015). As a result, the exploration space may be narrowed, leading the crowd to focus their attention on a set of topics they believe are most relevant to the problem. This tendency towards "tunnel vision" can lead to proposals that converge towards a specific set of topics, thus decreasing topic divergence. Nevertheless, a less concrete task description provides more flexibility for the crowd to interpret the challenge in their own way (Ward et al. 2004), inspiring them to approach the societal challenge from different perspectives and apply their own unique experiences and knowledge to generate creative solutions. This leads to a higher level of topic divergence. Accordingly, we hypothesize that:

Hypothesis 1a: Task description concreteness is negatively related to topic divergence.

Comparatively, high task description concreteness enables participants to focus deeply on specific aspects of the task, resulting in a high level of convergent thinking. The crowd may be directed to focus on generating the "correct" answer within a narrow range of possible topics. The resulting proposals may exhibit more quality divergence as crowds may focus on the same topic but approach the problem from different angles, leading to more variations in their solutions. Furthermore, a concrete task description may require a specific range of skills and knowledge (Karahan et al. 2020). Since the crowd possesses varying levels of expertise, some may struggle to generate ideas that meet the specific requirements, which can further increase quality divergence. Based on the above reasoning, we hypothesize that:

Hypothesis 1b: Task description concreteness is positively related to quality divergence.

Resource richness refers to the amount of information, materials, tools, and other external resources in each RFP provided to the crowd. A rich set of resources can facilitate collective divergent thinking process, since it exposes the crowd to various perspectives and knowledge about the problem space (Koh 2019). This increased exposure can inspire the crowd to consider a wider range of potential avenues for tackling societal challenge, resulting in a more diverse set of proposals covering varied topics submitted by the crowd. Moreover, with access to a rich pool of resources, the crowd can adopt diverse approaches and generate a great diversity of solutions, thus leading to high topic divergence. In contrast, inadequate resource support cannot provide enough stimulus or potential avenues for exploration to fully activate the collective divergent thinking process, resulting in a less diverse set of ideas covering a narrow range of topics, thus leading to low topic divergence. Consequently, we propose the following hypothesis:

Hypothesis 2a: Resource richness is positively related to topic divergence.

Comparatively, high resource richness can lead to less quality divergence in the proposals generated by the crowd. The availability of a wide range of external resources provides a common foundation of knowledge among the crowd, serving as a reference point for generating ideas grounded in evidence and research. Furthermore, with access to abundant resources, participants can feel more motivated and well-equipped to generate high-quality proposals. This increased determination and access to relevant knowledge can lead to convergence in the quality of proposals submitted by the crowd. Whereas limited external resources can prompt participants to rely more on their own personal skill sets and knowledge to generate ideas, resulting in high quality divergence as individuals possess varying levels of skill and knowledge. Hence, we hypothesize that:

Hypothesis 2b: Resource richness is negatively related to quality divergence.

Topic entropy refers to the extent of breadth of topics covered by each RFP provided to the crowd. Specifically, low entropy values indicate that the RFP has focused attention on a limited number of topics, while high values indicate that attention has been spread across a broad range of topics (Choudhury et al. 2019). We propose that the U-shaped relationship between topic entropy and topic divergence can be explained by the interplay between two mechanisms: the *stimulating effect of collective divergent thinking* and the *constraining effect of collective convergent thinking*. In contrast to the process of collective divergent thinking, collective convergent thinking inclines the crowd to emphasize similarities, refine preexisting concepts, and converge towards a common solution or viewpoint. This inclination can constrain the exploration of alternative possibilities that lie beyond the narrowed scope. Specifically, an increase in topic entropy is accompanied by a strengthening of the stimulating effect of collective divergent thinking and a weakening of the constraining effect of collective convergent thinking.

At low to moderate levels of topic entropy, the constraining effect of convergent thinking is likely to outweigh the stimulating effect of divergent thinking. This is because low to moderate topic entropy levels imply a narrow focus on specific topics, which can result in a "lock-on" effect where the crowd becomes fixated on a given topic (Stetler and Magnusson 2015). Such limited range of information makes it difficult for the crowd to fully engage in divergent thinking to generate creative ideas that are outside the box (Ulrich 2018). Instead, the crowd are likely to engage in convergent thinking and become attached to a particular topic direction. Taken together, topic entropy is negatively associated with topic divergence at low to moderate levels because the constraining effect of convergent thinking outweighs the stimulating effect of divergent thinking. Comparatively, when topic entropy is at moderate to high levels, the stimulating effect of divergent thinking will outweigh the constraining effect of convergent thinking. When the topic entropy of the RFP document is at a moderate to high level, the convergent thinking process is not fully activated since the crowd is presented with a wide variety of topics to consider. At the same time, moderate to high topic entropy levels contain substantial stimuli and inspiration for collective divergent thinking to flourish (Müller-Wienbergen et al. 2011). In turn, the crowd is encouraged to engage in a more open and free-flowing ideation process. By integrating the stimulating effect of divergent thinking and the constraining effect of convergent thinking, this study predicts a U-shaped effect of topic entropy on topic divergence such that topic divergence is lower under moderate topic entropy levels than under low or high levels.

