Worker Demographics and Earnings on AMT: An Exploratory Analysis

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ABSTRACT

Prior research reported that workers on Amazon Mechanical Turk (AMT) are underpaid, earning about $2/h. But the prior research did not investigate the difference in wage due to worker characteristics (*e.g.,* country of residence). We present the first data-driven analysis on wage gap on AMT. Using work log data and demographic data collected via online survey, we analyse the gap in wage due to different factors. We show that there is indeed wage gap; for example, workers in the U.S. earn $3.01/h while those in India earn $1.41/h.

1 INTRODUCTION

The low wage of online workers is a pressing problem given the prevalence of crowdsourcing market places [5,7]. Previous research argues that online workers lack income security in doing on-demand work [3,6]. The recent study by Hara *et al.* estimates that workers on Amazon Mechanical Turk (AMT) earn approximately $2/h [3]; this level of income is insufficient for people who live in regions with higher cost of living, such as the U.S where the federal minimum wage is $7.25/h. Unfortunately, the prior work by Hara *et al.* lacked worker demographics, which prevented the researchers to investigate relationship between hourly wage and other factors such as worker's country of residence, gender, and physical and cognitive ability. Thus, important questions like "is there an income gap between workers from different countries?" and "is there difference in earnings between workers with and without disabilities?" have not been answered yet.

In this article, we analyze the relationship between worker demographics and hourly wage on AMT. Similar to [3], we use the dataset collected via Crowd Workers Chrome plugin to calculate per-worker hourly wage. In addition, we conducted an online survey study to collect worker demographic information. We invited every worker who previously used the Crowd Workers Chrome plugin to answer an online survey questionnaire. In total, we invited 4,886 workers on AMT to participate in the survey and collected responses from 1,238.

This article presents the first large-scale quantitatively analysis of the differences in hourly wage between workers with different demography. As the first study, we focus on basic demographic information: *country of residence, gender,* and *health condition and disability*. We find that workers in the U.S. earn $3.01/h while workers in India earn $1.41/h on average. Male workers in the U.S. earn $3.68/h while female workers earn $2.79/h. Workers in the U.S. who self-identified as having disability or health conditions earned $2.80/h, while those without disabilities or health conditions earned $3.14/h.

2 Data Collection and Study Method

The task log data was collected using the Crowd Workers Chrome plugin to calculate hourly wage [2]. The plugin was used by workers in an opt-in basis. The plugin was designed to disclose the effective hourly wage rates of tasks for workers, providing an incentive for workers to use the tool. The plugin tracks what tasks workers perform and when workers accept and submit/return HITs—standalone unit of work undertaken by a worker on AMT—as well as other metadata about the HITs (*e.g.,* HIT reward) and workers (*e.g.,* worker ID)—see [2,3] for more details. In total, we had log data from 4,886 workers on AMT. The key data that we use are task reward and timestamps for the beginning and the end of the tasks ($Time_{accept}$, $Time_{submit}$, and $Time_{return}$); this piece of information allowed us to measure the time interval of each task. To calculate the task interval, we subtracted task end timestamp (*i.e.,* $Time_{submit}$, or $Time_{return}$) by task start timestamp (*i.e.,* $Time_{accept}$). The task interval and task reward information allowed us to calculate hourly wage for each task (*Reward / Interval*), as well as *per-worker hourly wage* (Σ *Reward* / Σ *Interval* summed over all tasks that a worker performed).

Disabilities and Health Conditions	Count
Problems or disabilities (including arthritis or rheumatism) connected with your arms or hands	72
Problems or disabilities connected with your legs and feet	79
Problems or disabilities connected with your back or neck	112
Depression, bad nerves, or anxiety	159
Mental illness or suffer from phobias or other nervous disorders	64
Learning difficulties	17
Chest or breathing problems, asthma, bronchitis	53
Difficulty in hearing	20
Difficulty in seeing (while wearing spectacles or contact lenses)	35
Other health problems or disabilities	64
Would prefer not to say	5

Table 1. Breakdown of the types of disabilities and health conditions that N=270 workers self-reported. The Count column does not add up to 270 because some workers reported having more than one disabilities or health conditions.

