Solidarity and A.I. for Transitioning to Crowd Work during COVID-19

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Abstract

Due to the COVID-19 pandemic, a number of gig workers who engaged in location-based gig work (e.g., Taskrabbit, Care.com, or Wag) have had to transition to new jobs that are independent of location (e.g., online freelancing or crowd work). However, this has been a difficult transition. Especially because in this new environment, gig workers now have to compete globally for work, and they also have to focus on work interactions that are primarily online (instead of gig work that takes place within specific physical locations or within in-person meetings). In this paper, we build on our extensive research on gig work, gig literacy and the design of crowdsourcing systems, to present an intelligent architecture for helping workers transition to new gig jobs in times of global crisis. Our intelligent architecture uses machine learning and draws on collective action theory to introduce "Solidarity Brokers." Our Solidarity Brokers are computational mechanisms that identify the best ways to build solidarity between workers with the purpose of mobilizing workers to help each other transition to new jobs. We finish by presenting a brief research agenda for intelligent tools that facilitate work transitions during the global pandemic and beyond.

Introduction

Many of the jobs in location-based gig work have disappeared due to the COVID-19 pandemic and the need to maintain social distancing (Chandler 2020). For instance, to adhere to the social-distancing policies enacted by the Center for Disease Control (CDC), a majority of dog owners have stopped using the location-based platform "Wag," which matches their dogs to gig workers who can walk them (Freedman 2020). For the most part, location-based gig work has turned into a health hazard (Stabile et al. 2020; Paul 2020; Conger et al. 2020) or is no longer available due to people having to stay home (e.g. clients on Taskrabbit, another type of location-based gig market, have had to limit how much they use the service as it can put workers or themselves in danger (Paul 2020)). Consequently, a number of workers have started switching to location-independent gig work, such as freelancing or crowd work (Rahul De et al. 2020).

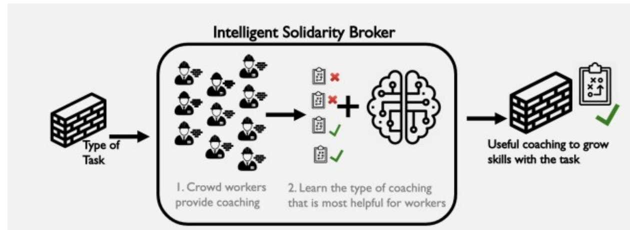

Figure 1: Overview of our intelligent architecture which: (1) builds solidarity between workers; (2) uses the solidarity to mobilize novice workers to help each other transition into crowd work.

Many of these transitioning workers are already familiar with gig work and digital labor platforms. However, the dynamics of location-independent digital labor can still be different and overwhelming for them. Crowd work and online freelancing occur on a global and remote scale which can mean global competition, varying cost of living, and differences in minimum standard wages for workers (Jager et al.¨ 2019). Global competition means that the "cheapest offer" can be more influential in hiring than the "best quality" offer (Jager et al. 2019). This translates to the state of competi-¨ tion being different from location-based gig services where clients and workers are local (i.e., usually meeting up in person) and there is a "shared notion of reputation as value (Gandini 2016)." Thus, factors such as being able to adequately identify who is a legitimate client or employer based solely on online cues becomes critical (McInnis et al. 2016; Savage et al. 2020; Kittur et al. 2013). Workers who are unable to do so, can end up stuck doing low paying labor, or even have their identity stolen by fraudsters. Working with a bad client can cost workers' their livelihood (Savage et al. 2020; Hara et al. 2018; Toxtli et al. 2020). As a result, newcomers to crowd work and freelancing are often required to develop "gig literacies."

Gig Literacies as Invisible Work. Gig literacies are strategies used by gig workers to take advantage of digi-
tal labor platforms creatively and productively while avoiding their drawbacks (Sutherland et al. 2020). Gig literacies emerge from the invisible labor that workers have to perform in addition to the specific core tasks which they

get paid to do. Notice that invisible labor is typically defined as *"unpaid activities that occur within the context of paid employment that workers perform in response to requirements from employers and that are crucial for workers to generate income (Crain et al. 2016).*" Past research also often refers to invisible labor as "articulation work", which is similarly defined as the critical activities that workers have to do beyond their core paid work tasks, and that must be performed to enable core work (Strauss 1988).

