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# Crowdsourcing intelligent design*

Wei XIANG[1, 2], Ling-yun SUN[‡1, 2], Wei-tao YOU[1, 2], Chang-yuan YANG[3]

[1]*State Key Lab of CAD & CG, Zhejiang University, Hangzhou 310058, China*

[2]*Modern Industrial Design Institute, Zhejiang University, Hangzhou 310027, China*

[3]*International User Experience Business Unit, Alibaba Group, Hangzhou 310000, China*

E-mail: wxiang@zju.edu.cn; sunly@zju.edu.cn; weitao_you@zju.edu.cn; changyuan.yangcy@alibaba-inc.com

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**Abstract:** Design intelligence, namely, artificial intelligence to solve creative problems and produce creative ideas, has improved rapidly with the new generation artificial intelligence. However, existing methods are more skillful in learning from data and have limitations in creating original ideas different from the training data. Crowdsourcing offers a promising method to produce creative designs by combining human inspiration and machines' computational ability. We propose a crowdsourcing intelligent design method called 'flexible crowdsourcing design'. Design ideas produced through crowdsourcing design can be unreliable and inconsistent because they rely solely on selection among participants' submissions of ideas. In contrast, the flexible crowdsourcing design method employs a cultivation procedure that integrates the ideas from crowd participants and cultivates these ideas to improve design quality at the same time. We introduce a series of studies to show how flexible crowdsourcing design can produce original design ideas consistently. Specifically, we will describe the typical procedure of flexible crowdsourcing design, the refined crowdsourcing tasks, the factors that affect the idea development process, the method for calculating idea development potential, and two applications of the flexible crowdsourcing design method. Finally, it summarizes the design capabilities enabled by crowdsourcing intelligent design. This method enhances the performance of crowdsourcing design and supports the development of design intelligence.

**Key words:** Crowdsourcing; Flexible crowdsourcing design; Design intelligence
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## 1 Introduction

The new generation artificial intelligence (AI) combines data-driven machine learning approaches and knowledge-guided reasoning approaches, and therefore integrates both human and machine intelligence. This strategy is expected to develop a robust and general AI, and to reshape the landscape of AI research (Pan, 2017). Among the popular research topics in the new generation AI, design intelligence, namely, artificial intelligence to solve creative problems and produce creative designs, has made significant progress in recent years. Researchers have developed design intelligence algorithms that can be used to transfer image styles (Gatys et al., 2016), produce menus (Pinel et al., 2015), refine layouts for graphic designs (O'donovan et al., 2014), and manipulate the contents of natural images (Zhu et al., 2016). These algorithms learn the rules and styles of training data in these domains to support large-scale design production. However, such algorithms have limited creative ability because they struggle to create novel designs that differ from the training data.

Crowdsourcing offers a promising method to enhance the creative ability of AI. Compared with techniques that rely solely on machine intelligence,

‡ Corresponding author

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ORCID: Ling-yun SUN, http://orcid.org/0000-0002-5561-0493

crowdsourcing integrates human inspiration with machines' computational ability to produce creative designs. Because crowds embody a variety of expertise, crowdsourcing can provide new insights that are beyond an organization's current body of knowledge (Michelucci and Dickinson, 2016). This approach has achieved great success in multiple domains (Li et al., 2017). Both governments and companies use crowdsourcing methods to collect ideas and feedback, providing guidance for policy-making and supporting product development. In the United States, the platform 'Challenges.gov' has launched over 700 crowdsourcing design competitions and awarded over 250 million dollars in rewards. Also, companies such as Starbucks and Dell have collected over 200 000 ideas.

These examples display the potential of crowdsourcing intelligent design. However, the quality of design ideas is not consistent. Most crowdsourcing methods follow a selection procedure in which they collect as many ideas as possible, and then select those of the highest quality. These methods thus simply wait for the emergence of high-quality ideas, with little interaction over the crowdsourced design. This leads to an inefficient process and produces variable results. For instance, many design competitions on websites, such as Zhubajie (http://www.zbj.com/) and Zhanku (http://www.zcool.com.cn/), are not effective because they did not collect high-quality submissions. Similarly, Starbucks collected thousands of design ideas while implementing less than one percent of them. This selection approach hinders the improvement of the performance of crowdsourcing in design creation.

We propose a crowdsourcing intelligent design method called 'flexible crowdsourcing design', and introduce a series of studies on the method to enhances its performance (Fig. 1). The flexible method uses a cultivation procedure to integrate crowd participants' ideas and cultivate these ideas until they evolve into high-quality ones. Compared with the selection procedure, flexible crowdsourcing design encourages participants to propose a variety of ideas, evaluates the development potential of ideas for promising design directions, and refines design ideas with high development potential rather than those of high quality, thus continually improving the originality of ideas. Therefore, the flexible crowdsourcing design method can produce highly original designs consistently and enhance the creative capacity of AI.

