Exploring the effects of different achievement goals on contributor participation in crowdsourcing

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Abstract

Purpose – This study examines how contributors with different achievement goals participate under the influence of two common motivators/demotivators on crowdsourcing platforms, namely system design features and task nature.

Design/methodology/approach – A free simulation experiment was conducted among undergraduate students with the use of a crowdsourcing platform for two weeks.

Findings – The results indicate that contributors with a strong performance-approach goal get better scores and participate in more crowdsourcing tasks. Contributors with a strong mastery-avoidance goal participate in fewer heterogeneous tasks.

Research limitations/implications – Contributors with different achievement goals participate in crowdsourcing tasks to different extents under the influence of the two motivators/demotivators. The inclusion of the approach-avoidance dimension in the performance-mastery dichotomy enables demonstrating the influence of motivators/demotivators more specifically. This article highlights differentiation between the quality and the quantity of heterogeneous crowdsourcing tasks.

Practical implications – Management is advised to approach performance-approach people if a leaderboard and a point system are incorporated into their crowdsourcing platforms. Also, management should avoid offering heterogeneous tasks to mastery-avoidance contributors. System developers should take users' motivational goals into consideration when designing the motivators in their systems.

Originality/value – The study sheds light on habitual achievement goals, which are relatively stable in comparison to contributors' motives and states. The relationships between achievement goals and motivators/demotivators are more persistent across time. This study informs system designers' decisions to include appropriate motivators for sustained contributor participation.

Keywords Crowdsourcing, Achievement goals, Motivators, Homogeneous crowd rating, Heterogeneous crowd solving

Paper type Research paper

1. Introduction

Crowdsourcing harnesses the intelligence and efforts of the crowd, a large pool of "everyday people using their spare cycles to create content, solve problems, even do corporate R & D (research and development)" (Howe, 2006, p. 1). As a concept extended from outsourcing, crowdsourcing aims to reduce operational and recruitment costs as well as utilize the collective wisdom of a large population (Surowiecki, 2005). Crowdsourcing has been commonly adopted in various industries (Estellés-Arolas and González-Ladrón-de-Guevara, 2012). A variety of tasks have been posted on crowdsourcing platforms. For example,

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organizations can outsource trivial tasks to the crowd through crowdsourcing systems like Amazon Mechanical Turk. Learners can post questions and answer enquiries on crowdsourcing websites such as Stack Overflow and ResearchGate. Travelers can rate hotels and tourist spots on crowdsourcing platforms (e.g. TripAdvisor). Some crowdsourcing tasks are rather trivial. The work quality of these tasks is not a concern. Some tasks, on the other hand, require creativity and domain knowledge. The work quality of these tasks varies among contributors.

One common problem faced among crowdsourcing platforms is low and non-sustained participation by contributors (Sun *et al.*, 2012). Accordingly, researchers have explored how to motivate contributors to participate more on the crowdsourcing platforms. Whereas some previous studies have focused on the influence of various motivators on general contributor participation, (e.g. Feng *et al.*, 2018; Wu and Gong, 2020; Ye and Kankanhalli, 2017), this study sheds light on differences in contributors' motivational goals. The study delves into the orientation of achievement goals (Elliot and McGregor, 2001), one habitual pattern of motivational goals and investigates the influence of achievement goals on contributor participation on crowdsourcing platforms. The achievement goal orientation is developed in infancy and is stable over time (Elliot and McGregor, 2001; Elliot and Thrash, 2010). This stability supports the orientation as a more persistent predictive factor of sustained participation in comparison to contributors' dynamic motives or states.

We propose that contributors with different achievement goals behave differently under the influence of motivators/demotivators that are incorporated into crowdsourcing platforms. We argue that not only the system design features but also the task nature may result in different levels of participation by contributors with different achievement goals. Specifically, this study aims to address the following research question: How do achievement goals affect user participation in different types of tasks in a crowdsourcing system environment? The answers to this question will inform system designers' decisions to incorporate appropriate motivators into crowdsourcing platforms. The focal motivators/demotivators in this study include a typical system design feature in crowdsourcing environments, namely a leaderboard together with a point system (Morschheuser *et al.*, 2017), and a typical nature of crowdsourcing task offered on the crowdsourcing platforms, namely the heterogeneity of the tasks (Geiger *et al.*, 2012).

Performance achievement goals are concerned with comparison with counterparts (Ames, 1992; Dweck, 1986). We propose that contributors with a strong performance-approach goal participate more under the influence of a leaderboard. This system design feature creates an environment in which contributors can compare themselves with others and gain a sense of achievement. The contributors with a strong performance-approach goal tend to participate more to collect points in the system so that they can show their presence on the leaderboards and seek attention from other contributors (Kaufmann *et al.*, 2011; Lakhani and Wolf, 2005; Weiss, 1995). They are more easily motivated by the positive sense of achievement gained from social comparison (Bargh *et al.*, 2001; Shah, 2003).

Mastery achievement goals are concerned with self-perception and evaluation (Ames, 1992; Dweck, 1986). Mastery-avoidant contributors tend to prevent themselves from negative self-judgment of their abilities and avoid making mistakes (Elliot and McGregor, 2001), so these contributors are rather demotivated by heterogeneous tasks, such as brainstorming tasks, which commonly have no standard correct answers. They likely consider a heterogeneous task to be a threat rather than a positive challenge (Icekson *et al.*, 2014). Given that the contributors have their own choices of work in crowdsourcing settings, we propose that contributors with a strong mastery-avoidance goal tend to participate in fewer heterogeneous crowdsourcing tasks and perform worse in these tasks than contributors with other achievement goals do.

To uphold the fundamental principle that contributors can follow their own work preferences and choose their own work tasks (Geiger and Schader, 2014), we conducted a two-week free simulation experiment among undergraduate students in a computer science

course. The undergraduate students were invited to use a crowdsourcing system which had a leaderboard and a point system, and they were allowed to follow their own preference to choose their work tasks. The students' achievement goal orientation (Elliot and McGregor, 2001) and creative self-efficacy (Tierney and Farmer, 2002) were measured by surveys before they used the system, and the students' participation in both crowd-rating and crowd-solving tasks over the two-week duration was recorded.

This study aims to make several contributions. On theoretical contribution, the study provides us with a better understanding of the interplay between achievement goals and two motivators/demotivators that are commonly incorporated in crowdsourcing platforms. The motivators/demotivators on the platforms are not effective for all types of people to the same extent. Also, in contrast to some previous studies that consider completion of a task as resulting product of contributors' functions of positive motivations, we shed light on the negative possibility that task nature can exist as a demotivator to contributor behaviour.