Hypothesis 3a: There is a U-shaped relationship between topic entropy and topic divergence.

Consistent with the above reasoning, the inverted U-shaped relationship between topic entropy and quality divergence can be explained by the interplay between the effect collective divergent thinking and convergent thinking. At low to moderate topic entropy levels, the effect of convergent thinking can outweigh the effect of divergent thinking. As we have mentioned in H3a, low to moderate levels of topic entropy can facilitate convergent thinking that constrains the crowd on a narrow range of topics. In such case, some participants may have focused and specialized knowledge and expertise to the topics at hand, while others may not have as much knowledge or experience in those areas and struggle to generate ideas of the same caliber, leading to high quality divergence. Comparatively, when topic entropy is at moderate to high levels, a wide range of perspectives is available to the crowd to inspire collective divergent thinking, rather than convergent thinking (Müller-Wienbergen et al. 2011). It can lead to a decrease in quality divergence because there is less emphasis on finding the "best" solution to the societal challenge. Therefore, we propose that:

Hypothesis 3b: There is an inverted U-shaped relationship between topic entropy and quality divergence.

Post-ideation Stimulus

Beyond the above three pre-ideation stimuli that influence the way the crowd generate ideas; post-ideation stimuli are critical factors that can exert impacts on the way that crowd shapes their ideas. Specifically, judging criteria listed in the RFP can affect how the crowd aligns or matches their ideas with the requirements formulation (Lüttgens et al. 2014). In this line, we argue that the relationship between the above three pre-ideation stimuli and divergent innovation are moderated by *judging criteria comprehensiveness*, which refers to the extent to which the evaluation criteria specify the requirements that should be meet in the proposal. RFPs with high judging criteria comprehensiveness describe the elements that should be involved in the proposal, the requirements that must be fulfilled, and any prohibited or discouraged approaches. In contrast, less comprehensives judging criteria provide loosely-defined requirements, leaving significant latitude for the crowd to shape their ideas.

We expect that the negative effect of task description concreteness on topic divergence is amplified by judging criteria comprehensiveness. High judging criteria comprehensives provide clear and specific guidelines for the crowd to follow when shaping their ideas. This high precision in the RFP does not leave much room for creative solutions and poses risks for the crowd that they cannot meet all specifications listed in the document (Pollok et al. 2019). In such case, the crowd tend to be cautious and more likely to focus on the specific requirements outlined in the task description, rather than exploring a more diversified solution space. Consequently, the alignment between concrete task description and comprehensive judging criteria lead to lower topic divergence. By contrast, less comprehensive judging criteria can be seen as a form of "constraint removal" that empowers the crowd to broaden the scope of topics that they can consider, even if they are not strictly aligned with the task description. Under such circumstance, the detrimental effect of task description concreteness on topic divergence can be weaker. Accordingly, we hypothesize that:

Hypothesis 4a: Judging criteria comprehensiveness strengthens the negative effect of task description concreteness on topic divergence.

We propose that the positive effect of task description concreteness on quality divergence can be strengthened by judging criteria comprehensiveness. Highly comprehensive judging criteria provide clear guidance for the crowd on what constitutes high-quality ideas and how the proposals will be evaluated (Yin et al. 2022). While concrete task description provides a strong starting point for a targeted idea generation process, comprehensive judging criteria serve as a reference point where the crowd further refine their proposals based on specific evaluation criteria (Harvey and Kou 2013). However, the combination of concrete task descriptions and judging criteria may be more demanding and require a higher level of expertise to fulfil the requirements. Some participants may comprehend the requirements better and possess the necessary skills and knowledge to generate high-quality proposals, while others may struggle to come up with ideas that meet the specific requirements, resulting in higher quality divergence. In contrast, when judging criteria are less comprehensive, the crowd is not restricted to a narrow set of criteria to generate the "correct" idea. In such case, participants with varying levels of expertise may have a better chance of contributing high-quality proposals, leading to low quality divergence, even with a concrete task description in place. Therefore, we propose that:

Hypothesis 4b: Judging criteria comprehensiveness strengthens the positive effect of task description concreteness on quality divergence.