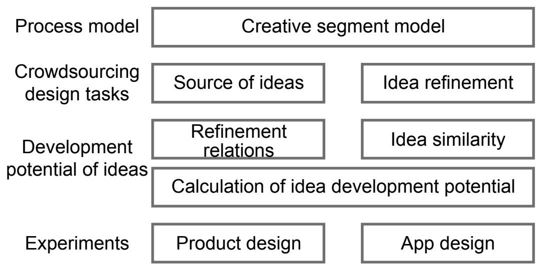


**Fig. 1 Flowchart of the flexible crowdsourcing design method**

## 2 Related work

Crowdsourcing involves recruiting a large number of participants via the Internet to complete tasks that a machine cannot perform independently. The vast data collected through crowdsourcing support many different applications, including image categorization (Wah et al., 2014), product fabrication (Lafreniere et al., 2016), movie rating (Zhao et al., 2016), human-computer interaction (Schneider et al., 2016), and medical diagnosis (Warby et al., 2014). These applications adopt a divide-and-conquer approach, in which task directors divide the tasks into small ones and then combine participants' fulfillments to finish each given task. Because design creation is an open and exploratory process that is hard to sub-divide (Cross, 2006), crowdsourcing directors instruct participants to submit their design ideas and choose the best designs.

### 2.1 Refinement of crowdsourcing design tasks

Crowdsourcing tasks affect the quality of participants' design ideas. Some researchers have incorporated design strategies into crowdsourcing tasks and turned to design experts for inspiration. Yu et al. (2016) studied four kinds of crowdsourcing task descriptions, and found that the combination of a detailed question and an abstract domain resulted in more creative ideas. Flores et al. (2015) instructed participants to use TRIZ during their design, and collected high-quality design ideas. Yu et al. (2014) also applied TRIZ to improve participant performance in crowdsourcing tasks. In their study, participants first collected existing design ideas that use TRIZ, and then applied TRIZ to solve new problems.

Experts' design approach is also a valuable reference for designing crowdsourcing tasks. Dontcheva et al. (2014) designed crowdsourcing tasks according to Photoshop guidelines. Kim et al. (2015) also summarized experts' patterns and then instructed participants to follow these patterns in crowdsourcing tasks. Xu et al. (2015) instructed participants to evaluate posters according to experts' feedback structures; the feedback was then provided to the original designers to improve the quality of posters. Besides expert strategies, researchers have recruited experts in crowdsourcing to offer participants timely guidance and instructions. Suzuki et al. (2016) asked experts to offer suggestions to participants during their development of software programs. Chan et al. (2016) recruited experts as directors in crowdsourcing design to whom participants submitted their ideas for feedback. Participants continued to generate design ideas based on expert feedback until they achieved satisfactory designs. These refinements of crowdsourcing tasks were effective in enhancing the quality of design ideas. However, they focused only on improving the performance of individual participants, ignoring the potential for collaboration among individuals. The quality of crowdsourcing results was thus limited by the capacity of individual participants.

### 2.2 Refinement of the crowdsourcing procedure

The crowdsourcing procedure is another factor that affects the quality of crowdsourcing results. Crowdsourcing tasks are simpler than a standalone design; design also involves broad information searches, constant communication (Wiltschnig et al., 2013), and continual refinement of design ideas (Pieter et al., 2013). Researchers have arranged crowdsourcing procedures to integrate participants' ideas (Ren et al., 2014). Yu and Nickerson (2011) imported a generative algorithm into their crowdsourcing design; participants refined the highest-quality ideas of the prior generation, and submitted their ideas for further selection.

Apart from idea refinement, crowdsourcing researchers arranged nominal and actual groups so that participants could complete complex design tasks. Chang et al. (2014) employed a divide-and-combine procedure, in which participants proposed design ideas for specific functional needs, and then combined these ideas to build the final designs. This method performed well for design optimization of mature products. Park et al. (2013) proposed a platform on which participants joined designer teams and competed together to become the final winning team. Ikeda et al. (2016) built a similar platform to organize online groups and support group communication. Using groups as the basic organizing unit to complete tasks, these methods support the crowdsourcing of more complex design tasks.

In summary, existing crowdsourcing methods generally follow a selection procedure. They improve the quality of final results through enhancing the quality of participants' submissions, and select one of the highest quality. Even in crowdsourcing methods that assemble groups, the groups still submit design ideas and compete to provide the final winning result. The selection procedure remains focused on the quality of submissions and has little influence on the crowdsourcing process. In contrast, we assume a more holistic perspective of crowdsourcing, and propose a cultivation method called 'flexible crowdsourcing design'. This method involves designing crowdsourcing tasks and refining crowdsourced ideas according to the status of the ideas, in a way that consistently improves the originality of ideas.

## 3 Flexible crowdsourcing design method

### 3.1 Procedure of flexible crowdsourcing design

Flexible crowdsourcing design supports collaboration and mutual inspiration among participants and evaluates the development potential of design ideas to find promising design directions. It then encourages refinement of these designs to continually enhance their quality. In this way, the method can produce creative designs consistently. This method includes three flexible features.

First, the method proactively evaluates the development potential of design ideas through combining multiple indicators involving idea distribution, idea relationships, and idea quality. It arranges design tasks to refine ideas that have high development potential rather than those that simply have high quality.

Second, this method employs adaptive crowdsourcing tasks to engage participants with different backgrounds and then integrates their design ideas. It instructs participants to design from their individual area of expertise, and optimizes crowdsourcing tasks to inspire participants with each other's designs.