In addition, the inclusion of the approach-avoidance dichotomy enables us to demonstrate that the influence of the motivators/demotivators on the approach-avoidance dimension of an achievement goal is not symmetrical. The results of the study highlight the consideration of the approach-avoidance dimension and the corresponding perceived positive/negative possibilities generated by various motivators/demotivators in the context of crowdsourcing.

Lastly, this study reveals that the quality and quantity of completed crowdsourcing tasks are not necessarily positively or negatively correlated. In this study, we show that the desire of performance-approach contributors to get more points than others on the platforms does not lead to deterioration of work quality. Also, mastery-avoidance contributors' work quality of heterogeneous tasks is not significantly worse in comparison to others, even though they work on fewer heterogeneous tasks.

On managerial contribution, we suggest that the management of crowdsourcing platforms can improve and maintain contributors' participation rate in two ways. Provided that the platforms consist of a leaderboard and a point system, management should approach people with a performance-approach goal and invite them to be contributors in order to improve the initial contributor participation rate. After the recruitment process, the management should cautiously select suitable tasks for contributors with different achievement goals. They should avoid offering heterogeneous tasks without explicit model answers to mastery-avoidance contributors in order to maintain a good participation rate.

The rest of the paper is organized as follows: Section 2 reviews related work on individual differences in crowdsourcing, background literature on achievement goals, related work on system design features in crowdsourcing and different types of crowdsourcing tasks. Section 3 develops and presents our hypotheses. Section 4 introduces the design of our study and presents our data analysis methods and results. We discuss our findings and the theoretical and practical implications of our study in Section 5, and we conclude our paper with some suggestions for future research in Section 6.

2. Literature review

2.1 Individual differences in crowdsourcing and achievement goals

Efforts have been made to examine the effects of contributors' personal characteristics on their participation on crowdsourcing platforms. Some researchers have focused on personal skills and knowledge (e.g. Dissanayake *et al.*, 2015; Liu *et al.*, 2014; Lee *et al.*, 2018; Majchrzak *et al.*, 2013), some have examined the role of individual task preferences (e.g. Alam and Campbell, 2017), some have investigated contributors' proximity to the tasks (e.g. Miao *et al.*, 2016; Pee *et al.*, 2018; Wu *et al.*, 2018) and some have examined the effect of contributor group heterogeneity (e.g. Qiu *et al.*, 2020). These previous studies indicated that not all people participate to the same extent in a crowdsourcing environment.

Since crowdsourcing contributors enjoy much freedom to choose their work tasks (Geiger and Schader, 2014), how to motivate contributors becomes a key issue in the adoption of crowdsourcing. In particular, low and non-sustained participation by contributors has been a common problem among crowdsourcing platforms (Sun *et al.*, 2012). Previous studies have discovered some underlying motivations of contributors. Eickhoff *et al.* (2012) found that contributors could be classified as either entertainment-motivated or money-motivated. Montola *et al.* (2009) interviewed contributors of a photo-sharing mobile application and identified three different types of attitudes toward achievement in the mobile application: indifferent users, confused users and appreciative users.

Background information of contributors' habitual motivational goals, such as achievement goals, enables the management of crowdsourcing platforms to evaluate the persistent effects of different motivators/demotivators on different contributors. An achievement goal is defined as "an integrated pattern of beliefs, attributions, and affect that produces the intentions of behavior" (Ames, 1992, p. 261). It is concerned with the underlying aims of achievement behaviour. Various dimensions have been proposed to measure individuals' achievement goals. One traditional dimension is mastery-performance. These two goals represent different concepts of success and approaches adopted to reach successful outcomes (Ames, 1992). The mastery goal is concerned with people improving their abilities and mastering new skills. The performance goal, on the other hand, focuses on individuals gaining a sense of achievement through comparison against their counterparts (Dweck, 1986).

Elliot and McGregor (2001) proposed the approach-avoidance dimension and integrated it into the mastery-performance dichotomy. Approach motivation features active acquisition of positive outcomes, whereas avoidance motivation highlights avoidance of negative possibilities. The two motivations differ in their sensitivity towards positive environmental cues (e.g. rewards, senses of recognition) and negative environmental cues (e.g. punishment, fear of losses).

Elliot and McGregor's framework outlines four achievement motivations, namely mastery-approach, mastery-avoidance, performance-approach and performance-avoidance (see Table 1). The goal orientation is developed in infancy and is stable over time (Elliot and McGregor, 2001; Elliot and Thrash, 2010). When people encounter stimuli in terms of valence, valence-based processing will respond reflexively without awareness or intention. Individuals differ in their orientation of achievement goals.

Scholars have explored the relationships between achievement goals and creativity performance. A number of previous studies found that approach-oriented people perform better in creativity work, and avoidance-oriented people's innovative performance is relatively mediocre (Friedman and Forster, 2005; Elliot *et al.*, 2009). It was argued that approach-oriented people are more creative, given that these people are more sensitive to positive environment cues and therefore can easily experience positive emotion which is an antecedent of innovation (Baas *et al.*, 2008; Johnson *et al.*, 2013). On the other hand, some studies of achievement goals in contexts other than crowdsourcing revealed possible linkages between the mastery-approach goal and creativity performance (e.g. Lu *et al.*, 2012; Miron-Spektor and Beenen, 2015). These studies argued that creativity tasks can enhance self-development and therefore mastery-approach contributors are more interested in working on the tasks.

Table 1.
The 2 × 2 achievement goal framework (adapted from Elliot and McGregor, 2001)

		Definition	
		Mastery	Performance
Valence	Positive (Approaching Success)	Mastery-approach Goal	Performance-approach Goal
	Negative (Avoiding Failure)	Mastery-avoidance Goal	Performance-avoidance Goal

2.2 System design features in crowdsourcing

Developers of crowdsourcing platforms design various system features to create a motivating environment that is conducive to contributor performance. A point system together with a leaderboard is one typical motivational system design feature in crowdsourcing (Morschheuser *et al.*, 2017). Leaderboards and point systems have been recommended to enhance contributor performance in various studies (Dissanayake *et al.*, 2019; Feng *et al.*, 2018; Lee *et al.*, 2013). Contributors' attention to the system design feature has been shown to affect their work preference and participation (Domínguez *et al.*, 2013).

