Mooqita: Empowering Hidden Talents with a novel Work-Learn Model

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The definitive version was published as:
Krause, M., Schiöberg, D., & Smeddinck, J. D. (2018). Mooqita: Empowering Hidden Talents with a Novel Work-Learn Model. Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems, CS14:1-CS14:10. https://doi.org/10.1145/3170427.3174351

Abstract
We present a case study of Mooqita, a platform to support learners in online courses by enabling them to earn money, gather real job task experiences, and build a meaningful portfolio. This includes placing optional additional assignments in online courses. Learners solve these individual assignments, provide peer reviews for other learners, and give feedback on each review they receive. Based on these data points teams are selected to work on a final paid assignment. Companies offer these assignments and in return receive interview recommendations from the pool of learners together with solutions for their challenges. We report the results of a pilot deployment in an online programming course offered by UC BerkeleyX. Six learners out of 158 participants were selected for the paid group assignment paying $600 per person. Four of these six were invited for interviews at the participating companies Crowdbotics (2) and Telefonica Innovation Alpha (2).

ACM Classification Keywords
H.5.3. [Information Interfaces and Presentation (e.g. HCI)]: Group and Organization Interfaces—*Computer-supported cooperative work*

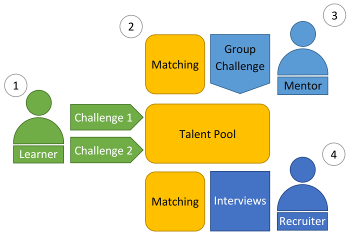

Figure 1: The process that implemented the novel work-learn model in our pilot study. Please reference the Introduction for a description.

Author Keywords

Online Education; Online Work; Online Recruiting; Talent Scouting; Work Learn Balance; Computer Supported Recruiting; Human Resources

Introduction

Over the past decades classic work environments have changed rapidly from manually intensive labor to cognitively demanding jobs resulting in notable socioeconomic changes in cities with declining traditional industry such as Chicago (USA), Detroit (USA), or Manchester (UK). Additionally, artificial intelligence and other automation is threatening to take over tasks in many areas of traditional white-collar work. This illustrates a need for flexible and accessible education that allows workers to transition from less knowledge-intensive labor to high-skilled jobs. Online courses offer a more flexible model for education in which learners from all over the world can gain access to new skills. However, these courses alone do not adequately prepare learners to find gainful employment, nor do they attract those learners who can benefit the most from affordable higher education – 60% of learners in online education already have at least a bachelor's degree [4].

The Mooqita project investigates a new model for the *relationship between working and learning* that ultimately aims to enable learners to have an income while furthering their education and gathering qualifications. This *work-learn model* (see Figure 1) also aims at supporting learners with finding jobs that match their skill sets and personality.

In the first phase of the process, additional homework assignments are added to an online course hosted by BerkeleyX. We measure the performance of learners and collect this information in our *talent pool* (1). The talent pool is used by our matchmaking system (2) to find learners for the paid group challenge (3) and match learners with potential employing organizations (4).

We present results from a pilot deployment and exploratory study investigating research questions around three main concerns that are detailed later on: 1) *Are the involved parties interested in participating in the process?* 2) *Is the quality of task solutions and the extent of monetary rewards or gained credentials sufficient to drive the process?* 3) *Does the process lead to beneficial effects beyond each individual task integration?*

We collaborated with two companies: Crowdbotics (Bay Area, USA) and Telefonica Innovation Alpha (Barcelona, Spain) that are interested in interviewing hidden talents. The paid challenge was provided by Praveen Paritosh, a senior research scientist at Google. He also took on the role of a mentor for learners in the paid challenge.

The pilot successfully enabled learners to earn money while they participated in an online course. Learners also built a portfolio that increased their chances to be invited for a job interview. With this case study we contribute insights on approaches to bringing working and learning closer together, making education more affordable and accessible. We build on – and expand – concepts from crowdsourcing / the gig economy and (massive open) online education; both relevant and technically related areas in HCI.

Related Work

We implement a unique approach that contributes to the efforts to transform the worlds of working and learning. However, the process builds on – and combines – related ideas and systems. Feedback and practice are key elements in developing new skills [13] and gaining insight to better understand how one's work is perceived by others [5]. Feedback can be generated from various sources, including instructors [15, 8], self-assessment [3], crowd feedback [2], or peer feedback [12, 9]. An essential benefit of peer reviews is that students learn by providing feedback to peers [12]. Learners practicing revision skills strengthen their ability to identify and solve problems [12].