With regard to our prior discussion on gig work transitions, we note that there is an overlap with much of the gig literacies and invisible labor present in location-based and location-independent gig labor. For instance, in both settings, workers have to develop skills that involve "effectively communicating with clients," "balancing between personal and professional lives through time management," or "setting hourly minimum rates."

However, it is currently unclear how much of these skills actually overlap, or what specific new gig literacies have to be developed or boosted as gig workers approach crowd work and online freelancing. Examples include: "how to compete for jobs on a global scale", which directs attention to the ways through which one can present the skills one has in order to compete with other digital workers.

Notice that a key aspect of the precarity of gig work also concerns the fact that gig workers have to develop these skills on their own. This is one of the reasons why transitions into new gig jobs are deemed challenging (Lustig et al. 2020). It can take novice workers a significant amount of time before they learn the ropes of crowd work or online freelancing just to make a viable living.

In this short paper, we provide an overview of the current ecosystem in which crowd workers and freelancers develop themselves and grow their skills. We make an effort especially to highlight the limitations and problems with this current ecosystem. Next, we present our intelligent architecture that uses machine learning and collective action theory to: (1) build solidarity between workers; (2) use the solidarity to mobilize workers to help each other transition into crowd work. Figure 1 presents an overview of our proposed architecture. We finish by discussing research opportunities that can emerge from our proposed architecture.

Relevant Body of Work: Current Ecosystem.

Our previous work indicates invisible labor is often more time consuming and significant for newcomers to freelancing and crowd work platforms (Jarrahi et al. 2020). Transitioning into crowd work or online freelancing usually involves a steep learning curve since the new workers may lack key resources such as solid ratings or alreadyestablished work portfolios. In more conventional work settings (i.e. organizational work), the organization helps workers transition to new job positions through processes like formal orientation or cultural socialization (Klein et al. 2012). That is, traditional employment typically offers new workers the ability to develop skills and grow (Kramar 2004; Williamson 1998; Duffy 2000; Smith 2013) Work satisfaction theories have stressed the importance of providing processes to help workers transition to new jobs (Kramar 2004; Ramlall 2004). This is not only to help workers thrive at their job, but also to better motivate them (Ryan et al. 2000; Cartwright et al. 2006). Crowd workers and freelancers in general have often found it difficult to transition to new jobs on their own (Kaufmann et al. 2011). The problem is even more aggravated because digital labor platforms in general have not been designed to facilitate workers' development, let alone the process of transitioning to new job opportunities (Bigham et al. 2017; Dontcheva et al. 2014; Whiting et al. 2017; Suzuki et al. 2016). As a result of this shortcoming, workers have had to investigate, on their own, ways in which they can figure out how to transition to new jobs and develop the skills they need to earn a minimum living as freelancers or crowd workers (Kittur et al. 2013). Most of these workers typically turn to online forums to share tips and advice on how to grow and develop themselves (Savage et al. 2020; TurkerView ; Kaplan et al. 2018; Saito et al. 2019). However, crowd workers and freelancers encounter a considerable economic burden when they have to use unpaid time to learn the tricks of the job just to start making a decent living (Kelliher et al. 2008; Van Alstyne et al. 2017; Rosenblat et al. 2016; Alkhatib et al. 2017). Given the low pay of crowd work and freelancing (Paolacci et al. 2010; Berg 2015; Durward et al. 2016; Thies et al. 2011; Hara et al. 2018), this only adds to the burden of workers.

To address this issue, scholars have recently started to explore tools that facilitate skill growth while doing crowd work or freelancing (Dontcheva et al. 2014; Coetzee et al. 2015; Doroudi et al. 2016). However, many of these models have depended on either: (a) requesters (employers), who might not have the time, interest, or knowledge to help workers (Doroudi et al. 2016; Irani et al. 2013; Kulkarni et al. 2012); or (b) experienced workers who teach novices the ropes (Suzuki et al. 2016). However, involving experienced workers can be expensive. As a result of all of this, these models typically have not scaled well and workers report several limitations to their mass adoption (Silberman et al. 2010).

On the other hand, researchers have also argued that transitioning to new jobs on crowdsourcing markets and freelancing has been made difficult because the platforms limit the information that is made available to workers. Researchers and practitioners consider that the lack of transparency on digital labor platforms is one of the main reasons why transitioning is difficult and workers are so unfairly compensated (Hara et al. 2018; Jaffe et al. 2017).

