Worker's Cognitive Abilities and Personality Traits as Predictors of Effective Task Performance in Crowdsourcing Tasks

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Abstract

The increased popularity of crowdsourcing platforms raises today interesting questions with respect to the better definition, initiation, management and quality of work of crowdsourced tasks. Factors that influence the quality of work in crowdsourced tasks is in particular important as low quality has been reported as a major drawback of this new kind of labor. In this paper we investigate the impact of different cognitive and non-cognitive worker skills on the quality of work they provide in such environments. We conducted an experiment on a popular crowdsourcing site and the obtained results providing evidence that the performance of workers in such environments depends on three basic components namely work effort, character skills and cognitive skills as well as on the GDP per capita of the country of origin.

Index Terms: Crowdsourcing, online labor, quality of work, cognitive abilities, personality traits, workers

1. Introduction

The emergence of the Web 2.0 paradigm has -among others- transformed the way labor is nowadays demanded and supplied. In such context, crowdsourcing is one prominent example: it refers to a wide range of web-based activities characterized by the contribution from the crowd (Marsden 2009). More specific crowdsourcing, as a term, is a strategic model to attract an interested, motivated crowd of individuals capable of providing solutions superior in quality and quantity to those that even traditional forms of business can (Brabham, 2008a).

In traditional economic theory quality of work is motivated by reward (i.e. the item which constitutes the most immediate return to express the set of advantages and disadvantages related to transaction costs) (Berardi et al. 2014) or employees' self-determination (Gagne & Deci, 2005). In crowdsourcing environments however, it is still unclear which are the exact factors and to what degree they affect the quality of work submitted by workers.

In this paper we report on the factors that influence the quality of work in crowdsourcing environments. Towards this we conducted an experiment on the well-known crowdsourcing website microworkers.com requesting from workers to complete a task. The task was preceded by a demographic survey in which workers were asked to report on their gender, age, country of origin, computer & English language skills as well as their education level. Workers were also asked to fill in a questionnaire related to the Big Five Personality Test (John et al. 1999). In addition, we take into consideration the impact

of GDP per capita for the year 2015 as published by Knoema (Knoema, 2016). We construct an econometric model aiming at explaining and predicting the quality of work based on skill group factors. Using the model and analyzing the results, it is shown that there is a strong correlation between the quality of work and specific skill groups.

2. Related Work

With crowdsourcing gaining momentum and becoming mainstream, collective behavior on social media platforms has attracted increasing attentions from both academia and industry (Cheung and Lee, 2010 and Turel and Zhang, 2011), while at the same time research efforts focus on developing comprehensive frameworks for managing the accuracy and the quality of the submitted crowdsourcing work (Wang et al. 2013).

In this regard, it may be more appropriate to examine if the quality of results is directly influenced by crowd behavior and their characteristics. In the literature, work quality has been related to crowd demographics (Ross et al. 2010; Sheng et al. 2008), contributors' gender, profession and age (Downs et al. 2010) and workers' personality traits (Kazai et al. 2011). In general, the literature lacks studies that examine the quality of results under a combination of workers' cognitive and non-cognitive skills and effort. This paper adds to the growing body of research, which seeks to investigate the predictive power of workers' behavior (effort) and skills (cognitive, non-cognitive) on expected quality of results (Kautz et al. 2014).

Although non-cognitive skills are overlooked in most contemporary policy discussions and in economic models of choice behavior, personality psychologists have studied these skills for the past century. Psychologists primarily measure non-cognitive skills by using self-reported surveys or observer reports (Cunha et al. 2010). They have arrived at a relatively well-accepted taxonomy of non-cognitive skills called the Big Five Personality Test, which stands for: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (Linden et al. 2010). This type of test had the form of 44-likert scaled personality questions that measures an individual on the Big Five Factors of personality (Goldberg et al. 1993).

3. Experiment setup and methodology

The goal of the experiment was to investigate the impact of a group of variables on the quality of the work submitted by workers which include: the country of origin of the workers, their cognitive and non-cognitive skills as well as their effort put into completing the task. The experiment was conducted

on the crowdsourcing website microworkers.com.