Studies have shown that people differ in their attitudes towards motivational system design features in a crowdsourcing system. Dissanayake *et al.* (2019) found that contributors with strong self-efficacy tend to work harder and perform better under competitive conditions. Itoko *et al.* (2014) investigated the effectiveness of competition features for younger and older users in a crowdsourcing proofreading system. They found that younger users like competitive features more than old users. These differences in attitudes contribute to the diverse contributor behaviours in crowdsourcing systems. Landers *et al.* (2017) argued that contributors working in the presence of a leaderboard will complete crowdsourcing tasks as if they have set a difficult or impossible goal for themselves. Leaderboards, therefore, have little impacts on contributors who set difficult goals in the first place. Bowser *et al.* (2013) contended that competition features in a crowd creating mobile app cannot effectively motivate potential users who initially have a low tendency to use the app. Hence, not everyone is motivated to the same extent by motivational system features.

2.3 Types of crowdsourcing tasks

According to Geiger *et al.* (2012), crowdsourcing tasks can be classified into four types, including crowd solving, crowd creation, crowd processing and crowd rating. They differ from one another in two dimensions: values derived from contributions and values differentiated among contributions (see Table 2). Contributions of crowd processing and crowd rating are valued equally. Each of the contributions leads to identical or similar rewards. The tasks of crowd processing and crowd rating are usually rather homogeneous. Thus, the quality of the completed tasks varies little. As long as contributors' human processing abilities are up to a reasonable standard, their work is expected to be satisfactory. On the other hand, the tasks of crowd solving and crowd creation are heterogeneous. The tasks usually demand a certain extent of creativity and domain knowledge from contributors. Less creative and capable contributors likely perform poorly in these tasks. The value of each contribution in crowd solving and crowd creation is not the same. Contributors who provide work of good quality receive better rewards.

Values derived from aggregate contributions can be classified as emergent and non-emergent. Systems of crowd rating and crowd creation are considered as emergent crowdsourcing systems where fusion of contributions results in a better output. Crowd processing and crowd solving are non-emergent. Integration of their contributions yields no extra value.

There exist a few other studies that have distinguished between various types of crowdsourcing tasks. One example is the work of Majchrzak *et al.* (2013), which

Table 2. Four types of crowdsourcing information systems (adapted from Geiger *et al.*, 2012)

		Differentiation between contributions	
		Homogeneous	Heterogeneous
Value derived from contributions	Emergent	Crowd Rating	Crowd Creation
	Non-emergent	Crowd Processing	Crowd Solving

defined two types of crowdsourcing tasks on Wikipedia: adding knowledge and shaping knowledge. Alam and Campbell (2017) defined two similar types of crowdsourcing tasks, namely data-shaping tasks and knowledge-shaping tasks. The latter type of tasks was meta-analysis of the former type of tasks. Another example is that of Gong (2017), which differentiated knowledge-intensive tasks from other crowdsourcing tasks. These classifications seemed to be founded on whether domain knowledge is used for task completion.

The underlying motivations for working on different crowdsourcing tasks may not be the same. For example, Alam and Campbell (2017) found that contributors who work on data-shaping tasks are intrinsically motivated by instrumental issues, whereas those who work on knowledge-shaping tasks are extrinsically motivated by strategic matters. Zhang and Chen (2021) identified underlying motives for selection of different contests on ZBJ, a crowdsourcing platform in China. These motives include "to develop skills" and "to earn rewards".

3. Hypothesis development

Point systems and leaderboards cultivate competitive environments in which contributors can interact and compare themselves with other contributors. A motivational system design feature leads to larger exposure of the contributors to competition. Specifically, a leaderboard enables contributors to show their presence and draw attention from other contributors. The stronger sense of competition and social recognition forms an achievement stimulus that is more associated with the performance-approach goal, since the performance-approach goal is concerned with positive possibilities of social comparison with counterparts. If contributors possess a strong performance-approach goal, the cognitive link between the environmental stimulus of social comparison and the goal is closer (Bargh, 1990; McClelland *et al.*, 1953). In the presence of the stimulus, the contributors will spend more effort on the tasks for more points in a reflexive manner (Bargh *et al.*, 2001; Shah, 2003). They will be more likely to take up the tasks being offered on crowdsourcing platforms. We therefore hypothesized that:

H1a. Contributors with a stronger performance-approach goal would earn more points from their tasks in a typical motivational crowdsourcing environment [1].

H1b. Contributors with a stronger performance-approach goal would participate in more tasks in a typical motivational crowdsourcing environment.

A typical leaderboard together with a point system does not feature negative possibility generated from social comparison. Thus, contributors who possess a strong performance-avoidance goal are not sensitive to the competition for presence on a leaderboard. The contributors are not motivated as their performance-approach counterparts are. We therefore did not predict that performance-avoidance contributors would perform significantly worse than other contributors. Also, the leaderboard and the point system do not have a strong connection with self-judgement. We did not predict that contributors with a stronger mastery-approach/mastery-avoidance goal would perform differently from others because of the system design feature.

People with a strong mastery achievement goal are more concerned with self-evaluation. People with a strong mastery-avoidance goal tend to prevent themselves from negative self-judgment of their abilities (Elliot and McGregor, 2001). They aim to make no mistakes. They are more likely to define a difficult task in terms of threats (Icekson *et al.*, 2014). We propose that this attitude may adversely affect their participation in heterogeneous work, given that the criteria for correct answers in heterogeneous work are less objective and less explicit. The heterogeneous tasks appear to be motivators/demotivators to mastery-avoidance

contributors. We expected that these contributors would work on fewer heterogeneous tasks and perform worse in the tasks. Hence, we hypothesized that:

H2a. Contributors with a stronger mastery-avoidance goal would participate in fewer heterogeneous tasks in a typical motivational crowdsourcing environment.

H2b. Contributors with a stronger mastery-avoidance goal would perform worse in heterogeneous tasks and earn fewer points per tasks in a typical motivational crowdsourcing environment.

Although the heterogeneity of tasks serves as a demotivator to mastery-avoidance contributors, the homogeneity of crowdsourcing tasks is not necessarily connected to self-perception of improving one's skills and knowledge. Participation of mastery-approach contributors in homogenous tasks was not expected to be significantly better. Lastly, the heterogeneous/homogenous nature of a crowdsourcing task does not have much relevance to peer comparison. We did not predict that performance-approach or performance-avoidance contributors would participate particularly well in homogeneous or heterogeneous crowdsourcing tasks.