We argue that the positive effect of resource richness on topic divergence can be weakened by judging criteria comprehensives because it constrains and narrows the range of acceptable topics that the crowd can submit. Comprehensive judging criteria may create pressure on the crowd to conform to certain standards or expectations (Pollok et al. 2019), which can limit their collective divergent thinking inspired by the rich resource provided in the RFP. When the crowd feels pressured to adhere closely to the given parameters in the comprehensive judging criteria, they tend to be constrained and less willing to explore unconventional topics that they may not easily fit within the criteria (Gillier et al. 2018), resulting in a decrease in topic divergence. In contrast, less comprehensive judging criteria provide less prescriptive direction on what constitutes a high-quality idea, allowing the crowd to shape ideas according to their own perspectives and insights. This enables the crowd to fully draw on a wide range of external resource provided in the RFP, resulting in a broader range of topics being explored. Therefore, we propose that:

Hypothesis 5a: Judging criteria comprehensiveness weakens the positive effect of resource richness on topic divergence.

In a similar vein, we propose that judging criteria comprehensiveness can mitigate the negative effect of resource richness on quality divergence. Comprehensive judging criteria outline the specific elements that comprise a high-quality proposal, encouraging crowd to use external resources more critically. For instance, judging criteria that prioritize the incorporation of multiple perspectives or evidence-based approaches prompt participants to use external resources more critically and to concentrate on the most essential aspects. By providing clarity on the expected standards of high-quality proposals, comprehensive judging criteria steer participants towards using external resources in a more targeted way, rather than simply relying on them as a foundation for their proposals. Consequently, the negative impact of resource richness on quality divergence can be weakened. Hence, we hypothesize that:

Hypothesis 5b: Judging criteria comprehensiveness weakens the negative effect of resource richness on quality divergence.

We suggest that judging criteria comprehensive can flatten the U-shaped relationship between topic entropy and topic divergence. When judging criteria are highly comprehensive, it can mitigate the stimulating effect of divergent thinking while strengthening the constraining effect of convergent thinking. Specifically, with highly comprehensive judging criteria, the crowd can have a clear set of guidelines and expectations to follow, which may reduce their willingness to consider ideas that are too far outside the scope of the RFP or deviate too much from the predefined evaluation criteria (Pollok et al. 2019). Thus, the stimulating effect of divergent thinking that increases with topic entropy may be mitigated. On the other hand, highly comprehensive judging criteria can strengthen the constraining effect of convergent thinking since the crowd could become more focused on specific aspects of the proposal that are explicitly stated in the judging criteria and be less open to ideas that do not align closely with these criteria.

Overall, comprehensive judging criteria can have a dampening effect on the stimulating effect of divergent thinking while strengthening the constraining effect of convergent thinking, flattening the U-shaped effect of topic entropy on topic divergence. Specifically, when judging criteria are comprehensive, the constraining effect of convergent thinking is likely to be more prominent, leading to lower topic divergence, and the stimulating effect of divergent thinking may be suppressed, leading to reduced topic divergence at high levels of topic entropy. Accordingly, we propose the following hypothesis:

Hypothesis 6a: Judging criteria comprehensiveness weakens the U-shaped effect of topic entropy on topic divergence.

In contrast to the case for H6a, we propose that judging criteria comprehensiveness can steepen the inverted U-shaped relationship between topic entropy and quality divergence by strengthening the effect of convergent thinking while weakening the effect of divergent thinking. Specifically, when judging criteria are highly comprehensive, participants may be inclined to conform to established standards and guidelines to ensure their ideas are perceived as "high-quality", rather than exploring truly innovative or unconventional ideas. Under such case, at low to moderate levels of topic entropy, participants are directed to focus on limited topics and pursue high quality proposals with their own expertise, which can exacerbate the increase in quality divergence. For instance, participants without technical or scientific expertise may be less likely to contribute to high-quality ideas under comprehensive judging criteria that prioritize technical or scientific elements. On the other hand, at moderate to high levels of topic entropy, the comprehensiveness of judging criteria can provide an equal opportunity for participants with diverse backgrounds and experiences to contribute high-quality ideas. This is because a broader and more inclusive topic space enables the crowd to explore a wider range of ideas, decreasing quality divergence. Thus, we hypothesize:

Hypothesis 6b: Judging criteria comprehensiveness strengthens the inverted U-shaped effect of topic entropy on quality divergence.

Methodology

Data Collection

To test our hypotheses, we conducted an empirical study using data sourced from Climate Colab, an eminent global online crowd-ideation platform. The core mission of this platform is to harness the collective wisdom of myriad individuals hailing from diverse regions, all unified in their pursuit of addressing the multifaceted challenges posed by global climate change. As of 2022, the platform boasts a community of more than 120,000 members. Since its inception in 2009, the platform has hosted a total of 110 contests, each meticulously tailored to confront intricate challenges such as carbon pricing, transportation, energy supply, and waste management. We collected the RFP documents of 110 contest and all 3,055 proposals submitted across all contests on this platform and used them for our subsequent analyses.