We designed and posted an online survey on AMT. The survey questions were modeled after questionnaires used by International Labour Organization's survey study. We invited 4,886 people who previously used the Crowd Workers Chrome plugin to answer the survey. We paid each worker $2.5 as a reward. Our task took approximately 15 minutes to complete. We received 1,568 responses in total. Some workers submitted more than one responses; in those cases, we only took the first response. We excluded the records from 184 workers who copied their worker ids incorrectly (*i.e.,* the worker ID indicated as a survey response and their worker ID in our Crowd Workers dataset mismatched). After excluding these records, we had 1,238 survey responses.

Using the above mentioned data, we investigate the relationship between per-worker hourly wage and worker demographics. We focus on the per-worker hourly wage of the 1,238 workers who responded to the survey, excluding the hourly wage data of 3,648 workers. As an exploratory work, we focus our investigation on the relationship between wage and *country of residence, gender,* and *health condition and disability*. We stratify workers based on the demographic property and calculate median per-worker hourly wage in each group.

3 Result

Of 1,238 workers, 622 were female and 616 were male. N=815 responses were from the U.S., 298 were from India, and 125 were from other countries. When asked if they have any disabilities or health conditions that affect them to carry out crowd work, 270 answered *yes*, 942 answered *no*, and N=26 noted that they *prefer not to say*. The 270 workers provided detailed information on what kinds of disabilities or health conditions they have—see Table 1; note that the count column does not add up to 270 because some respondents reported they have multiple disabilities or health conditions.

Country of Residence

Because 90% of workers who responded to our survey are from the U.S. (N=815) or India (N=298), we focus on and contrast the hourly wages of workers from these two countries. The median hourly wages of the workers from the U.S. and India were $3.01/h and $1.41/h, respectively. The data shows that the U.S. workers earn significantly more than those in India. This result aligns with prior work by Martin *et al.,* in which the authors suggested that the workers in the U.S. earn more than those in India [8]. Nevertheless, even the U.S. workers who earn more are underpaid compared to the federal minimum wage ($7.25/h).

Gender

Prior work suggested that gender affects income on crowdsourcing marketplaces [1]. We investigate the wage gap between female and male workers to reinforce this finding. In addition to splitting the wage data only by *gender* (*i.e., female vs. male*), we also stratified the data with two layers: *country of residence* and *gender*. When the data was split solely based on gender, the median wage of female workers and male workers were $2.58/h and $2.30/h respectively, showing that the difference is marginal.

Country	Gender	Worker Count	Median Wage
U.S.	Female	527	2.79
U.S.	Male	288	3.68
India	Female	61	1.37
India	Male	237	1.43

Table 2. Median hourly wage breakdown by the country of residence and gender. Male workers earn more than female workers in both U.S. and India, but the income gap is larger in the U.S.

Country	Disability or Health Problem	Worker Count	Median Wage
U.S.	No	607	3.14
U.S.	Yes	208	2.80
India	No	253	1.43
India	Yes	45	1.26

Table 3. Median hourly wage breakdown by the country of residence and disability or health problem. People without disability or health problem earn slightly more compared to others.

When the data is stratified using the workers' *country of residence* and *gender*, however, we observed that male workers earn more than female workers (Table 2). The median wage of the female workers in the U.S. is $2.79/h and the median wage of the male workers in the U.S. is $3.68/h. The median wage of the female workers in India is $1.37/h and the median wage of the male workers in the India is $1.43/h. The results suggest that both male and female workers in the U.S. earn more than the workers in India, but the wage gap is large in the U.S.

Disability and Health Condition

Researchers claimed that online work environment could be good alternative to contemporary office work environment [4,9]. For example, people who have challenges in commuting to distant office space could benefit from at-home work. We investigate the wage of people with and without disabilities to study if there is wage gap due to disabilities. The median hourly wage of people without disability and with disability or health problem are $2.50/h and $2.47/h respectively, showing only marginal difference in hourly wage.

When we stratify the data using both *country of residence* and *disability and health problem*, we observed that people without disabilities or health problems earned slightly more than the other group. In the U.S., median wage of people with and without disability or health problem were $3.14/h and $2.80/h, respectively. Likewise, the wage were $1.43/h and $1.26/h in India. However, the gap seems smaller compared to that due to gender difference, particularly in the U.S.

Discussion and Conclusion

We conducted the first large-scale study on the relationship between quantitative crowd worker hourly wage data and worker demographics. Our analyses suggested that there seems to be income gap between workers due to multiple factors, such as locale, gender, and disabilities. More specifically, workers in the U.S. and India earned $3.01/h and $1.41/h respectively. Our shows that workers in the U.S. earn more than those who live in India. It also supports that, even in a country with high standard wage like the U.S., online workers earn significantly less compared to the minimum wage (*e.g.,* the U.S. federal minimum wage is $7.25/h).