A growing body of research is concerned with measuring feedback quality [10, 19, 8, 13] and with ways to improve such feedback [18, 1, 10, 20]. The general takeaway from this work is that peer reviews among learners do work if supported by structured guidance and that reviews improve if the reviewer receives feedback. In this first case study of Mooqita the value of learning to review is even more relevant since code reviews are part of the necessary skill sets of software developers. A core component of Mooqita is online team work. Others have shown that it is possible to step up the complexity of crowd working tasks by enabling strangers to perform as a team [17, 16].

Lastly, the concept of learning on the job is fairly well-known and tested. Recently it appears to face adoption in the online work and tasks world with projects such as `www.agileventures.org`, which offers learners to work on real world open source projects (currently without a review-feedback system and option to build up more diverse credentials). Mooqita attempts to combine the best of all these ideas as mentioned above to maximize the benefits for every party involved in the process.

Research Questions

The pilot deployment and feasibility study that we report on aimed to gather first corroborative insights regarding the following successive exploratory research questions that investigate whether the system attracts the target groups, whether the exchange leads to convincing results, and whether there are effects beyond each individual task-solution transaction:

Q1: Motivation and incentives: Are the involved parties interested in participating in the process? Are learners in online courses interested in tackling optional – possibly paid – tasks? Are organizations interested in task solutions and hiring leads?

Q2: Quality of contributions: Are the involved parties capable of providing adequate contributions? Are the learners able to provide satisfactory task solutions and reviews? Does the review-feedback process lead to a good task solution quality? Are the organizations able to contribute significant monetary rewards relative to the regular income of the learners, given the lower experience level of the learners?

Q3: Impact: Does the process lead to beneficial effects beyond each individual task integration? Do the earned credentials help learners to be invited to interviews? Do the organizations benefit from getting in touch with learners that have shown how they tackle tasks that are relevant to the organization?

Terminology

For the remainder of this publication we will use the following terms as defined here:

- *Learner*: A person participating in a class or any other event with the purpose to gain new skills and/or knowledge. In our case study learners are the participants of a publicly accessible online course.
- *Mentor*: Person who guides a learner or a team of learners through a project. This can be a member of any involved party. In this case the team members of

Mooqita took this role but also the parties providing the paid challenges.

- *Recruiter*: A representative from the party looking for hidden talents, either for hire or for a single project. The role is not necessarily the same the person has within her organization.

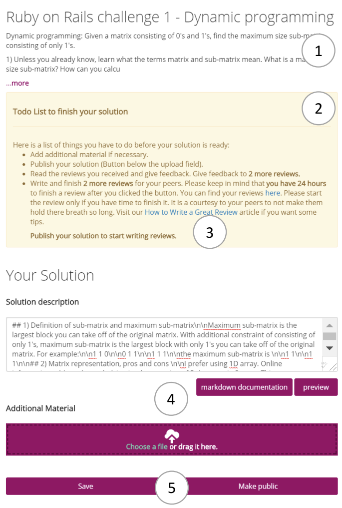

Figure 2: Screen shot of the user interface for learners. The challenge description (1) can also contain materials for download. A list of hints guides learners through the review process (2). The interface contains a guideline for writing reviews based on prior work [6, 20]. Learners can save a draft of their work (3) or publish their solution for review.

The Work-Learn Model

The work-learn process uses two types of additional homework assignments (*challenges*). 1) *Individual challenges* provide insights regarding the required basic skill set, reliability, and competence of learners. 2) *Group challenges* allow assessing personality traits, the ability to structure work, and organize a team.

Course Integration

The pilot augmented a BerkeleyX course on EdX (CS169.1x Agile Development Using Ruby on Rails)[1]. The first individual challenge was designed in cooperation with Crowdbotics, and included in the first part of the course which provided an introduction to the Ruby programming language. Learners who finished their second regular homework assignment were presented with an additional page on EdX inviting them to work on the first Mooqita challenge. It required learners to find a maximum size sub-matrix (given a matrix consisting of zeros and ones, implement a program that finds the maximum size sub-matrix consisting of only ones). The goal was to test the skills in the area of dynamic programming.

The second challenge was offered after the 5th homework assignment. Learners were asked to send e-mails via a ruby server. The according web app should accept an email address, check address validity, and send a message to that address. Creating interactive web forms and apps is an essential skill to the collaborating organization.