Third, this method employs responsive and dynamic criteria to evaluate the ideas. The criteria involve idea distribution, idea relationships, and idea quality, and change with the status of the crowdsourcing ideas. Therefore, these criteria prioritize ideas that meet the needs of current conditions.

The flexible crowdsourcing design method has three parts: idea generation, evaluation of idea development potential, and task publication (Fig. 2). During idea generation, participants scan ideas that have high development potential scores, refine these ideas, and propose new design ideas. In the evaluation of idea development potential, the crowdsourcing system evaluates the quality of design ideas, calculates the similarity distribution of ideas, records the refinement relations among ideas, and calculates the development potential score for each idea. In task publication, the system ranks ideas according to their development potential scores, and arranges tasks to refine and evaluate these ideas.

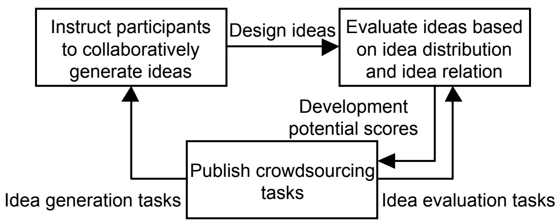


**Fig. 2 Three parts of the flexible crowdsourcing design method**

Consider an example of crowdsourcing chair design. Crowdsourcing methods based on a selection procedure import design strategies (for instance, usage scenario, ergonomics) into their crowdsourcing tasks and choose high-quality ideas to refine, producing ordinary ideas such as 'ergonomic chairs' or 'chairs with memory foam'. In contrast, the flexible crowdsourcing design method encourages participants to produce design ideas using their own professions and experiences. The system then analyzes the idea distribution and idea relationships to prioritize the refinement of ideas with high development potential. This method produces ideas that import new design criteria other than traditional ergonomics, such as 'chairs that adjust the emotional states of patience' and 'multi-functional chair for children's education'.

A typical flexible crowdsourcing design procedure proceeds as follows (Fig. 3):

1. Publish idea generation tasks based on the requirements of the design project and collect the initial design ideas.

2. Publish idea evaluation tasks. Publish similarity evaluation tasks and calculate the similarity distribution. Publish quality evaluation tasks. In the first round of quality evaluation, the system calculates the quality scores. In the following rounds, the system first filters out ideas with low quality scores and then publishes quality evaluation tasks.

3. Stop crowdsourcing if the ideas satisfy the project requirements; otherwise, go to step 4.

4. Calculate the development potential of ideas according to their similarity distribution, refinement relations, and quality scores.

5. Prioritize ideas with high development potential and publish idea generation tasks. Participants refine these referent ideas and propose new design ideas. Go to step 2.

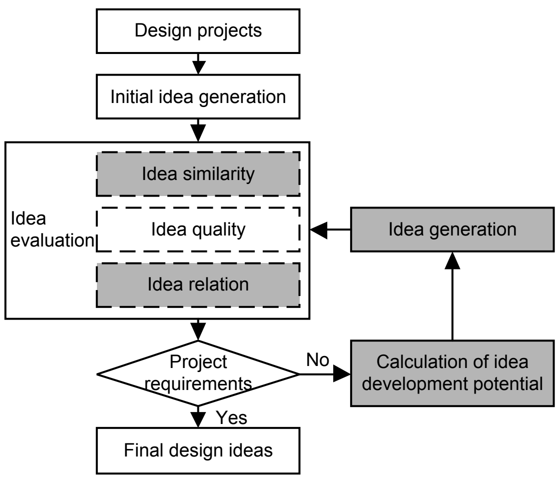


**Fig. 3 Typical procedure of the flexible crowdsourcing design method. The rectangles with dark background show the steps that are unique to this approach**

Whenever a participant joins in, the system allocates idea generation tasks or evaluation tasks according to the current progress of crowdsourcing. The system calculates the development potential of ideas and generates tasks at pre-defined intervals, guiding the design directions of the crowd.

The pseudo code of flexible crowdsourcing design is given in Algorithm 1.

**Algorithm 1 Flexible crowdsourcing design**

**Input:** requirements of design projects
**Output:** submitted design ideas SI, idea quality score Qua, idea similarity score Sim, and idea development potential score Pot

```
// initialization
r←the proportion of ideas that would be developed
m←the number of tasks in each round
t←the number of reference ideas presented in each idea generation task
QR←quality requirement in this project
RI←referent ideas
n=0
repeat
 // idea generation
 for j=1 to m do
   if 1st round then
     SI_j←submitted idea
   else
     Sample t ideas from RI, present the t ideas, and collect submitted ideas
     Si_{n+j}←submitted idea
   end if
 end for
 n←the number of round×m
 // idea evaluation
 Publish quality evaluation and similarity evaluation tasks
 Qua_{1:n}←Quality(SI_{1:n})
 Sim_{1:n}←Similarity(SI_{1:n})
 if Qua matches the QR then
   Terminate this program
 else
   // calculation of idea development potential
   for j=1 to n do
     Pot_j←Potential(Qua_j, Sim_j)
   end for
   RI_{1:n×r}←Select n×r ideas from SI that have top development potential scores
 end if
 return SI, Qua, Sim, Pot
until ideas of the highest quality do not change
```

The calculation of idea quality scores, similarity scores, and development potential scores is described in Section 3.4.2. In the following sections we introduce the components of the flexible crowdsourcing design method.