Dependent Variable: Divergent Innovation

Topic divergence. To measure topic divergence, we employed an unsupervised topic modeling approach known as the Latent Dirichlet Allocation (LDA) model (Blei et al. 2003). A key advantage of LDA is that it does not require human classification, which would be infeasible given the large number of proposals and the unknown nature of the topics under investigation (Haans 2019). The LDA model allows the text to "speak for itself" by uncovering the most relevant and informative topics that emerge from the text. Prior to performing the topic modeling analysis, we employed a set of standard preprocessing techniques to process the text, allowing us to obtain a "clean" proposal corpus (Choi et al. 2021). We aggregated the proposals submitted to the same contest and applied the LDA algorithm at the contest level. The LDA model enables us to produce a topic-keyword matrix representing the distribution of keywords within each topic, and a document-topic matrix representing the distribution of topics within each submitted proposal.

After generating the probability distribution of topics for each proposal, we used Jensen-Shannon (JS) divergence, a suitable metric for depicting dissimilarity between two probability distributions (Lin 1991), to calculate topic divergence at the contest level. The range of JS divergence is [0,1], with higher values indicating greater dissimilarity between the topic probability distribution of two proposals. We calculated topic divergence as the average value of JS divergence between the topic probability distributions of each pair of proposals within the same contest.

Quality divergence. The crowd-ideation platform employs a four-dimensional criteria to assess the quality of proposals: 1) Feasibility: the extent to which the proposal is technically, economically, socially, legally, and politically acceptable; 2) Impact: the extent to which the proposal clearly applies to the stated problem and can really make a sustainable impact(social and/or ecological); 3) Originality: the extent to which the proposal differentiate itself from the current status quo; and 4) Presentation: the extent to which how well written the proposal is and how well it uses graphic or other visual elements. Each proposal submitted to the contests will be rated by expert judges on these four aspects. Since only the ratings for proposals that become semi-finalists are presented on the platform, we leveraged Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art language model that has achieved exceptional results in various language understanding tasks (Devlin et al. 2019), to predict quality scores for proposals that did not advance to the semi-finals. Specifically, we used the 626 proposals with complete quality scores out of all 3,055 submissions as the training data to predict quality scores for the remaining proposals based on the text contents of proposal. We employed Mean Absolute Percentage Error (MAPE) for predictive accuracy assessment (Gneiting 2011). Model_Feasibility, Model_Impact, Model_Originality, and Model_Presentation yielded MAPEs of 5.784%, 3.812%, 19.295%, and 2.367%, respectively, indicating good accuracy in quality score prediction by our fine-tuned BERT model.

For each proposal, we created a vector that consists of the four-dimensional quality scores (i.e., scores for Feasibility, Impact, Originality, and Presentation). To measure the difference between each pair of proposals' quality scores, we used the Euclidean Distance. We define quality divergence as the average Euclidean Distance between the quality vector of each pair of proposals within the same contest. For a pair of arrays [x1, x2, x3, x4] and [y1, y2, y3, y4], the Euclidean Distance is defined as follows:

$$\text{Euclidean Distance}= \sqrt{\sum_{i=1}^{4}\left(x_i - y_i\right)^2} \tag{1}$$

Independent Variables and Moderator

Task description concreteness. We derived the measure for task description concreteness through content analysis of RFP for each contest using Linguistic Inquiry and Word Count (LIWC) 2015 software. Following the approach introduced previously (Pan et al. 2018), we included six LIWC word categories for our concreteness measure: verbs, adjectives, numbers, nonspecific quantifiers, past-focused, and future-focused. We generated the concreteness measure by summing the scores of verbs, numerals, and past-focused words and subtracting the scores of adjectives, nonspecific quantifiers, and future-focused words.

Resource richness. Resource richness was measured as the number of resource links each RFP contains. In the RFP of each contest, there is a special section where contest facilitators can provide hyperlinks of external online resources to support crowds to come up with ideas. We analyzed the information in this section for each RFP and identified the number of resource links.

Topic entropy. Topic entropy measures the diversity of topics covered by the RFP for each contest. Following prior literature (Choudhury et al. 2019), we used LDA model to obtain the topic probabilities inferred from each RFP document, and subsequently computing the entropy score based on the topic distribution. The topic entropy of each RFP document *i* is defined as follows:

$$\text{TopicEntropy}_i = -\sum_{t=1}^{T}\tilde{\theta}_{it}\log(\tilde{\theta}_{it}) \tag{2}$$

Where $\tilde{\theta}_{it}$ denotes the probability that RFP *i* belongs to topic *t*, T is the total number of topics.

Judging criteria comprehensiveness. In the RFP for each contest, a section exits where contest facilitator outlines information about criteria that judge panel will utilize to select the winning proposal. We define judging criteria comprehensiveness as the number of evaluation criteria that the contest facilitator elaborates in the RFP.