4. Methods and data analysis

4.1 The crowdsourcing platform

A crowdsourcing platform developed by an IT company in Hong Kong was used in our study. A typical motivational system design feature, namely a leaderboard together with a point system, was incorporated into the platform. Contributors could freely choose to work on any outstanding tasks related to natural language processing (NLP) applications. These tasks included homogeneous crowd-rating tasks and heterogeneous crowd-solving tasks. For heterogeneous crowd-solving tasks, contributors were instructed to give answers to brainstorming tasks concerned with daily conversation in different business contexts. Table A1 shows a sample of questions appearing in the system and the corresponding points per contribution (by contribution, we mean an answer to a question). Questions for these crowd-solving tasks were designed in such a way that little domain knowledge was required to complete them. These questions resembled Malaga's (2000) questions designed for their brainstorming sessions, such as the following: "Produce a list of as many new delicious ice cream flavors as possible" (p. 132). Homogeneous crowd-rating tasks were reviewing other users' contributions. Answers that were endorsed by more than three contributors were considered correct answers. This satisfied the emergent requirement of crowd rating.

Contributions were evaluated on the basis of quantity as well as quality. Not every task had the same rewards. More points per contribution were assigned to more difficult tasks. There were two levels of difficulty. Easier tasks involved brainstorming daily conversation in common scenarios. The settings in those more difficult tasks were more specific situations that contributors might not necessarily encounter during their daily lives. Points would be awarded to contributors whose answers were endorsed by three reviewers. The endorsement of three reviewers aimed to strengthen the accuracy of the review results. Bonus points were also given to the first contributors who provided answers not yet seen by the system. These contributors likely spent more effort to generate these more innovative answers.

In addition, points were awarded to reviewers of the brainstorming tasks. Equal points were awarded for each homogeneous review task. The total score for each contributor was the sum of the points received for the brainstorming tasks (heterogeneous crowd-solving tasks) and the points received for reviews of answers (homogeneous crowd-rating tasks). Figure 1 shows details of the point system. Figures 2 and 3 are the interfaces of the starting page and a review task.

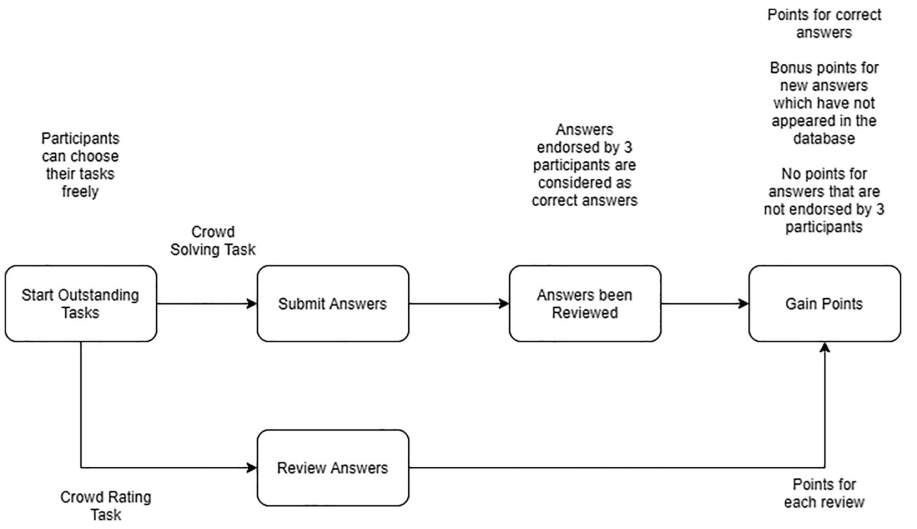

Figure 1.
Details of the point system

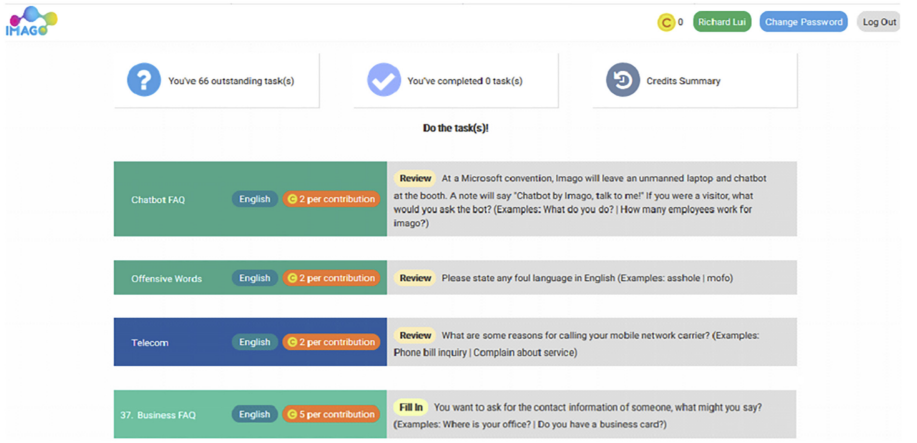

Figure 2.
The starting page of the crowdsourcing platform

4.2 Data collection

A free simulation experiment with the crowdsourcing platform was conducted. "Free" here refers to that fact that there were no specifically manipulated variables in the experiment. The treatments were "allowed to range freely and to occur naturally as responses to the experimental tasks" (Gefen and Straub, 2000, p. 12). This experimental approach has been used to examine trust in a mobile commerce portal (Vance *et al.*, 2008) and perceived ease of use of an e-commerce website (Gefen and Straub, 2000).

We conducted a free simulation experiment because the study places stronger emphasis on realism than control (Fromkin and Streufert, 1976). According to Geiger and Schader (2014), one fundamental principle of crowdsourcing is that the crowd can follow their own work preferences. By allowing contributors to select and complete their preferred tasks in the