### 3.2 A process model applied to flexible crowdsourcing design

Crowdsourcing involves a large number of design ideas. We need a model that can describe the evolving process from the initial inspiration to the final idea to analyze the key factors of crowdsourcing intelligent design that support participants' collaborative idea generation. Most existing design models focus on the design solutions or design activities, and cannot support analysis of the crowdsourcing design process. This section describes the creative segment model (Sun et al., 2014a), a process model that describes design as the evolution and combination of creative inspiration. If we can describe the design process using the creative segment model, we can then apply this model to crowdsourcing design. From this perspective, we can think about crowdsourcing intelligent design as a holistic design process, in which the final ideas evolve from participants' mutual inspiration. This holistic design process supports participant collaboration and idea cultivation.

The creative segment model describes design as a tree of creative segments. Designers come up with 'inspirations' during the design process, where each inspiration is a breakthrough that reveals new design possibilities. Creative segments refer to the segments of time and effort during which the inspirations emerge. If we use a tree structure to organize the emergence of these creative segments, the tree grows with the design process and the 'leaves' of the tree finally produce satisfactory ideas. Examples of creative segments and creative segment trees could be referred to Sun et al. (2014a, 2014b).

Two experiments to examine the validity of the creative segment model for the design process were described in Sun et al. (2014a, 2014b). Specifically, we analyzed designers' activities and eye movements around creative segments. It was found that designers displayed activity modes that centered on the inspiration of creative segments. They displayed such exploratory activities prior to creative segments as text description and scanning, and such explanatory activities after creative segments as idea evaluation and application.

Designers' eye movements also centered on the inspirations of creative segments. They reviewed prior inspirations before creative segments, and exhibited longer fixations during creative segments. After those creative segments, designers continued to focus on the inspirations for a while before turning to other exploratory content.

In summary, designers' activities and eye movements marked key outputs during the design process, which could be described by a creative segment model. Given this validation of the model for the basic design process, we chose to use the creative segment model to model the organization of participants in a crowdsourcing design process. Participants' ideas correspond to 'inspirations' in the creative segment model. While ideas may not satisfy all the design requirements, they can be used to inspire other ideas (inspirations) that eventually yield satisfactory results. The flexible crowdsourcing design method must fulfill two key functions: (1) refining crowdsourcing tasks to support mutual inspiration and idea evolution and (2) evaluating the ideas to find appropriate design paths to more creative outcomes.

We discuss the design of these functions in the next two subsections.

### 3.3 Crowdsourcing design tasks

Effective crowdsourcing requires participants produce diverse ideas and effectively refine ideas to support idea evolution. We studied characteristics of participants, and then designed crowdsourcing tasks that accounted for their sources of ideas and idea refinement processes.

#### 3.3.1 Source of ideas

We first conducted a short survey to identify sources of ideas in idea generation tasks. We found three main sources: (1) professional knowledge, which is the knowledge and techniques related to participants' professions; (2) personal experience, which is the experience learned in daily life; (3) related information, which is the information learned through web and other media.

We designed three crowdsourcing tasks that required participants design ideas based on their professional knowledge, personal experience, and related information, respectively, and compared the results of these three tasks with a basic task that had no requirements.

We conducted an experiment involving 307 crowd participants on Amazon Mechanical Turk to examine the effectiveness of crowdsourcing tasks. The results indicated that participants performed the three refined tasks better than the basic task. Participants who undertook the three refined crowdsourcing tasks submitted more detailed descriptions, and proposed more varied, more original, and more useful ideas. Therefore, we concluded that instructing participants to use specific sources of knowledge in their designs produced more diverse and creative ideas.

#### 3.3.2 Idea refinement in crowdsourcing design tasks

Crowdsourcing the idea generation task required less time and effort than an individual design process. However, participants only submitted ideas and did not know each other, and this limited the refinement of ideas. Therefore, we added a reflection step in the idea generation task to help participants understand and refine ideas. Specifically, this idea generation task required participants reflect after describing their ideas. Participants first submitted their ideas, and then described the features, intent, and possible limitations of their ideas. Subsequently, other participants could check these reflections to fully understand the earlier ideas and refine them.

We conducted a design experiment involving 241 participants on Amazon Mechanical Turk to compare this idea generation and reflection task with the basic idea generation task. Participants in round 1 proposed ideas, and those in round 2 refined the ideas from round 1. The change in idea quality between the two rounds showed the relative effectiveness of these two tasks. Specifically, the results showed a larger quality improvement when using the idea generation and reflection task versus using the idea generation task without the reflection step.

#### 3.3.3 Steps in idea generation tasks

In a conventional idea generation task, crowdsourcing participants simply propose their ideas.

Based on the experimental results, the refined idea generation task includes the following steps:

1. Participants scan the referent ideas and review their descriptions, which include the features, intent, and limitations of each idea.

2. Participants recall their professional knowledge and personal experience, search for related

information, and propose their new ideas.