Individual Challenge Delivery and Reviews

The interface for learners to access challenges is shown in figure 2. The learners were given three weeks to submit their *solution* and provide the required peer reviews. Each learner writes two peer *reviews* encompassing a textual description and a numerical quality rating ranging from 1 (low) to 5 (highest). As writing reviews is challenging we provide a digital guideline for learners based on Yuan et al. [20] and Krause et al. [6]. A completed review cycle is shown in figure 3

The reviews help other learners working on the same challenge. They are informed about newly available reviews via e-mail notifications and messages sent through the platform. Learners are asked to consider the reviews and to provide *feedback* on the review quality. The interface appears similar to the review interface, asking for a rating and a justification. A solution is considered complete when the learner provided a solution, two peer reviews, and feedback to the reviews they received. To estimate outcome quality independent experts reviewed each solution, review, and feedback. The solutions were reviewed by two expert ruby programmers from an independent company. The quality of the reviews and feedback was estimated by a post-doctoral researcher with teaching experience and by a teaching assistant.

Group Challenge

The top six learners were selected for the final group challenge, based on the ratings learners received for their reviews as the first indicator, their solution quality, as well as the quality of their reviews and the feedback they provided to their peers. The challenge tasked the learners with implementing a novel text comprehension test. The test was

[1] EdX (https://www.edx.org/school/uc-berkeleyx)

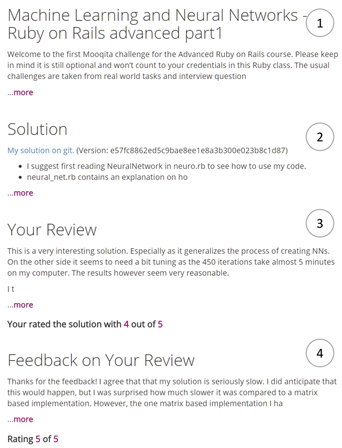

Figure 3: The learner's view of a completed review including 1) challenge description, 2) peer solutions, 3) the own review, and 4) the feedback received on the review.

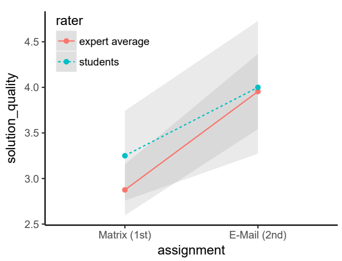

Figure 4: Solution quality ratings of students and experts appear to converge in the second individual challenge.

proposed by Praveen Paritosh and Gary Marcus in AAAI Magazine in 2016 [11]. Although the apparatus was described in the publication it was never implemented or tested. The proposed test uses *"a three-person game, the Iterative Crowdsourced Comprehension Game (ICCG). ICCG uses structured crowdsourcing to comprehensively generate relevant questions and supported answers for arbitrary stories [fiction or nonfiction] presented across a variety of media [videos, podcasts, still images]."* [11]

Praveen Paritosh acted as a *mentor*, providing on-demand feedback sessions to the learners, dedicating 16hrs of supervision over a period of 10 weeks. Each learner earned a total of $600 for the task solution, dedicating 90hrs on average to the project – work effort is self reported. The payment to learners was given in batches of 300$ for the first milestone –a first working prototype– and 300$ for completing the project.

Results

Since this pilot deployment aimed to be an exploratory proof of concept and the ability of the approach to support large numbers of learners had not yet been shown, the presence of the integration with a potentially well-paying final task was not openly announced. Instead, leads to the optional additional assignments were included at the bottom of the regular course assignments and thus left for ambitious learners to discover.

258 learners accessed the first regular homework assignment on EdX. 158 followed the optional task link. 88 (~55%) started the challenge, 14 (~9%) submitted a solution for the first challenge, and 12 (~8%) for the second challenge. Finally six (~5%) learners were invited for the paid group challenge. The cost of mentoring (16hrs) is estimated at (~$2000). Members of the Mooqita project contributed 20hrs of management and organizational support (~$1600). With 6 learners earning $600 each the total cost for the pilot project was ~$7200.

Solution and Review Quality

The average peer review rating for solutions was 3.2 (SD=.9, N=19) out of 5. We saw the full spectrum of ratings (1 to 5). The average solution length was 326 words (SD=406, N=19) plus source code. The average rating of reviews was 4.5 (SD=.8, N=35) out of 5. The average review length was 170 (SD=117, N=35) words. The average feedback length was 80 (SD=64, N=35) words. Learner *solution quality ratings* were compared with ratings from two expert ruby programmers. Cohen's Kappa agreement between the experts was .59, z=(3.5), p=.0005.