Economists consider that a market is transparent when all of the different actors on the market can access a wide range of information about the market, such as: the type of products that are available, the type of services that the market offers (including quality), or the capital assets (Strathern 2000; Overgaard et al. 2008). In this space, Silberman et al. discussed how not having transparency on gig markets can hurt workers earnings: “A wide range of processes that shape platform-based workers’ ability to find work and receive payment for work completed are, on many platforms, opaque (Metall 2016).”

Part of the problem is that most digital labor platforms have focused much more on providing transparency information solely to employers, by allowing them to access indepth knowledge about the workers on the platform, and provide much less information to workers (e.g., on Amazon Mechanical Turk (MTurk), one of the most popular crowdsourcing markets, workers previously could not profit from knowledge about requesters’ previous hiring record or the estimated hourly wage of the tasks on the market, although as of July 2019, this has started to change[1]). This lack of transparency for workers can lead them to invest significant time in a task but receive anywhere from inadequate to no compensation. This is one of the main reasons why transitioning can be difficult.

To begin addressing the issue of transparency, scholars and practitioners have developed web browser extensions (Irani et al. 2013; TurkerView) or created online forums[2]to bring greater transparency to Turkers. These tools and forums provide Turkers with otherwise unavailable information about requesters, tasks, and expected payment. For instance, TurkerView allows workers to obtain an overview of how much money they will gain per hour if they work for a given employer. We are seeing a rise in the number of workers, including novices, who use these types of tools and forums to access transparent information about digital labor platforms (Kaplan et al. 2018). However, despite this, only a fraction of Turkers’ earnings are well above the minimum wage (Hara et al. 2018). Perhaps, part of the problem is that adopting and using transparency tools to earn higher wages is not simple. Each transparency tool displays a wide range of metrics. It is not straightforward for workers to easily decide which transparency metric they should analyze to ensure better wages. This complexity has led a number of workers to employ transparency tools ineffectively (Kaplan et al. 2018; Saito et al. 2019). Overall, the transitioning process proves to be still difficult.

Based on this, we argue that an effective route to facilitate the transition of new workers into location-independent digital work (e.g., crowd work or online freelancing) is threefold. We need intelligent systems that: (1) do not depend on employers or external expert workers to facilitate the transition; (2) help workers to navigate transparency data, regardless of their analytical backgrounds; (3) help workers to effectively manage the invisible labor associated with crowd work and freelancing.

We therefore propose a system’s architecture with “Solidarity Brokers”, which is also based on sociology theory of collective action (Marres 2017) and theories in collective intelligence (Malone 2018). In particular, we envision systems where gig workers are mobilized for collective action based on the solidarity they have with each other. In this case, the collective action involves organizing workers to help each other transition to new jobs on crowdsourcing markets and freelancing (which implicitly involves skill development to access higher wages). Collective action theory argues that a way in which you can mobilize, or motivate, people around a common goal is by creating a bond of unity between people, or a “common goal relationship” (Lindenberg 2006). Based on this, we design an architecture that uses machine learning to learn the best ways to create a bond between workers to mobilize them for different goals related to transitioning to digital labor platforms. In the following, we present an overview of our architecture and discuss how it can be used to help workers transitioning to new jobs in crowd work and online freelancing.

Architecture for Transitioning to Crowd Work

Our intelligent architecture is composed of “Solidarity Brokers,” that focus on using machine learning to identify the best ways to build solidarity between workers and then mobilize workers to help each other transition to new jobs. In this short paper, we focus particularly on helping workers to build skills for completing crowd work, and discuss briefly how this same approach can be used to help workers manage transparency information and invisible labor on crowdsourcing markets to earn higher wages. Figure 1 presents a diagram of our Solidarity Broker architecture.

While there are many ways we could computationally organize workers to bond and collectively help each other, we focus on collective help that could occur while on the job. In our design, we took into account that it was critical to reduce the amount of time that crowd workers spent outside gig markets, as this was time where they would not be receiving wages. It was in this setting that we considered that workers would be collectively helping each other via a web plugin that would enable them to continue working on the gig market and earning money. Additionally, we considered that participating in the collective help would not be the main task that workers are doing. It was thus important for us to design solutions that would allow for the collective help to be provided in a manner that was

[1] https://blog.mturk.com/new-feature-for-the-mturk-marketplace-aaa0bd520e5b

[2] www.turkernation.com/

lightweight and would not distract workers from their main job. Our design is based on ideas from “Twitch Crowdsourcing” (Vaish et al. 2014) where people do micro-tasks as a side activity that does not disturb their main task.