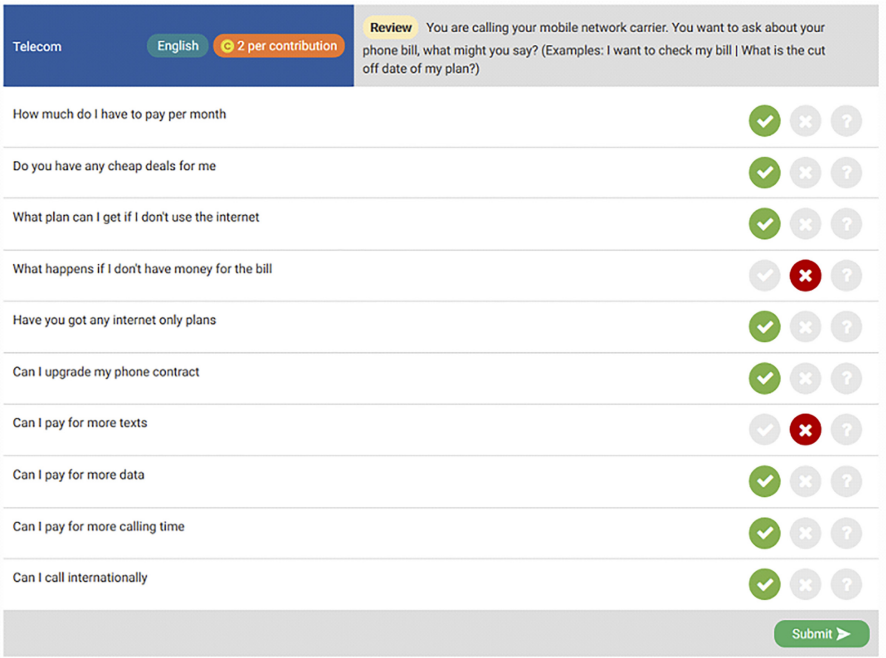

Figure 3.
An example of a review task in the crowdsourcing platform

crowdsourcing system, the experimental environment would be more comparable to the real setting. The results therefore can provide us with more practical insights.

Fifty-nine undergraduate students (9 female; 50 male) who were enrolled in one computer science course were invited to participate in the study. They were told that the crowdsourcing work on the platform would be used to support a research project of chatbot development in the computer science department. The students were also told that their performance on the platform was not relevant to their scores in the course. They were allowed to use the crowdsourcing platform for two weeks. During the two-week period, the students could freely work on any tasks on the platform. Before using the platform, they filled out online questionnaires which measured their achievement goals and creative self-efficacy. Items of achievement goals were adapted from Elliot and McGregor (2001), whereas questions of creative self-efficacy were adapted from Tierney and Farmer (2002) (see Table A2). The platform recorded the quantity of completed homogeneous crowd-rating tasks, the quantity of completed heterogeneous crowd-solving tasks and the points scored in both types of tasks respectively. These numerical records were used to develop the dependent variables of our analysis.

To test the hypotheses, we followed Elliot and McGregor (2001) to conduct a simultaneous multiple regression analysis to predict each dependent variable from the four achievement goals and creative self-efficacy. Simultaneous regression was used so that the four achievement goals were treated on equal footing. Creative self-efficacy was included as a control variable. It is a measurement of individuals' belief in their capabilities and is specific to the creativity domain. It is an indirect measurement of individual creativity (Tierney and Farmer, 2002). It is believed that creativity may affect the performance of brainstorming tasks.

4.3 Data analysis

Table 3 shows the results from a simultaneous regression analysis that predicted the aggregated points scored in all tasks from the achievement goal orientation and creative self-efficacy. The analysis was conducted on one specific achievement goal under the circumstance that creative self-efficacy and remaining achievement goals were controlled. The coefficient estimate of the performance-approach goal is positive (β = 1848.1). The results indicate that the performance-approach goal is a strongly significant, positive predictor of the aggregated points scored in all tasks ($p < 0.01$). H1a is supported. Contributors who have a stronger performance-approach goal tend to gain more points.

Table 4 presents the results from a simultaneous regression analysis that predicted the quantity of all completed tasks from the four achievement goals and creative self-efficacy. The coefficient estimate of the performance-approach goal is positive (β = 919.8). The results demonstrate that the performance-approach goal is a strongly significant, positive predictor of the quantity of all completed tasks in the crowdsourcing environment ($p < 0.01$). H1b is supported. Contributors who have a stronger performance-approach goal tend to participate in more tasks.

Table 5 presents the results from a simultaneous regression analysis that predicted the quantity of completed homogeneous crowd-rating tasks from the four achievement goals and creative self-efficacy. The coefficient estimate of the performance-approach goal is positive (β = 781.19). The results indicate that the performance-approach goal is a strongly significant, positive predictor of the quantity of the completed crowd-rating tasks ($p < 0.01$).

Table 3. Simultaneous regression analysis predicting the aggregated points scored in all tasks from the achievement goals and creative self-efficacy

Variables	Coefficient estimate (β)	Standard error	t	p-value	Hypotheses
Mastery-approach	−483.0	973.8	−0.496	0.6220	N/A
Mastery-avoidance	−1837.8	840.5	−2.187	0.0332*	N/A
Performance-approach	1848.1	665.2	2.778	0.0076**	H1a supported
Performance-avoidance	1160.2	789.0	1.470	0.1474	N/A
Creative self-efficacy	−1937.5	1173.8	−1.651	0.1047	N/A

Note(s): R^2 = 0.1494; N = 59; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

Table 4. Simultaneous regression analysis predicting the quantity of all completed tasks from the achievement goals and creative self-efficacy

Variables	Coefficient estimate (β)	Standard error	t	p-value	Hypotheses
Mastery-approach	341.3	468.8	0.728	0.4697	N/A
Mastery-avoidance	−472.4	404.6	−1.168	0.2482	N/A
Performance-approach	919.8	320.2	2.872	0.0059**	H1b supported
Performance-avoidance	234.6	379.8	0.618	0.5394	N/A
Creative self-efficacy	−1804.6	565.0	−3.194	0.0024**	N/A

Note(s): R^2 = 0.1942; N = 59; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

Table 5. Simultaneous regression analysis predicting the quantity of completed homogeneous crowd-rating tasks from the achievement goals and creative self-efficacy

Variables	Coefficient estimate (β)	Standard error	t	p-value	Hypotheses
Mastery-approach	484.9	418.01	1.160	0.2512	N/A
Mastery-avoidance	−266.25	360.80	−0.738	0.4638	N/A
Performance-approach	781.19	285.55	2.736	0.0085**	N/A
Performance-avoidance	85.63	388.70	0.253	0.8014	N/A
Creative Self-efficacy	−1823.52	503.84	−3.619	0.0007***	N/A

Note(s): R^2 = 0.2113; N = 59; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

Table 6 focuses on the heterogeneous crowd-solving tasks, presenting the results from a simultaneous regression analysis that predicted the quantity of completed crowd-solving tasks from the four achievement goals and creative self-efficacy. The coefficient estimate of the mastery-avoidance goal is negative ($\beta = -206.15$). The results show that the mastery-avoidance goal is a strongly significant, negative predictor of the quantity of the completed crowd-solving tasks ($p < 0.01$). H2a is supported. Also, contributors who have a strong performance-approach goal tend to participate in more heterogeneous tasks in comparison to their counterparts. The coefficient estimate of the performance-approach goal is positive ($\beta = 138.65$). The results show that the performance-approach goal is a statistically significant, positive predictor of the quantity of the completed crowd-solving tasks ($p < 0.05$).