Workers were asked to listen to an unknown music sample containing lyrics with a total of 56 English words and submit as many of the correctly identified lyrics as possible. The experiment was conducted in two different settings: in the first setting the experiment was performed in the form of an open call soliciting submissions from all workers (called "open call" setting) while in the second setting workers from countries with a low GDP per capita were excluded (called the "excluded" setting). Moreover, each worker that accepted the task were asked to complete a demographic survey which asked them about their age, country of origin, computer & English language literacy skills as well as their education level. In addition, workers were asked respond to a questionnaire based on Big Five Personality Test. A worker could participate in only one setup of the experiment. We received 50 responses in each experiment, with a cost of $41.06 per experiment setting. In order to gather the appropriate data for our research we needed to consider the basic components of crowdsourcing, each of which plays an integral part in the success of our approach (Keating et al. 2013)(Fig.1). Having already established the goal of our research and having defined the specific audience segments, we had to identify the suitable crowdsourcing platform in which our experiment would take place. We needed a platform that would have workers familiar with microjobs (as the type of our task was) and would provide us with a friendly and effective framework for our experiment (i.e. mechanisms that would allow us to control from which countries the workers would be) (Gardlo et al. 2012). Hence, taking in consideration the above mentioned aspects, we choose the well-known platform microworkers.com (Hirth et al. 2011).
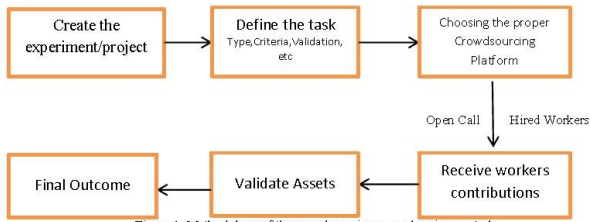

Figure 1. Methodology of the crowdsourcing procedure in our study.

Thus, a microworkers campaign was launched, through which crowdsourcing workers could access a soundcloud link with the music sample and perform the experiment under a 0.75$ compensation.

4. Data Analysis

4.1 Overview
As a measure of the quality of submissions, we considered the percentage of correctly identified words in the music sample calculated as the ratio of the number of words correctly identified by the worker divided by total number of words in music sample, henceforth referred to as quality of results. For our analysis we solicited fifty answers in each experiment. The study ran for several hours with the same overall cost in each case. More specifically, in the case of the "open call" setting the workers needed about twenty (20) hours to complete the total number of fifty answers while in the "excluded setting", the total task's completion time was about ten (10) hours. In the first experiment setting the average percentage of correctly identified word was about 45 % ($\overline{y_1}$) while in the second setting the corresponding percentage was about 65 % ($\overline{y_2}$)(Table 1 & Table 2).

Variable	Obs	Mean	Std. Dev.	Min	Max
Quality (Y)	50	0.45	0.19	0.18	0.83

Table 1. Quality of work, in terms of percentage of correctly recognized words in the "open call" setting of the experiment ($\overline{y_1}$ near to 0.45).

Variable	Obs	Mean	Std. Dev.	Min	Max
Quality (Y)	50	0.65	0.17	0.35	0.93

Table 2. Quality of work, in terms of percentage of correctly recognized words in the excluded call setting of the experiment ($\overline{y_2}$ near to 0.65)

4.2 Demographics
As mentioned before a total of 50 participants in each setting of the experiment was ought to answer to several demographics questions.

- *Age*. The age distribution in each setting of the experiment is shown in the following table.

Variable	Obs	Mean	Std. Dev.	Min	Max
Age (exp1)	50	26.60	5.93	18	49
Age (exp2)	50	29.92	8.40	20	59

Table 3 Age of each setting of the experiment

- *Gender*. The gender distribution in each setting of the experiment is shown in the following tables.

Gender exp.1	Freq.	Percent	Cum.	Gender exp.2	Freq.	Percent	Cum.
Male	41	82.00	82.00	Male	30	60.00	60.00
Female	9	18.00	100.00	Female	20	40.00	100.00
Total	50	100.00		Total	49	100.00	

Table 4 Gender of the participants in each setting of the experiment

- *Country of origin*. The workers' continent in each setting of the experiment is also shown in the following figures.
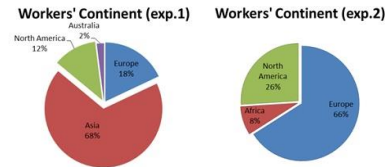

Figure 2. Workers' residence in each setting of the experiment

In both experiment settings, workers from South American countries did not submit any work.