Control Variables

We controlled for several factors that could potentially affect crowd's divergent innovation. We used the logarithm of *text length* to control for the information richness of the RFP document. We included *number* *of proposals* submitted to the contest, *number of winners*, and *number of judges* in our model since they can impact solvers' enthusiasm to invest sufficient efforts towards working on ideas. We also included a categorical variable to capture differences across prize categories (i.e., no prize, monetary prize, and non-monetary prize). To rule out the effects of different contest stage settings, we controlled for *number of contest stages*. We also added *contest duration*, which is the logarithm of the number of days the contest lasted, to control for the impact of different time spans across different contests. To control for the possibility that contests inspiring crowds to reuse prior proposals may receive fewer divergent ideas, we controlled *inspire knowledge reuse*, a dummy variable indicating whether the contest design encourages knowledge reuse for innovation (1) or not (0).

Analysis and Results

Table 2 presents the basic descriptive analysis of all variables, including their means, standard deviations, minimum and maximum values. Additionally, we assessed the correlation between each construct and found that all correlations were less than 0.6.

Variable	Mean	SD	Min	Max
Task description concreteness	4.464	4.837	−9.640	24.990
Resource richness	10.373	7.594	0	37
Topic entropy	0.574	0.476	0.014	1.643
Judging criteria comprehensiveness	4.309	4.240	0	16
Topic divergence	0.740	0.193	0	1
Quality divergence	0.493	0.147	0	0.938
Text length	6.038	1.057	3.892	7.885
Number of proposals	27.773	19.038	1	94
Number of winners	2.264	1.171	0	6
Number of judges	3.791	1.868	0	10
Prize	1.245	0.623	0	2
Number of contest stages	4.173	1.471	0	6
Contest duration	5.553	0.803	3.367	7.751
Inspire knowledge reuse	0.073	0.261	0	1

Table 2. Descriptive Statistics of Variables

To test our hypotheses, we performed an ordinary least squares (OLS) regression. The hierarchical regression model results are reported in Table 3 and 4. We standardized all the independent and moderator variable. Model 1 presents the basic regression models with all control variables. Model 2 tests the direct relationships between three independent variables with topic divergence and quality divergence, respectively. The results show that task description concreteness has a negative influence (β=−0.012, p < 0.01) on topic divergence, while has a positive influence (β=0.005, p < 0.05) on quality divergence. Therefore, H1a and H1b are supported. Conversely, resource richness is positively related to topic divergence (β=0.005, p < 0.05) but negatively related to quality divergence (β=−0.003, p < 0.05), thereby supporting H2a and H2b. Model 3a investigates the U-shaped effect of topic entropy on topic divergence. Model 3a shows that the coefficient for the linear term of topic entropy is significantly negative (β=−0.110, p < 0.01), whereas the quadratic term is significantly positive (β=0.174, p < 0.05), thereby indicating a U-shaped effect of topic entropy on topic divergence. To further examine the U-shaped relationship, we conducted a U test that was recommend by Haans et al. (2016). The overall test of the U-shape is significant (t-value = 2.03, p>|t|= 0.023). The turning point of the U-shape occurs at topic entropy=0.883, which is well within the topic entropy data range of [0.014, 1.643]. The slope at the minimum topic entropy is significantly negative (β=−0.330, p < 0.001), whereas the slope at the maximum topic entropy is significantly positive (β=0.288, p < 0.05). Our results thus validate the U-shaped effect of topic entropy on topic divergence, providing strong support for H3a. However, Model 3b indicates an insignificant linear effect of topic entropy on quality divergence (β=−0.040, p > 0.1). The quadratic term is also insignificantly related to quality divergence (β=0.022, p > 0.1). Hence, H3b that predicts an inverted U-shaped relationship between topic entropy and quality divergence is rejected.