3. Participants reflect on the features, intent, and limitations of ideas.

The optimized idea generation task pushes participants to generate ideas based on their own knowledge and then reflect on their ideas. This enhances the variety of ideas and supports idea refinement. Therefore, this task supports idea cultivation in crowdsourcing design.

### 3.4 Development potential of ideas

The evaluation criteria for the flexible crowdsourcing design method need to focus on further development of ideas to cultivate new ideas. We use the concept of development potential to represent the possibility that an idea inspires new ideas with higher quality scores. Through constantly refining ideas with high development potential, we can build design paths on which the quality of ideas is continually improved. Therefore, development potential scores indicate promising design directions for the current status of the crowdsourcing. In this section, we first introduce two factors that affect the development of ideas, and then offer a formula to calculate the development potential scores.

#### 3.4.1 Factors affecting the idea development process

Two prior studies have explored the effect of refinement relationships and idea similarity on the development of ideas (Sun et al., 2015; Xiang et al., 2017). The first study explored the features of ideas that encouraged further refinement. It displayed the refinement relationships among ideas, and examined whether high-quality ideas could inspire other high-quality ideas subsequently in the crowdsourcing process. Specifically, this study developed an iPad app to collect crowdsourcing ideas and arrange them into an idea tree according to their refinement relationships (Sun et al., 2015). Fig. 4 shows the interface of this app. Crowdsourcing participants chose ideas on the tree to refine and proposed new ideas; these ideas were then marked and became nodes on the tree, available for further refinement.

In this study, a crowdsourcing experiment was conducted to analyze participants' refinement behaviors and the change in the quality of ideas during idea refinement. Participants proposed a total of 90 ideas and produced an idea tree with 20 branches.

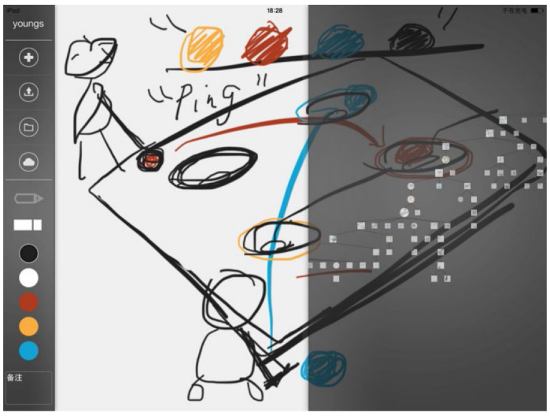

**Fig. 4 Interface of an iPad app that displays refinement relationships**

The results showed that the final high-quality ideas did not correspond to earlier high-quality ideas. Instead, ideas of lower initial quality attracted more refinements than those of higher quality and were improved more. The development paths of the best ideas displayed similar results. The best ideas originated from several rounds of refinement and appeared near the end of the branches; some of them even originated from early low-quality ideas. Therefore, ideas with moderate and lower quality scores, rather than those with high-quality scores, appear to offer more inspiration for improvement and present better opportunities to evolve creative ideas.

The second study proposed a crowdsourcing generative algorithm (CQ) that considers both idea similarity and idea quality (Xiang et al., 2017). Specifically, this algorithm recruits design experts to categorize ideas and evaluate the quality of ideas, and attaches greater importance to high-quality ideas in categories having fewer ideas. In this way, the crowdsourcing design guides a balanced exploration.

Using this approach, we conducted an experiment on Amazon Mechanical Turk to compare two generative algorithms. The CQ algorithm filtered ideas on the basis of both the category of an idea and the idea quality. The basic generative algorithm (Q) filtered ideas only according to their quality. The crowdsourcing procedure of both algorithms was identical except for the filtering criteria. During each round of idea generation, the two algorithms selected the same number of ideas and recruited participants to refine them. During this experiment a total of 281 ideas were collected through three rounds of crowdsourced idea generation, and then the number of idea categories and the quality of ideas produced by the two algorithms were compared.

The results showed that the CQ algorithm (filtering on category and quality) outperformed the Q algorithm (filtering on quality only), producing more categories of ideas and more high-quality ideas. Analysis of the process for developing ideas revealed that the quality-only algorithm selected similar high-quality ideas to refine, which limited idea diversity in later rounds (Table 1). In contrast, the CQ algorithm increased the priority of unique ideas and reduced the possibility of selecting similar high-quality ideas, thus inspiring new thoughts over a wide and balanced exploration space during the three rounds of idea generation, and producing high-quality ideas.

### 3.4.2 Calculation of idea development potential

The two prior studies revealed two factors that affect idea development. The study of refinement relationships demonstrated that idea quality affected development potential in a nonlinear way. The study on idea similarity demonstrated that the distribution of ideas affected the quality of final ideas emerging from a crowdsourcing design process; crowdsourcing processes producing ideas of high similarity got stuck easily. For the calculation of the development potential of ideas, both factors were thus considered.

The calculation of development potential scores required evaluation of both idea quality and idea similarity. In crowdsourcing design, the evaluation of a large number of ideas exceeded the capacity of a group of experts. Therefore, the evaluation method used crowd participants to evaluate ideas and then integrated their evaluation results.