While factors like gender and disability and health conditions affect the income level both in the U.S. and India, the income gaps on crowdsourcing marketplace due to these factors seem more prevalent in the U.S. Our analysis showed that male workers earned 31.9% more compared to female workers in the U.S. ($3.68/h *vs.* $2.79/h), whereas the gap is smaller in India where male workers and female workers earned $1.43/h *vs.* $1.37/h respectively. Income gap due to disability and health problem is more prevalent in the U.S., too. Workers with and without disabilities or health problems earned $2.80/h and $3.14/h and in the U.S, whereas the wages were $1.26/h and $1.43, respectively, in India.

While our exploratory analyses suggest the aforementioned income gaps due to multiple factors, further research is needed to explain what causes these differences. For instance, our study cannot answer "why do female workers earn less?" Is it because they have more sporadic work practice where they have to manage more responsibility compared to male workers? Future work should conduct in-depth analyses on what causes the wage gap, which could inform the design of the future crowdsourcing marketplaces. Similarly, further investigation is necessary to understand what kinds of disabilities affect hourly wage for crowd work. Interesting questions include: What are the types of disabilities that significantly affect hourly wage? Do having upper body motor impairments affect hourly wage more significantly compared to other disabilities due to difficulties in interacting with devices like mice and keyboards that are needed to perform many of crowdsourcing tasks?

Our analyses are not without limitations. First, our data analyses are exploratory; we are not arguing for confirmatory insights. Even so, our analyses are important in guiding future research. The hourly wage results were calculated for the plugin users, who may be more tech-savy and more fluent in performing crowdsourcing tasks. Our estimate of work intervals may not correspond to the time spent actively working on HITs. Our analyses did not take bonus payment into account.

REFERENCES

1. Abigail Adams and Janine Berg. 2017. *When Home Affects Pay: An Analysis of the Gender Pay Gap among Crowdworkers.*
2. Chris Callison-Burch. 2014. Crowd-workers: Aggregating information across turkers to help them find higher paying work. In *Second AAAI Conference on Human Computation and Crowdsourcing.*
3. K. Hara, A. Adams, K. Milland, S. Savage, C. Callison-Burch, and J.P. Bigham. 2018. A data-driven analysis of workers' earnings on Amazon Mechanical Turk. In *Conference on Human Factors in Computing Systems - Proceedings.* https://doi.org/10.1145/3173574.3174023
4. Kotaro Hara and Jeffrey. P. J.P. Bigham. 2017. Introducing People with ASD to Crowd Work. In *Proceedings of the 19th International ACM SIGACCESS Conference on Computers and Accessibility, ASSETS 2017.* https://doi.org/10.1145/3132525.3132544
5. Seth D. Harris and Alan B. Krueger. 2015. *A Proposal for Modernizing Labor Laws for Twenty-First-Century Work: The "Independent Worker."*
6. Brent Hecht, Lauren Wilcox, Jeffrey. P. Bigham, Johannes Schöning, Ehsan Hoque, Jason Ernst, Yonatan Bisk, Luigi De Russis, Lana Yarosh, Bushra Anjum, Danish Contractor, and Cathy Wu. 2018. It's Time to Do Something: Mitigating the Negative Impacts of Computing Through a Change to the Peer Review Process. *ACM Future of Computing Blog.*
7. Siou Chew Kuek, Cecilia Paradi-Guilford, Toks Fayomi, Saori Imaizumi, Panos Ipeirotis, Patricia Pina, Manpreet Singh, and others. 2015. *The global opportunity in online outsourcing.*
8. Philippe Marcadent, Janine Berg, Mariya Aleksynska, Valerio De Stefano, Martine Humblet, Christina Behrendt, Susan Hayter, Christopher Land-Kazlauskas, Angelika Muller, Niall O'Higgins, Friederike Eberlein, Simone Marino, Bao Chau Le, and Calum Carson. 2016. *Non-Standard Employment Around The World.*
9. Lucas Rosenblatt, Patrick Carrington, Kotaro Hara, and Jeffrey P Bigham. 2018. Vocal Programming for People with Upper-Body Motor Impairments. In *Proceedings of the Internet of Accessible Things* (W4A '18), 30:1--30:10. https://doi.org/10.1145/3192714.3192821