Variable	Topic Divergence			Quality Divergence		
	Model 1a	**Model 2a**	**Model 3a**	**Model 1b**	**Model 2b**	**Model 3b**
TDC		-0.012^{**} (0.004)	-0.009^{*} (0.004)		0.005^{*} (0.003)	0.006^{*} (0.003)
RR		0.005^{*} (0.002)	0.007^{**} (0.003)		-0.003^{*} (0.001)	-0.004^{*} (0.002)
TE		-0.076^{*} (0.038)	-0.110^{**} (0.040)		−0.032 (0.023)	−0.040 (0.026)
TDC square			−0.000 (0.000)			0.000 (0.000)
RR square			−0.000 (0.000)			0.000 (0.000)
TE square			0.174^{*} (0.072)			0.022 (0.047)
Text length	-0.083^{***} (0.024)	-0.093^{***} (0.023)	-0.122^{***} (0.024)	$-0.024^{\dagger}$ (0.014)	−0.015 (0.014)	−0.016 (0.016)
Number of proposals	0.002^{*} (0.001)	0.003^{**} (0.001)	0.003^{**} (0.001)	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)
Number of winners	0.026 (0.019)	0.021 (0.018)	0.022 (0.018)	0.026^{*} (0.011)	$0.023^{\dagger}$ (0.011)	$0.023^{\dagger}$ (0.012)
Number of judges	$0.026^{\dagger}$ (0.014)	0.020 (0.013)	$0.024^{\dagger}$ (0.013)	−0.002 (0.008)	−0.002 (0.008)	−0.002 (0.008)
Monetary prize	$0.211^{\dagger}$ (0.124)	0.289^{*} (0.119)	0.315^{**} (0.117)	-0.451^{***} (0.074)	-0.456^{***} (0.073)	-0.451^{***} (0.076)
Non-monetary prize	0.075 (0.125)	0.193 (0.123)	0.176 (0.122)	-0.460^{***} (0.075)	-0.450^{***} (0.076)	-0.444^{***} (0.079)
Number of contest stages	−0.012 (0.018)	-0.050^{*} (0.020)	-0.059^{**} (0.020)	0.101^{***} (0.011)	0.114^{***} (0.013)	0.114^{***} (0.013)
Contest duration	−0.014 (0.034)	−0.024 (0.033)	−0.027 (0.032)	-0.098^{***} (0.020)	-0.091^{***} (0.020)	-0.090^{***} (0.021)
Inspire knowledge reuse	0.062 (0.071)	0.068 (0.067)	0.104 (0.066)	-0.145^{***} (0.043)	-0.154^{***} (0.041)	-0.151^{***} (0.043)
Constants	1.001^{***} (0.284)	1.219^{***} (0.279)	1.400^{***} (0.283)	1.132^{***} (0.170)	0.990^{***} (0.172)	0.976^{***} (0.183)
R^2	0.310	0.414	0.474	0.573	0.616	0.620
Adjusted R^2	0.247	0.341	0.391	0.534	0.568	0.559
RMSE	0.167	0.156	0.151	0.100	0.0963	0.0973
F value	4.983	5.705	5.657	14.900	12.960	10.220

Table 3. Regression Results for Hypotheses 1, 2, and 3

Notes: TDC refers to task description concreteness, RR refers to resource richness, TE refers to topic entropy. $^{\dagger}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. Standard errors in parentheses.

To test the moderating effect of judging criteria comprehensiveness, the main effect of the moderator was first introduced to Model 4. All interaction terms were then added to Model 5. Model 5a indicates that judging criteria comprehensiveness negatively moderates the relationship between task description concreteness and topic divergence (β = −0.005, p < 0.01). Conversely, Model 5b reveals that judging criteria comprehensiveness positively moderates the relationship between task description concreteness and quality divergence (β = 0.002, p < 0.05), thereby supporting H4a and H4b. Plots of these results (Figure 2) further support H4a and H4b. Besides, Model 5a shows that the interaction term between resource richness and judging criteria comprehensiveness for topic divergence is significant and negative (β = −0.001, p < 0.05), thereby supporting H5a. Model 5b shows that the interaction term between resource richness and judging criteria comprehensiveness for quality divergence is significant and positive (β = 0.001, p < 0.05), supporting H5b. Plots of these results (Figure 3) further support H5a and H5b. Furthermore, Model 5a indicates that the coefficient for the interaction term between judging criteria comprehensiveness and topic entropy square is significantly negative (β = −0.051, p < 0.01), thereby supporting H6a. Figure 4 depicts the changes in the U-shape at different levels of judging criteria comprehensiveness. While Model 5b shows that the coefficient for the interaction term between judging criteria comprehensiveness and topic entropy square is insignificant (β = 0.014, p > 0.1), thus rejecting H6b.