We used pairwise comparison in the crowdsourcing evaluation. Compared with other evaluation methods requiring scores, pairwise comparison was more stable because it involved only a relative judgement, which was suitable for crowd participants with varied opinions. Participants in qualityevaluation tasks chose one of two ideas that was more original. Participants in similarity evaluation tasks scanned the referent idea, and then chose up to five out of six candidate ideas that were similar to the referent idea. We then used the Glicko system to calculate the originality scores of ideas (Glickman, 1999), and employed the T-STE algorithm to calculate the similarity scores of ideas (Maaten and Weinberger, 2012). The Glicko system regarded the comparison between two ideas as a competition; the winner gained scores while the loser loses scores. Then, the scores were normalized to give an originality score for ideas. The T-STE algorithm calculated the coordinates of ideas in a two-dimensional space on the basis of the similarity among them. The average distance of the nearest ideas represented the similarity of an idea to other ideas. The development potential of an idea was then calculated using the following formula:

$$s_{\mathrm{io}} = (-r_{\mathrm{io}}^2 + c_1 f_i) - \delta\left|-r_{\mathrm{io}}^2 + c_2 f_i\right|, \tag{1}$$

$$f_i = \frac{1}{m}\sum_{j=1}^{m}\left\|X_i - X_j\right\|^2, \tag{2}$$

$$\delta = \begin{cases} c_2 t, & t \ge t_{\mathrm{c}}, \\ 0, & t < t_{\mathrm{c}}, \end{cases} \tag{3}$$

where $s_{io}$ indicates the development potential score, $r_{io}$ the originality score, $f_i$ the similarity score of ideas,

**Table 1 The ideas that CQ and Q algorithm chose to refine**

| Top-ranked ideas (Q) | Category | Adjusted top-ranked ideas (CQ) | Category |
|---|---|---|---|
| Chair that has safety belt | Chair | Use current to stimulate muscle | Current |
| Chair that has modular back | Chair | Monitor users' attention | Eye |
| Chair with ropes | Chair | Chair that has safety belt | Chair |
| Chair with belts | Chair | Chair that has modular back | Chair |
| Chair with bendable back | Chair | Sensors that measure posture | Sensor |
| Chair with hooks and loops | Chair | Sensors that measure pressure | Sensor |
| Chair with waist pillow | Chair | Back belts | Belt |
| Use current to stimulate muscle | Current | Belts that adjust itself to users' posture | Belt |
| Sensors that measure posture | Sensor | Timer that reminds exercise | Timer |
| Sensors that measure pressure | Sensor | Board that supports the body | Board |

which is the average distance of $m$ nearest ideas, $X_i$ and $X_j$ the coordinates of ideas, $c_1$ and $c_2$ adjust the weight between originality scores and similarity scores of ideas, and $\delta$ adjusts the development potential of ideas according to the referential times of ideas. After an idea have been presented $t_c$ times, the development potential score of $\delta$ decreases.

## 4 Experiments

In this section we introduce the application of the flexible crowdsourcing design method in two design contexts involving product design and app (mobile application) design. The crowdsourcing process in both contexts involved three rounds of idea generation, in which each generation refined the top 40% of prior ideas ranked according to their development potential scores. The crowdsourcing task and the number of ideas collected during crowdsourcing processes are listed in Table 2.

**Table 2 Number of ideas collected in each round**

| Crowdsourcing task | Number of ideas collected | | | Total number |
|---|---|---|---|---|
| | Round 1 | Round 2 | Round 3 | |
| Robot that accompanies kids | 30 | 40 | 59 | 129 |
| App that makes user happy | 30 | 39 | 66 | 135 |

The flexible crowdsourcing design method performed well in both contexts. Figs. 5 and 6 show the similarity distribution of product ideas and app ideas. The design space continually expanded with the crowdsourcing process. The designs collected in round 1 were located in the center of the graph, while those collected in rounds 2 and 3 were more distributed. Note that some of the later ideas were similar to those in round 1, indicating that the flexible crowdsourcing design method kept refining existing inspirations while exploring new spaces. We then analyzed the design directions that participants proposed during crowdsourcing. In Fig. 5, among the six design