The agreement between the learners and the mean of the experts was .61, z=(3.9), p=.0001. We also compared the *review quality ratings* of learners to a group of two experts teaching computer science as a teaching assistant and lecturer respectively. The agreement between experts was .70, z=(4.21), p<.0001 while the agreement between learners and the average rating of experts is .46, z=(3.1), p=.001. Figures 4 and 5 show the solution and review ratings over the two different tasks.

Using *expectation maximization* [14] and the *Best-Fit Kappa approach* [7] to correct the bias of the learners the Kappa value increases to .62, z=(3.92), p<.0005. Figure 6 shows the improvement using the bias correction.

We also included an anonymous questionnaire after the pilot to capture the level of satisfaction with the reviews and other parameters of the course. The learners rated the overall quality of reviews they received as 4.5 (SD=.5, N=9) on average.

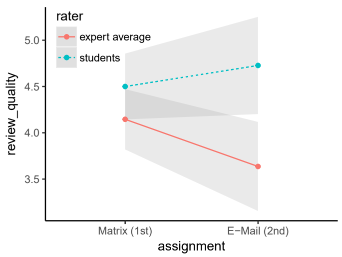

Figure 5: Learner and expert ratings of reviews diverge significantly. The distance increases in the second challenge suggesting a grade inflation.

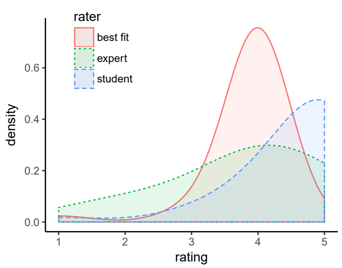

Figure 6: The student grade distribution (blue) is skewed further to the right than expert ratings (green). The best-fit kappa method reduces this effect (red). The difference between best-fit and experts is no longer significant $t(50.34)=.41$, $p=.679$

Median Household Income Increase
Learners in the group challenge earned US$600 over a period of two months and with a self-reported work load for the group challenge of 90hrs in total. To understand how significant their earnings within the course are we asked learners about their yearly income. We used the OECD equivalence scale for learners living in a household.

All our learners either lived alone or were the sole financial provider of their household. Using the OECD comparative price levels to achieve power purchase parity income values the median per-capita household income per year of the learners is $3000; very close to the global median of $2920. Hence, the $600 mark an increase of 20%. Five out of six participating learners reported that they consider their earning due to the task submission to be substantial.

Interview Chances Increase
We collaborated with two companies interested in hiring learners from our pilot study: a bay area start-up Crowdbotics and Telefonica Innovation Alpha. The qualitative input from recruiters from both companies was positive. The following quote represents the dominant sentiment:

This is such a neat idea. Normally MOOCs are a poor substitute for experience but this [work-learn process] is a game changer.

— Recruiter Telefonica

Furthermore, learners reported the impression that the project was helping them in their career.

Makes the difference. I've found Mooqita challenges very motivating. Not only learning by doing in real world examples, but also rewarding as you can join to a paid project. They have also helped me to get in touch with some companies looking for hiring developers!

— Learner 1 (Spain)

One of the technically most experienced learners was even able to find a new position with Crowdbotics.

As a MOOC junkie, I found myself benefit from Mooqita and got a job that pays as a Rails developer. There should be more people join[ing] the force to help online students the way Mooqita is doing.

— Learner 2 (China)

Challenging Project Management
Despite the positive outcomes and experiences of our learners, they mostly lack necessary management and leadership skills needed for solving complex challenges that require group coordination and team work.

The students are brilliant.
..teams lacked internal leadership [...]
..teams had communication issues [...]
There is exciting success in sparks of clever individual contributions, but the glue is missing.

— Mentor

Especially when learners aim to get hired for jobs that require them to lead teams, it is necessary to improve their team work and leadership abilities.

I think they would be great as interns. I just do not see they can inspire or take ownership yet; which they need to do in this position.

— Senior Researcher Telefonica

Discussion

Q1: Motivation and incentives: Are the involved parties interested in participating in the process?
Based on the reported findings we can see interest by all involved parties. The pilot deployment was not openly promoted among the learners and we still saw a large number of learners starting a challenge. Those who finished both challenges provided very positive feedback. As seen in the quotes above the companies showed keen interest too. We learned that the process should be simplified for the recruiter side as they struggled with staying within the time frames regarding communication and sending tasks.