In line with our expectation, the two achievement goals, namely the performance-avoidance goal and the mastery-approach goal, do not have significant influence on the quantity of the completed heterogeneous tasks or the quantity of the completed homogeneous tasks.

Crowd-rating tasks are trivial and homogeneous. Variation in the work quality of this type of tasks is small. In contrast to crowd-rating tasks, crowd-solving tasks are concerned with the quality of work. Thus, we examine not only the quantity but also the quality of work done by the contributors in heterogeneous crowd-solving tasks. We define the quality of tasks as the points scored per completed heterogeneous crowd-solving task. Table 7 focuses on the defined quality of crowd-solving tasks and presents the results from a simultaneous regression analysis that predicted the work quality from the four achievement goals and creative self-efficacy. All achievement goals have no significant influence on the quality of crowd-solving tasks. The results show that there is no significant relationship between mastery-avoidance goal and the quality of the completed crowd-solving tasks. H2b is not supported.

In order to demonstrate the importance of adopting a more detailed classification of achievement goals, that is mastery-approach, mastery-avoidance, performance-approach and performance-avoidance goals, in contrast to a simple dichotomy of mastery/performance

Variables	Coefficient estimate (β)	Standard error	t	p-value	Hypotheses
Mastery-approach	−143.56	89.02	−1.613	0.1128	N/A
Mastery-avoidance	−206.15	76.83	−2.683	0.0097**	H2a supported
Performance-approach	138.65	60.81	2.280	0.0267*	N/A
Performance-avoidance	148.98	72.13	2.066	0.0438	N/A
Creative self-efficacy	18.97	107.29	0.177	0.8603	N/A

Note(s): $R^2 = 0.1471$; $N = 59$; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

Table 6. Simultaneous regression analysis predicting the quantity of completed heterogeneous crowd-solving tasks from the achievement goals and creative self-efficacy

Variables	Coefficient estimate (β)	Standard error	t	p-value	Hypotheses
Mastery-approach	0.372	0.326	1.142	0.259	N/A
Mastery-avoidance	−0.002	0.281	−0.007	0.995	H2b not supported
Performance-approach	−0.165	0.223	−0.740	0.463	N/A
Performance-avoidance	−0.074	0.264	−0.279	0.782	N/A
Creative self-efficacy	−0.703	0.393	−1.790	0.079	N/A

Note(s): $R^2 = -0.0060$; $N = 59$; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

Table 7. Simultaneous regression analysis predicting the quality of the completed crowd-solving task from the achievement goals and creative self-efficacy

goals, we conducted two post-hoc studies. The two studies include a simultaneous regression analysis predicting the quantity of the completed crowd-rating task from the mastery/performance goals and creative self-efficacy, and a simultaneous regression analysis predicting the quality of the completed crowd-solving task from the mastery/performance goals and creative self-efficacy. No significant relationship between the mastery/performance goals and the quantity of the completed crowd-rating task was found. No significant relationship between the mastery/performance goals and the quality of the completed crowd-solving task was found either. These two results further support that the behavioural differences among the contributors in different types of tasks in a typical motivational crowdsourcing system environment can only be found with the use of more detailed classification of achievement goals.

5. Discussion and implications

5.1 Discussion

The results indicate that performance-approach contributors gain more points and participate more in both types of tasks in a crowdsourcing environment. The typical motivational system design feature, namely the leaderboard together with the point system, fosters social comparison and competition among contributors. Performance-approach contributors are more sensitive to the positive stimulus of comparison and competition. They are therefore more motivated to work on all types of tasks offered in order to collect more points to earn a presence on the leaderboard. The quality of their work in heterogeneous crowd-solving tasks is not significantly lower in comparison to their counterparts. This indicates that performance-approach contributors do not gain more points at the expense of work quality. It is also noteworthy that performance-approach contributors work on significantly more crowd-rating tasks as well as crowd-solving tasks. The homogeneity/heterogeneity or emergent nature of a task does not appear to affect the participation of performance-approach contributors in crowdsourcing environments.

The results are also aligned with our expectation that the influence of the leaderboard and the point system is not symmetrical on the approach-avoidance dimension of the performance-oriented achievement goal. The aggregated points of performance-avoidance contributors are not significantly different from those of contributors with other achievement goals. The leaderboard on the crowdsourcing platform features positive possibility of social comparison. Contributors with the lowest points are not shown on the leaderboard. Motivators/demotivators that are related to failure in competing against other contributors do not exist in our experimental setting.

The results concur with some prior studies that suggested that leaderboards have stronger motivating effects on some types of contributors only (Dissanayake *et al.*, 2019; Ipeirotis and Gabrilovich, 2014; Lander *et al.*, 2017; Preist *et al.*, 2014). Among various explanations of the differences in the effects on contributors (e.g. individual goal setting in Landers *et al.* (2017)), the mechanism that pertains to social comparison and competition is further supported in our study. Specifically, Preist *et al.* (2014) argued that a leaderboard may result in a descriptive norm at which users will aim, if the users possess a strong personal norm (i.e. strong mastery-approach goals). However, similar results are not found in our study. Mastery-approach contributors are not significantly affected by the leaderboard and the point system in our study. In addition, in contrast to Dissanayake *et al.*'s (2019) suggestion that competition is conducive only to contributors with strong self-efficacy, our study controls contributors' creative self-efficacy and shows that the relationship between the performance-approach goal and participation in heterogeneous crowd-solving tasks is still significant in a typical motivational crowdsourcing environment.

Moreover, our study found that mastery-avoidance contributors participate in fewer heterogeneous crowd-solving tasks in a crowdsourcing environment. Compared to their counterparts, mastery-avoidance contributors are demotivated to work on crowd-solving tasks because of their heterogeneous nature. On the other hand, their participation in homogeneous crowd-rating tasks is not significantly worse or better in comparison to their counterparts. This demonstrates that the fewer completed heterogeneous crowd-solving tasks are rooted in their heterogeneous work nature, which generates the fear of failure, but not in the system environment. This also mitigates the possibility that mastery-avoidance contributors divert their energy and attention from crowd-solving tasks to crowd-rating tasks because of the attractiveness of the homogeneity of crowd-rating tasks.