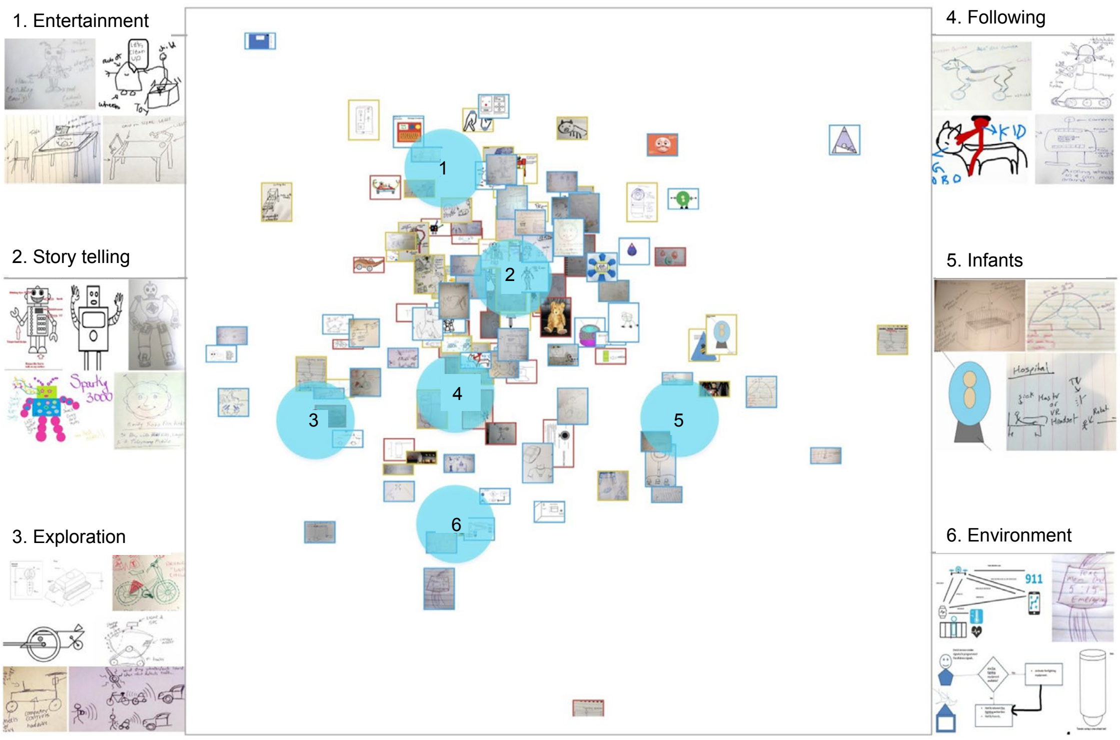


**Fig. 5 Similarity distribution of product ideas**

Ideas in round 1 were marked with a red border, ideas in round 2 were marked with a yellow border, and ideas in round 3 were marked with a blue border. References to color refer to the online version of this figure

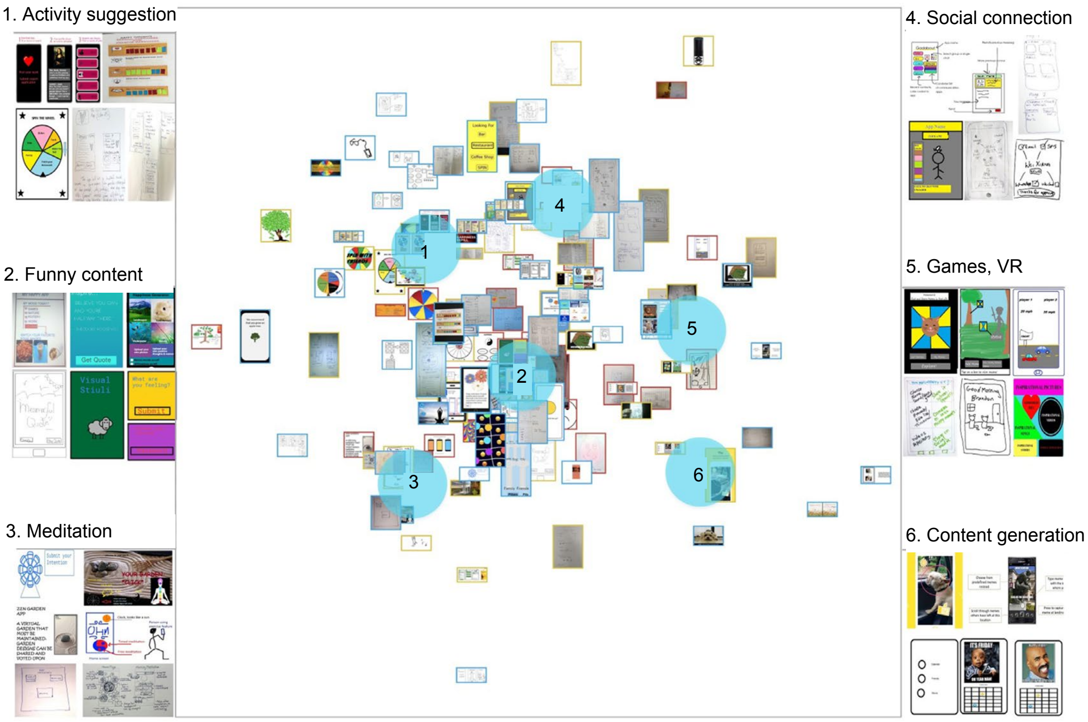


**Fig. 6 Similarity distribution of app ideas**

Ideas in round 1 were marked with a red border, ideas in round 2 were marked with a yellow border, and ideas in round 3 were marked with a blue border. References to color refer to the online version of this figure

directions for product design, two (directions 2 and 4) started from round 1 and kept producing new ideas, while the other four directions emerged from later rounds of idea generation. A similar pattern appeared among the six design directions for app design (Fig. 6); three (directions 2, 3, and 4) started from round 1 and the other three directions emerged in later rounds.

In addition, the flexible crowdsourcing design method continually increased the originality of highly original ideas. In Fig. 7, ideas collected in later rounds had more highly original ideas. In both the product design and app design applications, the 10 most original ideas also appeared in later rounds (Table 3).