Variable	**Topic Divergence**		**Quality Divergence**	
	Model 4a	**Model 5a**	**Model 4b**	**Model 5b**
TDC	−0.011** (0.004)	−0.014** (0.004)	0.006* (0.003)	0.008** (0.003)
RR	0.005* (0.002)	0.005* (0.002)	−0.003* (0.001)	−0.004** (0.001)
TE	−0.113** (0.041)	−0.108** (0.038)	−0.046† (0.025)	−0.047† (0.025)
TE square	0.184* (0.072)	0.222** (0.068)	0.029 (0.045)	0.017 (0.044)
JCC	−0.002 (0.004)	−0.001 (0.005)	0.006* (0.003)	0.007* (0.004)
TDC*JCC		−0.005** (0.002)		0.002* (0.001)
RR*JCC		−0.001* (0.000)		0.001* (0.000)
TE*JCC		0.007 (0.009)		0.005 (0.006)
TE square*JCC		−0.051** (0.015)		0.014 (0.010)
Text length	−0.110*** (0.023)	−0.107*** (0.022)	−0.018 (0.014)	−0.022 (0.014)
Number of proposals	0.003** (0.001)	0.004*** (0.001)	−0.000 (0.001)	−0.001 (0.001)
Number of winners	0.024 (0.018)	0.020 (0.017)	0.019† (0.011)	0.023* (0.011)
Number of judges	0.023† (0.013)	0.019 (0.012)	−0.003 (0.008)	−0.001 (0.008)
Monetary prize	0.281* (0.116)	0.210† (0.108)	−0.437*** (0.072)	−0.408*** (0.070)
Non-monetary prize	0.155 (0.121)	0.080 (0.113)	−0.439*** (0.075)	−0.413*** (0.073)
Number of contest stages	−0.048* (0.020)	−0.028 (0.019)	0.109*** (0.012)	0.100*** (0.012)
Contest duration	−0.022 (0.032)	−0.041 (0.031)	−0.086*** (0.020)	−0.079*** (0.020)
Inspire knowledge reuse	0.107 (0.067)	0.090 (0.063)	−0.165*** (0.042)	−0.157*** (0.041)
Constants	1.248*** (0.272)	1.303*** (0.253)	0.998*** (0.169)	0.998*** (0.164)
R^2	0.456	0.559	0.638	0.679
Adjusted R^2	0.376	0.472	0.585	0.616
RMSE	0.152	0.140	0.0945	0.0908
F value	5.687	6.417	11.970	10.720

Table 4. Regression Results for Hypotheses 4, 5, and 6

***Notes*:** JCC refers to judging criteria comprehensiveness. $^{\dagger}p$<0.1, $^{*}p$<0.05, $^{**}p$<0.01, $^{***}p$<0.001; standard errors in parentheses.

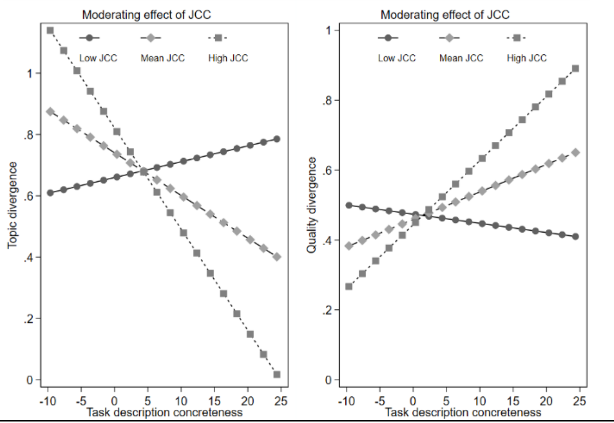

Figure 2. Moderating Effect of JCC on the Relationship between TDC and Divergent Innovation

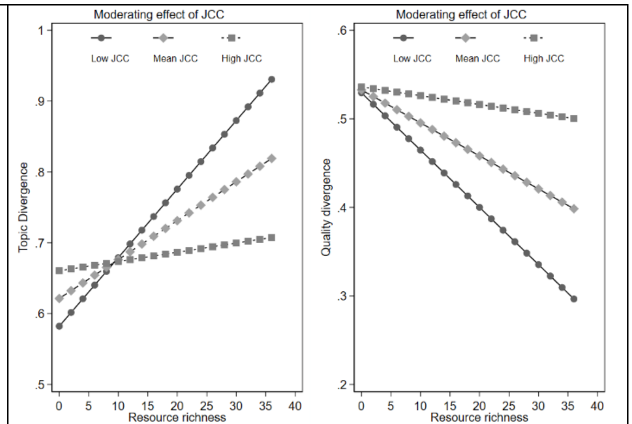

Figure 3. Moderating Effect of JCC on the Relationship between RR and Divergent Innovation

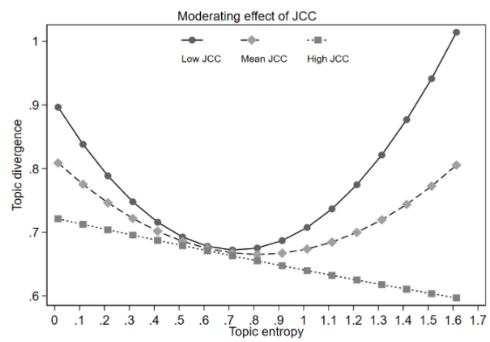

Figure 4. Moderating Effect of JCC on the Relationship between TE and Topic Divergence

Discussion

Our empirical findings indicate that task description concreteness has a negative impact on topic divergence but a positive impact on quality divergence. In contrast, resource richness is positively related to topic divergence but negatively related to quality divergence. Additionally, we uncovered a U-shaped relationship between topic entropy and topic divergence, whereas topic entropy has no significant impact on quality divergence. This insignificant result suggests that while the breadth of topics covered by an RFP may affect the diversity of ideas proposed by the crowd, it is not necessarily a direct determinant of quality divergence. Moreover, our results indicate that judging criteria comprehensiveness plays a critical role as a moderator in shaping the relationship between the three pre-ideation stimuli and topic divergence and quality divergence, respectively.