For this purpose, we frame the design of our Solidarity Brokers around: (i) Availability: workers should be able to engage in collectively helping each other with a click; (ii) Low Cognitive Load: workers should be able to collectively help each other without the task being a distraction from the main work they are doing on the crowd market. Finally, given the economically harsh labor conditions that crowd workers face, our design focuses on enabling: (iii) Paid Training: allow workers to receive the collective help for transitioning into crowd work while they are earning money.

To enable these points, our Solidarity Brokers utilize three components: 1) Collective Help Collector, 2) Intelligent Selector (to select the collective guidance that is most useful), and 3) Collective Help Display (to present to workers the help that is most useful). Figure 2 present an example of what our end-user interface looks like.

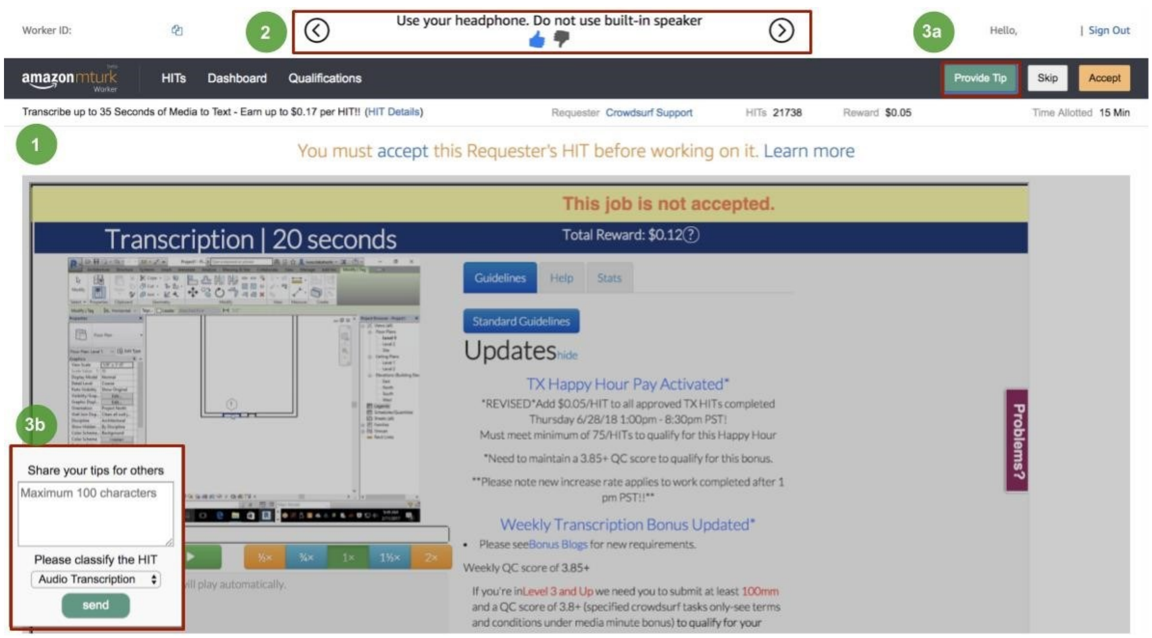

Figure 2: Screenshot of our architecture, which enables workers to develop their skills while on the job by: (1) integrating directly into crowdsourcing markets; (2) presenting selected advice to workers; and (3) allowing workers to have solidarity with each other and easily advise others.

1. Peer Help Collector. This piece enables workers to input advice to other workers that will help them transition to new micro-jobs. Notice that for this paper we focus on advice that helps workers complete micro-jobs, but the advice could also involve figuring out how to best interpret and utilize transparency information, or even best practices of handling invisible labor (i.e., tasks that workers are not paid to do, but must do in order to earn a minimum living wage). The collector lives as a plugin that connects with the given crowd market in which the worker is operating in. For the design of the plugin, we considered that workers would be able, with a simple click, to provide advice and assistance to other workers on how to improve on particular tasks on the crowd market (particularly the one the worker is currently doing). In contrast to prior work where workers have to provide lengthy assistance to others (Doroudi et al. 2016), our Solidarity Brokers focus on asking workers to provide micro-assistance.