4.3 Descriptive Statistics
Regarding the experiment conducted on the crowdsourcing site microworkers.com we had some noteworthy descriptive information in the three groups of skills (cognitive skills, non-cognitive skills, work effort).

4.1.1. Cognitive Skills
For this kind of skills the following information was collected for both experiments.

Education level (exp. 1)	Freq.	Percent	Cum.
Lower secondary education	7	14.00	14.00
Upper secondary education	17	34.00	48.00
Post-secondary non-tertiary education	13	26.00	74.00
Short-cycle tertiary education	3	6.00	80.00
Bachelor's or equivalent level	6	12.00	92.00
Master's or equivalent level	4	8.00	100.00
Total	50	100.00	

Education level (exp. 2)	Freq.	Percent	Cum.
Primary education	2	4.00	4.00
Lower secondary education	3	6.00	10.00
Upper secondary education	6	12.00	22.00
Post-secondary non-tertiary education	11	22.00	44.00
Short-cycle tertiary education	10	20.00	64.00
Bachelor's or equivalent level	11	22.00	86.00
Master's or equivalent level	7	14.00	100.00
Total	50	100.00	

Table 5. Education levels of microworkers.com participants in each setup of the experiment.

Computer Level (exp.1)	Percent	Computer Level (exp.2)	Percent	English Level (exp.1)	Percent	English Level (exp.2)	Percent
Amateur	10%	Amateur	2%	Amateur	4%	Amateur	2%
Basic	20%	Basic	22%	Basic	14%	Basic	24%
Intermediate	24%	Intermediate	26%	Intermediate	40%	Intermediate	28%
Advanced	32%	Advanced	22%	Advanced	34%	Advanced	28%
Professional	14%	Professional	28%	Professional	8%	Professional	18%

Table 6. Computer & English Levels in both experiments.

While differences were observed related to the level of education in all settings, the computer and the English literacy levels were rather close (computer literacy levels mean 3.20 vs. 3.54 and English literacy levels mean 3.28 vs. 3.36).

4.1.2. Non Cognitive Skills

This group of skills contains the Big Five Personality Test (Goldberg et al. 1992).

For our crowdsourcing experiments, we examined the workers under the following variables (John et al. 1999).

(I) Extraversion (talkative, assertive, energetic)
(II) Agreeableness (good-natured, cooperative, trustful)
(III) Conscientiousness (orderly, responsible, dependable)
(IV) Emotional Stability versus Neuroticism (calm, not neurotic, not easily upset)
(V) Openness to Experience (inventive, consistent, creativity)

Figure 3 shows the distribution of responses to the Big Five Personality questionnaire. For Openness we observe a mean score of 34.02 (std. dev. 5.45) in the first experiment and a mean score of 35.76 (std. dev. 5.21) in the second one, suggesting a tendency toward creativity and active imagination. The mean score of Conscientiousness is lower with 30.30 (std. dev. 5.50) in the first scenario and 32.74 (std. dev.6.26) in the second one, suggesting that we must expecting a more thorough job from workers in the second experiment than in the first. Extraversion has a mean 21.44 (std. dev. 5.85) (experiment 1) and 23.52 (std. dev. 5.20) (experiment 2) exhibiting no particular disposition on this trait. Moreover, we observe again a moderate score for agreeableness (experiment 1: mean 31.60 std. dev. 4.95 vs. experiment 2: mean 29.82 std. dev. 8.28), which is not allow us for this trait to extract conclusions. Finally, we find a low mean score for Neuroticism (it is the opposite of emotion stability) in both experiments (experiment 1: mean 23.10 std. dev. 5.35 vs. experiment 2: mean 22.90 std. dev. 5.59), which suggests a possible relaxed nature of the workers.
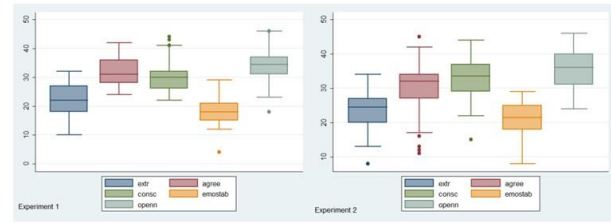

Figure 3. Workers' big five personality test boxplot among the two experiments

4.1.3. Work Effort

In order to investigate how serious a worker's attempt was, we gathered some descriptive statistics referring to task's completion time and number of task repetition before the final submission (Table 7).