Implications for Theory

This study delves into the unique context of crowd-ideation for tackling societal challenges. Previous research on tournament-based crowdsourcing has primarily focused on selecting a winning solution for a specific problem, emphasizing the role of convergent thinking (Cao et al. 2022; Lüttgens et al. 2014). Breaking from the previous line of research, we are among the first to suggest that collective divergent thinking is crucial for solving societal challenges, especially given the inherently complex and multifaceted nature of such challenges. To measure the outcome of collective divergent thinking, we introduce a new framework, divergent innovation, which captures two critical dimensions, namely topic divergence and quality divergence. In this regard, we offer a new theoretical perspective to deepen our understanding on how to direct crowds' thinking process to solve societal challenges in crowd-ideation platforms.

Second, the present study extends existing literature on divergent thinking and creativity by shifting the research focus from the individual level to the collective level (Dean et al. 2006; Guilford 1967). In doing so, we seek to examine the collective-level processes and outcomes of divergent thinking in our unique context, offering new insights into the dynamics of divergent thinking and ideation within crowdsourcing platforms.

Third, this study enhances our understanding of different ideation stimuli's impacts on divergent innovation. By synthesizing previous research on task instructions in crowdsourcing contexts (Gillier et al. 2018; Lüttgens et al. 2014; Yin et al. 2022), we identify task description concreteness, resource richness, and topic entropy as ideation stimuli that exert direct impacts on divergent innovation. Judging criteria comprehensiveness, on the other hand, moderates the direct impacts of the above three stimuli by influencing the way in which the crowd shapes their proposals. Importantly, we find that each ideation stimuli impacts topic divergence and quality divergence in contrasting directions, revealing a trade-off between these two dimensions of divergent innovation.

Implications for Practice

This research offers guidelines for contest facilitators to strategically formulate RFPs to harness the power of the crowd in tackling societal challenges. First, our findings suggest that a highly concrete task description can lead to less topic divergence but greater quality divergence, while a rich resource environment leads to greater topic divergence but less quality divergence. Therefore, contest facilitators should balance the concreteness of task description and the resource provided in RFP documents to achieve the expected outcomes of both types of divergence in the proposals received from the crowd.

Second, our findings demonstrate how contest facilitators can strategically manage the breadth of topics covered by RFP documents to enhance topic divergence. For instance, if the contest centers on sustainable energy solutions, the contest facilitators could design an RFP that primarily highlights a single category, such as solar energy. This approach would push the crowd to think outside the box and explore solutions beyond the specific topic. Alternatively, the RFP could cover a wide range of sustainability-related topics—ranging from solar and wind energy to water conservation and waste reduction—to stimulate more varied ideas from the crowd. However, it is prudent for contest facilitators to exercise caution when considering intermediate levels of topic entropy, since such scenario can lead to a potential standstill, known as being "stuck in the middle".

Third, our findings indicate that the impact of task description concreteness, resource richness, and topic entropy on divergent innovation will change with judging criteria comprehensiveness. On one hand, comprehensive judging criteria force the crowd to follow specific instructions presented in the RFP, leaving less room for free-flowing ideation. Our findings indicate that comprehensive judging criteria strengthen the negative effect of task description concreteness on topic divergence and mitigate the positive effect of resource richness on topic divergence. Moreover, comprehensive judging criteria weaken the U-shaped effect of topic entropy on topic divergence. On the other hand, comprehensive judging criteria set clear and high standards, informing the crowd what constitutes a high-quality proposal. When judging criteria listed in RFPs are comprehensive, the positive effect of task description concreteness on quality divergence can be strengthened and the negative effect of resource richness on quality divergence can be weakened. Overall, this study provides contest facilitators with actionable insights that can help them direct the wisdom of crowd to achieve divergent innovation through delicate formulation of the RFPs.

Limitations and Future Research Directions

Although our study has the potential to yield significant insights into the crowd-ideation literature regarding tackling societal challenges, we inevitably suffer from some limitations that warrant further investigation. First, the platform studied in this paper does not publicly disclose quality scores for all proposals submitted to the contest, resulting in missing quality data for some proposals. To overcome this, we utilized BERT to predict quality scores for the remaining proposals, using proposals with complete quality scores as training data. Although BERT is one of the state-of-the-art language models that has achieved exceptional results in various language tasks (Devlin et al. 2019), we acknowledge that potential biases may arise in the prediction results. For this reason, we deem it necessary to carry out a manual coding to calibrate the calculation process and corroborate our findings. Second, our current measure of quality divergence fails to reflect the actual values of quality. In future research, we would like to incorporate actual values of quality in the measure of quality divergence, ensuring that the expected results are achieved by receiving proposals that converge on high quality.

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