Although mastery-avoidance contributors work on fewer crowd-solving tasks, the quality of their work is not significantly worse than their counterparts. This is not aligned with our prediction. We reckon that contributors are free to choose their work tasks. They likely choose to work on a heterogeneous task when they do not consider the task as a threat. The contributors may occasionally be confident that their answers to the brainstorming tasks are correct, even if a standard correct answer does not actually exist. Thus, after the mastery-avoidance contributors choose to work on a brainstorming task, they do not tend to spend less effort or time on it. Therefore, the quality of their completed crowd-solving tasks is not significantly worse than that of their counterparts.

Our results show that mastery-approach contributors do not perform particularly well in heterogeneous tasks in a typical motivational crowdsourcing environment. This denotes that leaderboards together with point systems do not appear to be strongly positive cues in terms of emotional experience. If they are positive, emotional cues, mastery-approach contributors, according to Friedman and Forster (2005) and Elliot *et al.* (2009), should perform well in creativity tasks, namely crowd-solving tasks in this study. Thus, our results are contrary to the prior explanation that adopted the emotional perspective in studies such as Friedman and Forster (2005) and Elliot *et al.* (2009). Moreover, in contrast to some thoughts that mastery-approach people perform better in creativity tasks, for example Lu *et al.* (2012) and Miron-Spektor and Beenen (2015), our study does not show coherent evidence. Apparently, in the context of crowdsourcing, mastery-approach contributors do not view general crowd-solving tasks as something through which personal knowledge or skills can be acquired. Our results are more inclined towards Icekson *et al.*'s (2014) view that mastery-avoidance contributors consider creativity tasks as threats rather than positive challenges.

5.2 Implications

The results have several theoretical implications. First, prior studies have examined the influence of various crowdsourcing platform design features on different types of people. These studies have generally agreed that the influence on different types of contributors is different (Ipeirotis and Gabrilovich, 2014; Massung *et al.*, 2013; Preist *et al.*, 2014). For example, Majchrzak *et al.* (2013) found that a crowdsourcing community with a poorly developed transactive memory system fails to motivate contributors with strong knowledge depth and breadth to work on crowdsourcing tasks. Whereas the motives and states of contributors may affect contributor performance under the influence of various motivational stimuli, we argue that personal traits, such as achievement goals, serve as better predictive factors of long-term participation. Achievement goals are relatively more stable, and therefore the identified relationships between motivators and achievement goals are more persistent. The motivated participation can be more sustained. The results of our study highlight the importance of habitual achievement goals to contributor participation. Regardless of task types, the typical design feature of crowdsourcing systems (i.e. a point system together with a leaderboard) strongly motivates contributors with a strong performance-approach goal.

With the use of a free simulation experiment, we are also able to demonstrate that some types of tasks exist as a demotivator in a crowdsourcing environment. Whereas some previous studies have proposed different categories of crowdsourcing tasks, these studies have generally considered completion of different types of tasks as resulting products of contributors' functions of positive motivations (e.g. Alam and Campbell, 2017; Pee *et al.*, 2018). For example, Pee *et al.* (2018) found that contributors who are motivated by social affiliation tend to work on tasks that require collaboration with other contributors. Contributors who are motivated by self-development tend to work on tasks that require more efforts. Another example is Alam and Campbell (2017), which showed that contributors intrinsically motivated by instrumental issues tended to work on shaping data. Those who worked on shaping knowledge were extrinsically motivated by strategic matters. We shed light on the negative possibility that task nature can exist as a stimulus to contributors and demotivate contributors. Our study highlights the potential adverse impacts of task heterogeneity. It shows the demotivating impact of heterogeneous brainstorming tasks on mastery-avoidance contributors.

In comparison to some previous studies that focused only on the dichotomy between extrinsic and intrinsic motivation [e.g. Alam and Campbell (2017) and Wu and Gong (2020)], our study follows the work of Elliot and McGregor (2001) and includes an additional dimension of motivational goals, namely approach-avoidance dichotomy. Zheng *et al.* (2018) demonstrated that contributors are motivated to work harder in the face of reversed loss aversion. Wong *et al.* (2021) found that feedback may serve as surveillance and hurt the performance of contributors with a low mastery goal. They also suggested that negative feedback, may stimulate contributors with a strong mastery goal to work harder. Both studies indicated the potential influence of stimuli that generate perception of negative possibilities. Our results further enrich the discussion by showing that the influence of these stimuli on the approach-avoidance dimension of an achievement goal is not symmetrical. Only performance-approach contributors but not performance-avoidance contributors are motivated by their positive presence on the leaderboard. In addition, only mastery-avoidance contributors but not mastery-approach contributors are demotivated by the fear of failure that is generated by the lack of model answers in heterogeneous tasks.

Lastly, differentiation between the quantity and quality of heterogeneous tasks is critical. Our results demonstrate that quantity and quality are not necessarily positively or negatively correlated. Recent studies have investigated strategies of quality control in crowdsourcing (Daniel *et al.*, 2018). Miao *et al.* (2016) developed a model of task allocation that takes budget and work quality into consideration. Lukyanenko *et al.* (2019) proposed a contributor-centric information quality management strategy that takes contributors' personal characteristics, such as possession of professional knowledge, into consideration. They recommended that this strategy is particularly suitable for tasks for which the answers are open, with many unknowns. We advance our understanding by showing that even the inclusion of personal characteristics, such as orientation of achievement goals, may not improve the prediction of work quality. Given the work nature in crowdsourcing environments, mastery-avoidance contributors likely choose tasks that do not appear as threats to them. Thus, the demotivating heterogeneous nature of work tasks affects only the quantity but not necessarily the quality of the tasks completed by mastery-avoidance contributors.

As a practical contribution, we suggest that the management of crowdsourcing platforms should make efforts to identify the characteristics of their approachable "crowd of wisdom". To improve contributors' initial participation rate on the platforms, they may incorporate a leaderboard and a point system into their platforms and invite people with a performance-approach goal to register as contributors. Furthermore, management should continuously offer suitable tasks to contributors with different achievement goals. Specifically, they should avoid offering heterogeneous tasks without model answers to mastery-avoidance

contributors. This helps to increase the matching rate between tasks and contributors and to achieve a good continuous participation rate of contributors. Since achievement goals are habitual and remain relatively stable, the consideration of the two motivators/demotivators is conducive to a good participation rate over time.