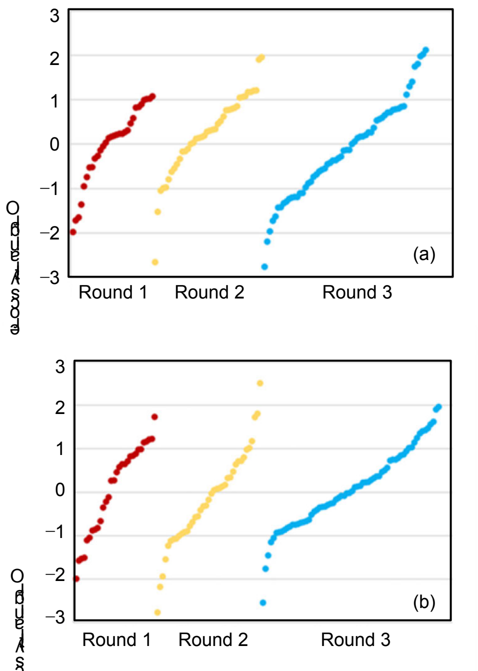


**Fig. 7 Originality scores of product ideas (a) and app ideas (b)**

**Table 3 Ten most original ideas in product design and app design**

| Application | Number of most original ideas | | |
|---|---|---|---|
| | Round 1 | Round 2 | Round 3 |
| Product design | 0 | 3 | 7 |
| App design | 1 | 3 | 6 |

The development process for achieving these highly original ideas could be separated into two pathways. One pathway involved continual refinement of ideas that had high originality. The second pathway involved large modification of ideas that had moderate originality and high dissimilarity. These latter ideas were unique, inspiring new design directions and producing highly original ideas. For example, during the crowdsourcing process for designing an app that makes the user happy, one participant proposed an app that used multiple ways to contact a person. This app idea was not very original, while it attended to interpersonal communication. Then, another participant refined this idea and proposed that an app could analyze a user's previous communication data and recommend the best way to communicate with a specific person, thus enhancing their communication effectiveness and making the user happy (Fig. 8). This refined app obtains a high originality score.

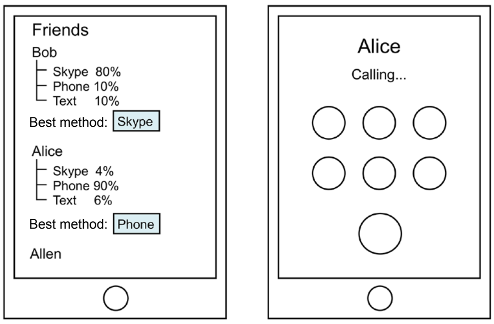


**Fig. 8 Interfaces for an app idea that makes the user happy**

## 5 Discussion

The flexible crowdsourcing design method takes a holistic perspective to continually produce creative ideas. In this section, we compare this crowdsourcing intelligent design method with prior individual and collaborative design approaches, and analyze the design capacities offered by this method. We explain these design capacities as follows:

1. Previous design studies have reported that expert designers search ubiquitous inspirations to develop and refine (Goldschmidt, 2015). The crowdsourcing intelligent design method engages multiple sources of professional knowledge, experience, and information, to produce a variety of ideas. This provides a rich database for further refinement that might offer a larger design space than that of individual designers.

2. Design studies have found that a large number of creative ideas originated from designers' rechecking their earlier ideas (Prats and Earl, 2006). When designers reinterpreted these ideas according to the current design status, they gained new insights. The crowdsourcing intelligent design method formalized this reinterpretation process. We analyzed the idea development process and found two factors that affected further development of ideas. Therefore, the development potential of ideas might explain part of designers' selection criteria when reinterpreting ideas. Moreover, development potential is a responsive criterion that changes with crowdsourcing status, thus matching designers' reinterpretation behaviors. In this way, this crowdsourcing intelligent design method improves design capabilities around status evaluation and idea reinterpretation.

3. Design studies have reported that designers applied a breadth-first design strategy and a rapid depth-first exploration to effectively propose design ideas (Ball and Ormerod, 1995). These two strategies corresponded to the two development pathways of achieving highly original ideas during crowdsourcing intelligent design. The crowdsourcing intelligent design method thus followed a balanced exploration process that was effective in producing creative ideas.

In general, the crowdsourcing intelligent design method broadens the design space, employs reliable criteria for status evaluation and for calculating idea development potential, and follows an effective exploration strategy. These features equip our flexible crowdsourcing design method with a high design capacity, which effectively organizes crowd participants to design and develop creative ideas, and thus improves the creative capacity of AI.

## 6 Conclusions

We have described a series of studies on a crowdsourcing intelligent design method called 'flexible crowdsourcing design'. This flexible method refines participants' crowdsourcing tasks to produce varied and original ideas, evaluates the development potential of ideas based on the status of all ideas, and leads to the development of ideas that inspire the original design solutions. The empirical applications of the method have demonstrated that it continually broadens the design space and produces highly original ideas, thus increasing the creative capability of crowd intelligence.

The flexible crowdsourcing design method employs a holistic perspective in the guidance of crowd intelligence. It adjusts design directions according to the status of crowdsourcing and effectively discovers the most valuable ideas during design. Future research possibilities include proposing new crowdsourcing intelligent design methods and combining this method with knowledge databases to improve the creative capability of new generation AI.

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