The Chrome extension interface of our Solidarity Brokers has a small “provide tip” button. Upon clicking the button, workers see a small pop-up window where they can provide their micro-advice that will help other workers transition into new crowd jobs. Notice that this setup enables our design principle of “availability.” Additionally, it was also important to us to limit the cognitive load that providing collective advice imposes on workers. This is why we limited the length of the micro-assistance that workers gave to each other to 100 characters (we set the characters limit to 100 characters through trial and error to make it as simple as possible for workers). In the pop-up window that our plugin showcases, workers then just have to select the type of tasks for which their micro-advice is relevant and then type their advice. This allows us to match the advice to the particular aspect of micro-jobs that a worker wants to transition to in a simple and direct manner.

2. Intelligent Selector. For each of the different tasks that workers have to do on gig markets, the Peer Help

Collector returns a long queue of micro-advice. However, not all advice might actually be helpful for workers in their job transitions. Especially with the large amount of micro-advice that workers provide, relevant “advice gems” might get lost in the muck. To overcome this issue, we have an Intelligent Selector that focuses on learning what type of advice is best for transitioning to a particular type of micro-job (the type of micro-jobs we consider are based on prior work (Gadiraju et al. 2014).)

We use a reinforcement learning algorithm where the algorithm focuses on maximizing the number of workers who consider that the micro-advice that is presented to them is useful. For this purpose, we first ask workers to microassess a particular micro-advice via upvotes or downvotes. (see Figure 2). Our Solidarity Brokers aim to have workers micro-assess advice that is related to the particular tasks that workers are currently doing. These assessments are fed into our reinforcement learning algorithm that aims to maximize the number of upvotes it obtains from workers. Notice that the algorithm can choose actions from the various microadvice that the tool has stored. Once chosen, the algorithm shows the micro-advice to the workers. Through this process our tool starts to learn the micro-advice that is best suited to present to workers to help them transition to new micro-jobs.

3. Collective Help Display. This component focuses on

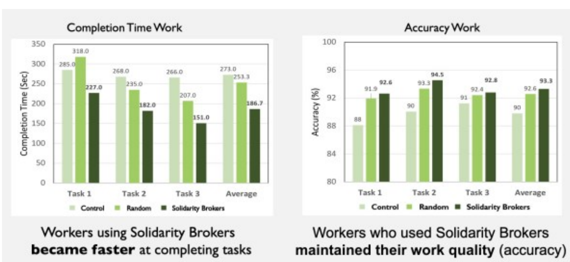

Figure 3: Results from our real world deployment that helped workers to develop their skills (become better and faster at their job).

presenting the micro-advice that our reinforcement learning algorithm considered would help workers the most in their new micro-job transitions. For a given task, the Collective Help Display presents to workers four different microadvice that the reinforcement learning algorithm ranked highest on the list. If workers want to read more advice, they can click the left or right button to view more. To ensure that new advice has the chance to be evaluated, our tool intermixes new advice that needs micro-assessments into the list of high ranking advice. Figure 2 presents how the microadvice is displayed to workers and how workers can provide advice to others to facilitate their job transitions.

Exploring Solidarity Brokers

We have deployed our Solidarity Brokers to help novice workers become faster and better at their job (see Fig 3) (Chiang et al. 2018b). Workers expressed how our architecture helped them transition into new types of micro-jobs they had never dared to do. We have also started to explore a similar approach for helping workers to earn higher wages (Savage et al. 2020). Overall we are finding that our Solidarity Brokers are effective for helping novice workers develop their skills and likely have the potential to help workers from location-dependent gig labor transition into crowd work and freelancing.

Implications

Through our real world deployment with our Solidarity Brokers, we have found that we can start to help workers transition into new micro-jobs and develop important gig literacies, especially in the form of skill development. We believe that architectures like our Solidarity Brokers have the potential of being especially useful in relation to the emerging realities of the COVID-19 era in which there are thousands of new workers who are transitioning to crowd work or online freelancing (Fabian Stephanym Vili Lehdonvirta 2020). Our goal is to help facilitate these transitions in order to be as efficient as possible.