Furthermore, our findings can inform system designers' decisions to include appropriate motivational stimuli for sustained contributor participation. The influence of motivators/demotivators not only on crowdsourcing platforms but also on platforms in other contexts should be evaluated together with users' motivational goals. The habitual motivational goals certainly affect the effects of the motivators/demotivators on users. Customized design for different types of contributors may be considered.

6. Future directions and conclusion

6.1 Limitations and future directions

The study involves several limitations. First, this study focuses on influential differences between the homogeneity and the heterogeneity of crowdsourcing tasks. With the use of the crowdsourcing platform, we had homogeneous crowd-rating and heterogeneous crowd-solving tasks as our focal tasks and compared contributors' participation in these two types of tasks. We did not specifically examine the impacts of the emergent nature of crowdsourcing tasks, although the significantly larger participation of performance-approach contributors in both crowd-rating and crowd-solving tasks provides no indication that the emergent nature matters. Nevertheless, scholars may extend our study and examine the effect of the achievement goal orientation on emergent and non-emergent tasks in the future.

Second, to limit the variety of effects generated by different motivational system design features in crowdsourcing, we included only one typical system design feature (i.e. point systems with a leaderboard) on the crowdsourcing platform in our study. In reality, crowdsourcing applications consist of a variety of motivational features. Features such as aesthetics and stories are very different from point systems and leaderboards. Inclusion of other social incentive mechanisms in the crowdsourcing system may also provide further insights into peer comparison and collaboration among contributors. Researchers may examine how these system features influence contributor participation and work quality respectively in the future.

Third, the sample size in the study is not large. The diversity of the population may be limited. Nevertheless, apparently many contributors to existing crowdsourcing systems are from the educated young generation. Also, the crowdsourcing system in the experiment was developed by an IT company that should have a good understanding of crowdsourcing in practice. The external validity of the study therefore should be strong (Cook and Campbell, 1979; Fromkin and Streufert, 1976; Gefen and Straub, 2000). In contrast to field studies, our setting allows us to measure the achievement goals of all registered contributors of the platform.

Lastly, we did not include financial incentives in this study. In practice, companies are not willing to pay much to contributors. Thus, the amounts of financial payments for crowdsourcing are rather limited. Nevertheless, the financial incentive is one motivation to participate in crowdsourcing (Brabham, 2008; Kaufmann *et al.*, 2011; Zheng *et al.*, 2011). Future scholars may conduct a study examining the effect of financial rewards on contributor performance with a large sample size.

6.2 Conclusion

The best use of crowdsourcing is more than an "open call" to the netizens (Howe, 2006, p. 1). Executives should make an effort to understand and recruit a suitable crowd to address their

business needs (Prpić *et al.*, 2015). This study shows that contributors perform differently across different tasks in a crowdsourcing environment. Researchers and managers should continue to examine the relationships between contributor characteristics and motivational stimulus in future studies of crowdsourcing.

Note

1. By a typical motivational crowdsourcing platform, we refer to a crowdsourcing platform that features a leaderboard and a point system.

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Appendix 1

Table A1. Sample questions in the crowdsourcing system

Questions	Points per contribution
At a Microsoft convention, Imago will leave an unmanned laptop and chatbot at the booth. A note will say "Chatbot by Imago, talk to me!" If you were a visitor, what would you ask the bot? (Examples: What do you do? | How many employees work for Imago?)	2
Please state any foul language in English	2
What are some reasons for calling your mobile network carrier? (Examples: Phone bill inquiry | Complain about service)	2
You are calling your mobile network carrier. You want to ask about your phone bill. What might you say? (Examples: I want to check my bill. | What is the cut-off date of my plan?)	2
You are calling your mobile network carrier. You want to cancel a service. What might you say? (Examples: I want to cancel this number. | I want to turn off roaming service.)	2
You are calling your mobile network carrier. You want to ask why the network speed issue has been slow lately, what might you say? (Examples: I keep getting disconnected | Why is it so slow lately?)	2
You are calling your mobile network carrier. You want to apply for a service. What might you say? (Examples: Any discount for joining your company? | What do I get if I extend my contract?)	2
You are calling your mobile network carrier. You want to buy a new phone. What might you say? (Examples: Can you recommend me a smartphone? | How much is the iPhone X?)	2
You want to ask whether someone speaks a different language. What might you say? (Examples: Can you speak Japanese? | What languages do you know?)	2
You are talking to a chatbot (robot online assistant). You want to ask about the weather. What might you say? (Examples: Weather forecast, please. | Will it rain today?)	2
You are talking to a chatbot (robot online assistant). You feel that the robot is not able to answer your question, and you want to request a live agent. What might you say? (Examples: I want to talk to someone irl. | Can you connect me to a live agent?)	5
You are talking to a company's chatbot. You want to ask about the company's recent news. How might you say this? (Examples: Show me the most recent news. | Can I see the latest company report?)	5
You are talking to a company's chatbot. You want to ask about possible job openings. How might you say this? (Examples: Are you guys hiring? | Is your company looking to hire?)	5

Appendix 2
Questionnaires

(a)		
Performance approach	(1)	It is important for me to do better than other students
	(2)	It is important for me to do well compared to others in this class
	(3)	My goal in this class is to get a better grade than most of the other students
Mastery avoidance	(1)	I worry that I may not learn all that I possibly could in this class
	(2)	Sometimes I'm afraid that I may not understand the content of this class as thoroughly as I'd like
	(3)	I am often concerned that I may not learn all that there is to learn in this class
Mastery approach	(1)	I want to learn as much as possible from this class
	(2)	It is important for me to understand the content of this course as thoroughly as possible
	(3)	I desire to completely master the material presented in this class
Performance avoidance	(1)	I just want to avoid doing poorly in this class
	(2)	My goal in this class is to avoid performing poorly
	(3)	My fear of performing poorly in this class is often what motivates me
(b)		
Creative self-efficacy	(1)	I feel that I am good at generating novel ideas
	(2)	I have confidence in my ability to solve a problem creatively
	(3)	I have a knack* for further developing the ideas of others
	(*"Knack" means a skill or an ability to do something easily and well.)	

Table A2.
(a) Achievement goal items adapted from Elliot and McGregor (2001) on a 7-point Likert scale from "not at all true of me" to "very true of me", (b) Creative self-efficacy items adapted from Tierney and Farmer (2002) on a 5-point Likert scale from "strongly disagree" to "strongly agree"