Effort Variables (exp.1)	Mean	Std. Dev.	Min	Max	Effort Variables (exp.2)	Mean	Std. Dev.	Min	Max
Time of Completion (minutes)	4.78	1.61	3	8	Time of Completion (minutes)	6.06	1.20	4	8
Number of repeats	6.44	5.84	1	33	Number of repeats	5.76	3.85	1	16

Table 7. Workers' task completion time & number of repeats in both experiments.

5. Experiment Results

5.1 Initial Results

The analysis indicates that the best results in terms of quality were achieved on the second experiment (65 % success rate on average) whose users were coming from countries with middle to high GDP per capita. In addition, in both cases of the experiment the workers' quality of results is strongly correlated with at least one variable of each skill group (cognitive and non-cognitive skills, work effort). It is also noteworthy to point out that the workers' quality of results coming from countries with middle to high GDP per capita in both experiments were comparable ($\bar{y}1= 0.55$, $\bar{y}2 = 0.65$).

5.1.1. Open call experiment setting

In general, in this setting of the experiment, the quality of results was not satisfactory with average quality ($\bar{y}$) near to 0.45 (tabl.8)

Variable	Obs	Mean	Std. Dev.	Min	Max
Quality (Y)	50	0.45	0.19	0.18	0.83

Table 8 Descriptive statistics of the provided answers in the "open call" format of the experiment. The minimum percent of lyrics correctly identified by the participants is 18% while the maximum is near to 83% on total of 50 observations.

5.1.2. Excluded experiment setting

In the second setup, we excluded workers from countries with low GDP per capita from participating in our experiment based on research that indicated that workers from these countries (specially countries from Asia) are low- trained to crowdsourcing and provide low quality of services (Khanna et al. 2010) due to several factors related to their way of life (Gupta et al. 2014).

The quality of results was satisfactory and in general better in comparison to the results received from workers in the "open call" setting of the experiment ($\bar{y}$ near equal to 0.65). More detailed results are presented on the following table (tabl.9)

Variable	Obs	Mean	Std. Dev.	Min	Max
Quality (Y)	50	0.65	0.17	0.35	0.93

Table 9. Descriptive statistics of the provided answers in the second format of the experiment. The minimum percent of lyrics correctly identified by the participants is 35% while the maximum is near to 93% on total of 50 observations.

5.2 Empirical Model

Towards investigating the impact of the observed variables to the quality of results of workers in crowdsourcing environments, we derived an OLS linear regression model which aims at predicting the quality of work based on the skill groups as well as environmental control variables. Following Heckman and Kautz (2012), we include a variety of "skills" and "environmental" controls for observed performance of crowdsourcing workers. The econometric specification is of the following general form:

$$Q_i = \alpha + \beta D_i + \gamma C_i + \delta NC_i + \varepsilon WF_i + \zeta CI_i + e_i \quad (1)$$

where Q_i is the aforementioned quality of results attainment indicator of the ith worker, D_i is a vector of demographics outcomes, C_i is a vector of cognitive skills outcomes, NC_i is a vector of non-cognitive skills outcomes, WF_i is a vector which includes the work effort variables and lastly CI_i is capturing the country specific fixed effect (log GDP per capita of ith worker's country of origin).

5.3 Multivariate Regression Analysis

In our prediction model we used the following variables.