Q2: Quality of contributions: Are the involved parties capable of providing adequate contributions?
The pilot deployment demonstrated that our process can support the task of finding technically excellent learners in a large online course. The results of the first two individual challenges and the results of the group challenge indicate that solutions are technically sound. The comparison of expert and learner ratings also shows that learners rated the quality with similar inter-rater reliability as our expert programmers did. The learner bias could be partially corrected using expectation maximization [14] and the best-fit Kappa approach [7]. The question how many learners in the course would also be able to solve the final group challenge was not tackled in the pilot.

The income increase was substantial for most learners. However, it is not yet easily predictable if the model can be scaled as presented. The quality of the individual contributions was exceptional, but bringing the groups to complete the project required substantial supervision – ~ 16 mentoring hrs and ~20hrs of management support from the Mooqita team in total. Yet, these results are similar to other projects that employ crowdsourcing for writing scientific papers or for building products with novices [17, 16] and the overall quality of contributions by learners was sufficient to support the process.

Q3: Impact: Does the process lead to beneficial effects beyond each individual task integration?
Feedback by the organizations and objective numbers indicate that learners have an increased chance of getting an invitation to interview. Although our learners have excellent skill sets, many lack the soft skills necessary to lead a project without external supervision. This made it hard for them to secure a position at Telefonica Alpha as the position required the ability to lead teams. The open position at Crowdbotics was less senior and therefore did not require leadership ability. Still the lack of management skills was an important aspect. In the broad picture, the participation in the process led to notable beneficial effects beyond each individual task integration for some learners and some organizations, but there is more potential that could not yet be harnessed.

Limitations and Future Work

Matchmaking plays an important role in the Mooqita process. Connecting learners with teams that actually match their personality and working style is one of the core ideas. Presenting learners with suitable tasks that were created in collaboration with the companies seeking a hire marks an important contribution towards this goal. In our ongoing work we are aiming to (partially) automate matchmaking. These steps will likely increase the success of placing learners with employers significantly.

Many of the administrative tasks in Mooqita, such as sending notifications and reminders, could be automated for scaling to make the platform more robust, reliable, and scalable.

When the first teams were put together to tackle the final task, we were happy to see a diverse group of skilled people from six different time zones and a large range of cultures. While this is great it also poses challenges in terms of team building. [17] have shown a method to build teams for software development in a fast way for online teams. The idea is to teach every participant the necessary skills for their role. We are aiming to implement a similar process that allows our learners to quickly function in the team but also learn how the team process as a whole works.

Conclusion

Can education be made more accessible and rewarding by integrating real world tasks that are provided by third-party organizations into online learning courses, generating potential payment rewards and opportunities to be considered for further employment? We presented indications that all parties that are required to facilitate a mutually beneficial exchange could be motivated to engage in using the system and were able to provide the required contributions. Task providers and organizations were willing to provide monetary rewards while select groups of learners were able to provide solutions to these considerable challenges. The organizations also made use of the opportunity to employ the Mooqita task-integration process as a means of generating leads.

Crucial challenges remain that evolve around the central question of scalability. In this regard the current heavy manual involvement in the negotiation process of task providers / mentors calls for a (partial) automation of the matchmaking between tasks and learners, organizations and courses, etc. In a similar fashion improved processes and support tools for forming and managing learner groups, at best in a self-organized and empowered manner, are clearly called for. Lastly, scaling will also require establishing clear processes and guidelines that support all involved parties with handling legal and regulatory aspects.

Regarding the feasibility of the suggested approach behind deployment of the process the pilot deployment led to positive indications. The most successful aspect of the exploration so far was how well the review and review feedback system worked to determine the most capable learners and thus also to provide telling and directed information on hiring leads.

Acknowledgements

We thank Praveen Paritosh for his time mentoring and providing a challenge. We thank Armando Fox from UC Berkeley for linking his course to our project and Samual Joseph from Agileventures for helping us integrating our challenges. We thank Anand Kulkarni and his team at Crowdbotics for providing challenges and feedback, and Monika Streuer for her support as a member of the Mooqita team.

This project received partial funding through the ICSI at UC Berkeley and the German Academic Exchange Program (DAAD) through the FITweltweit program.

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