Our empirical work (Chiang et al. 2018b; Savage et al. 2020) suggests that we can use our Solidarity Brokers to help workers transition to new job opportunities on crowd markets, especially since this does not require the help from external experts or employers. In the future, we would also like to explore how we could use our Solidarity Brokers to organize workers around more complex goals or professions, e.g., helping online workers transition into becoming CTOs, managers, or digital marketers. We also plan to explore the benefits of these types of architectures to help facilitate non-traditional populations transitioning into crowd work, such as rural communities (Hanrahan et al. 2020a; Chiang et al. 2018a; Angel et al. 2015; Hanrahan et al.´ 2020b). Within this space, we see value also in tools that can help new workers improve their productivity (Kaur et al. 2020). This can involve better management of their time (Williams et al. 2018), helping crowd workers to develop habits that will help them thrive at the job (Stawarz et al. 2015; Agapie et al. 2012; Yang et al. 2017), use different tasks as learning opportunities (JACKSON et al. 2019; Heckman et al. 2019) or even designing tools that help novice crowd workers more effectively communicate with employers and each other (Qiu et al. 2020) (e.g., by helping workers to know when is their best moment to speak (Rintel et al. 2016) or even helping them to communicate with employers from different cultural backgrounds (He et al. 2017b; 2017a; Crabtree et al. 2003)).

Prior work has found that the sequence in which workers perform tasks can impact how well they perform the tasks (Cai et al. 2016). This is true also within learning settings, for example, having spaced repetitions can impact the number of words a person can learn when learning a new language (Edge et al. 2011). Similarly, mixing tasks that have different levels of difficulty or similarity can impact a person's knowledge acquisition (Koedinger et al. 2012). In the future, we see value exploring our Solidarity Brokers with the automatic generation of "to-do lists." These to-do lists could further help workers transition to new micro-jobs. There is likely also value in combining these automatically generated lists with assistance collected from other workers. Our Solidarity Brokers could then select the best type of guidance to provide to workers to best facilitate their job transitions.

Conclusions

Within the new work environment being created by the COVID-19 Pandemic, it is likely that crowd markets and online freelancing platforms will become even more important employment hubs that will be sought by a large number of transitioning workers who have varying expertise and skill levels and who will want to be able to compete for employment opportunities and earn better wages (Kittur et al. 2013). In this environment, it is even more critical to create mechanisms that help newcomers transition into crowd work (Deng et al. 2013). We believe there is value to further explore tools that integrate machine learning into their workflow to facilitate workers' growth (Williams et al. 2016) and the onboarding process.

Future work Our proposed architecture presents some important limitations. For example, our Solidarity Brokers, through their guidance, could potentially shutdown workers' thought process on how to transition to new microjobs on the gig market. Novices might also suddenly start to feel incapable or that their approaches are not enough (i.e., it could affect the self efficacy of novices.) Future work could explore the most effective ways to facilitate workers' transition into new jobs, while still facilitating workers' own initiative and helping workers to innovate themselves (Chan et al. 2016). Here there might be value in exploring different reward mechanisms. For example, perhaps we can facilitate setups where workers are prized for completing creative tasks rapidly in their own way (Buxton 2010; Dow et al. 2009).

We have run real world deployments with our Solidarity Brokers (Chiang et al. 2018b; Savage et al. 2020). In the future, we are interested in running a longitudinal deployment of our architecture with workers who are transitioning to new jobs in this new post-COVID-19 era. It is unclear how our approach will play-out long term. Will workers continue sharing advice with each other if they feel they are losing opportunities in doing so? For example, if a worker advises others about how to best deal with a particular employer, it might limit the worker's opportunity to find good micro-jobs from that particular employer. Future work could quantify the benefits of our Solidarity Brokers for long term usage.

Additionally, we plan to study the sustainability of our Solidarity Brokers. It is unclear whether workers will continuously have advice to give each other to facilitate the onboarding process, or whether there is a finite advice set that can be given. Given that crowd work is continuously evolving (Hara et al. 2018), we believe it will be important to always have in place Solidarity Brokers where workers can receive assistance on the fly to better understand how to transition to new crowd jobs. Similar tools that thrive from knowledge input, such as Turkopticon (Irani et al. 2013; Williams et al. 2019), have had continuous input throughout the years. We also envision that our Solidarity Brokers could help more senior workers to take on manager roles and hence further facilitate growth on the platform. Here we will connect with research in ubiquitous computing that studied how to facilitate skill development in specialized areas (Girouard et al. 2018).

We are also interested in exploring the type of peer communication that workers should have within our Solidarity Brokers to ensure long term support, or to help crowd workers' to organize around a number of other collective goals, for instance goals around fighting for their rights. Here we plan on building on the vast CSCW research that has focused on designing computational tools for collective action (Vincent et al. 2019; Li et al. 2018; Wilkins et al. 2019; Grau et al. 2018; Savage 2020; Savage et al. 2016).

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