Variables	Description
Quality of results (y)	quality of workers' results
age	the number of years that someone has lived divided into four categories age>15 & age<=23, age>23 & age<=25, age>25 & age<=29,age>29
female	gender type
loggdppc	the natural logarithm of GDP per capita ((current US$)
edulevD	workers with at least tertiary education
comlev	levels of workers' computer competency divided into three categories poor,fair,excellent
englev	levels of workers' english language competency divided into three categories poor,fair,excellent
extr	extraversion
agree	agreeableness
consc	consciousness
emostab	emotion stability
openn	openness
time	task's completion time (minutes)
numberD	number of task repetition before the final submission (under 3 repetion excluded)(cheating indication)

Table 10 Variables used in the OLS prediction model

If we apply model (1) to our data set, we obtain the following OLS linear regression model:

Variables	OLS Regression	
	Open Call Setting R-squared = 0.87	Excluded setting R-squared = 0.84
Age cat		
up to 25	-0.075[b]	0.032
up to 29	-0.025	0.044
up to 50	-0.052	0.024
Female	0.043	-0.142
EdulevD	0.206[a]	0.041
ComlevCat		
2	0.084[b]	0.102[a]
3	0.117[a]	0.121[a]
EnglevCat		
2	0.008	0.001
3	0.029	0.042[c]
ExtrD	0.064[b]	0.064[c]
AgreeD	0.032	-0.002
ConscD	-0.013	-0.030
EmostabD	0.029	0.128[a]
OpennD	-0.078	-0.011
Time	0.036[a]	0.037[a]
NumberD	-0.152	-0.105
Loggdppc	0.036[b]	0.016

Table 11. OLS estimation in each setup of the experiment

6. Discussion

At the outset, we firstly notice, that the effect of computer level is statistically significant across the quality of results among the two setups of the experiment (for high computer literacy levels of workers the results have shown strong correlations at the 1% level of significance and the right hand variable is positively relate to the left hand variable, while for medium computer literacy levels are statistically significant at 5% level of significance and the right hand variable is also positively relate to the left hand variable). It is noteworthy, that the effect of a workers competency in English is detectable only in the "excluded" setup of the experiment. In this context only high levels of English language competency are statistically significant at 10% level of significance (r= 0.042, p=0 .098). Similarly, education level is a strong predictor only in the "open call" setup of the experiment (r= 0.206, p=0 .000), meaning that workers with at least tertiary education provided 20% better results than those with non-tertiary education.

Regarding the effect of a worker's age, we observe that the effect is weak and totally different among the two setups of the experiment. More specifically, in the "open call" setup, the workers in every age category provided worse results regarding the reference age variable (workers aged up to 23 years); while in the "excluded" setup workers aged up to 23 years provided better results.

Among the personality traits, we find that extraversion has a remarkable effect in quality of results, regardless the setup of the experiment (open call: r=0.064 & p.value=0.048, excluded: r=0.064 & p.value=0.078) and is positive correlated with the quality of results of workers. For example workers with high levels of extraversion provided 6.4% better results in the "open call" setup and 7.8% better results in "excluded" setup of the experiment. Equally important is that, one more variable of non-cognitive skills group of variables, emotion stability, is strongly correlated (at the 1% level of significance) to the quality of the work submitted (emotion stability: r = 0.128 & p.value=0.001). However, this correlation is evident only when workers from countries with a low GDP per capita are excluded from the "open call" setting of the experiment.

Furthermore, there is also a strong correlation between the quality of results and the task's completion time (at the 1% level of significance) and the right hand variable is positively related to the left hand variable in both setting of the experiment (open call: r=0.036 & p.value=0.001 and excluded: r=0.037 & p.value=0.007), meaning that a worker's work effort is a strong predictor of task performance.

Finally our data analysis reveals a noticeable correlation (at the 5% level of significance) between the quality of results and the GDP per capita of worker's county of origin, with the right hand variable being positively related to the left hand variable. This may suggest that a country's economic performance may be considered a useful indicator for estimating a worker's task performance.

7. Conclusions

Skills are emerging as a critical factor in achieving high quality of work in crowdsourcing tasks. Measuring and assessing these skills is also a crucial aspect, which has received attention (Stasz 2001). In this paper, a first attempt is presented to understand the role of cognitive and non-cognitive skills as well as work effort and their interaction on task performance.

The obtained results indicate that although in general the workers' quality of results is correlated with their skill levels, different skills sets contribute to the quality of work in crowdsourcing tasks with GDP per capita being the regulating factor. This may be the aftereffect of the difference in socioeconomic status, among crowdsourcing workers, meaning the social and physical environment in which an individual lives and works and culture he is exposed to (including the beliefs, values, behavior and material objects that constitute a people's way of life)(Sackman, 2011).

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116