

# Aggregated On-Demand Worker Profiles

Anonymized for Review

## ABSTRACT

### ACM Classification Keywords

H.5.3. Information Interfaces and Presentation (e.g. HCI): Group and Organization Interfaces

### Author Keywords

TODO

## INTRODUCTION

something

**crowd work has a reputation problem;** on-demand work has grown significantly; task diversity is growing; new platforms continue to emerge; trust still a problem

**this is a cold start problem;** workers new to the platform are stuck slogging it; workers new to a requester stuck too.

**existing platforms aren't great at this stuff;** Mechanical Turk

**clever solution: résumés for on-demand workers;**

in “conventional” work, the problem of signaling a worker’s quality was solved by using past worker performance as a proxy for future performance

on-demand work platforms have tried to do this with approval and rating systems, but they’re generally too vague to be useful

conventional work résumés usually allow the worker to emphasize and omit information that’s not relevant — **what if we facilitated that?**

we built a system that collected data from workers’ profiles on online crowdsourcing platforms (first AMT, then others), and parsed that data to present more meaningful analytic data on things like

1. the nature of the task; objective (i.e. factually based and evaluable) versus subjective (e.g. survey )
2. the type of requester; academic versus industry
3. *others*

we also built a proof-of-concept qualifications management system abstracted from both our worker profile system and the work platform itself (to explore the potential to abstract worker qualifications and credentials from the system itself, allowing other parties to specialize in this task)

we evaluated this system from two perspectives:

1. did requesters who used this system find that the worker data better-informed their qualifications management and worker solicitation? in other words, was the output of the work more reliably accurate when they relied on the analytic data that we provided versus the coarse approval/rejection rating?
2. did *workers* benefit from having high level data providing some insight into their work trends? did this lead them to better work more quickly? did they take a more active role in the management of their reputation / “worker profile” / résumé?

we also explored whether the externalized worker qualification system worked effectively, and considered the potential advantages and disadvantages of a set of decoupled systems rather than an integrated one (market, qualifications assessment system, payment platform, etc...).

## DEAD KITTENS

Today’s on-demand labor markets don’t seem to be driving toward a bright future for workers. At one end of the spectrum, workers are treated as interchangeable cogs whose purposes are as backdrops upon which to project rubrics, workflows, and processes [6]. In this space, workers’ lack of expertise is precisely what makes this form of labor compelling — as an opportunity to show that, when arranged and managed correctly, “...non-experts can achieve better coverage and latency than a professional...” [5]. At the other end of the spectrum, workers in on-demand labor markets are seen as the walking dead — human laborers who will “satisfice” until artificially intelligent agents can take over .

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## Graveyard of old paragraphs

<sup>0</sup> In the past decade, as markets for transient on-demand labor have grown in popularity, a number of challenges associated with these modes of work have emerged and grown as well. In particular it remains to be seen how, or indeed *if*, expert workers will participate in on-demand labor markets. While crowdsourcing and the gig economy have made it possible for millions of people to participate in the workforce in ways that were previously unavailable to them [7, ], the longer-term trajectories of these people’s careers are still as uncertain as they were when Kittur et al. called crowd work “...largely a dead-end job” [4]. So we find ourselves more than 5 years later answering the same question: will these people have the opportunity to engage in high-skill work in time? While research has found myriad ways to arrange and manage non-expert crowd workers to produce expert quality work, these achievements nevertheless do little to affirm that the future of work will afford for skilled workers, instead suggesting that the work experts do today may someday be done by a handful of non-experts.

Lack of trust and reputation has held back high-skilled work. Much of the work into complex crowdsourcing applications has operated on the premise that workers are roughly similar; they’re all non-experts from a nebulous pool that can be sourced arbitrarily. Even where researchers recognize worker persistence, workers are often perceived and treated as untrustworthy [2]. As a result, crowdsourcing innovations typically focus in the domain of workflows and processes [1, 3]. And, on some level, this is in line with the ethos of on-demand work itself: as researchers have found, many crowd workers appreciate the fleeting nature of their relationship with the platform and with the people for whom they work

The reputation problem is closely related to a “cold start” problem. Workers who are new to a platform can’t signal to the platform that they’re any good. Even when they’re established in the platform, it can be difficult for requesters to discern high-quality workers; rating inflation (exhibited both in AMT as well as on Uber, etc...) complicates simple approval rating-based judgments, and in general these platforms only offer aggregate, coarse data on a worker’s quality — for example, their approval rate overall, or over the past several months, rather than within certain subsets of tasks.

A historical analysis of on-demand work can inform potential solutions.

Aggregated places for people to store and reference their résumés

What we built

What we found quantitatively

What we found qualitatively