Exploration versus Exploitation: An Empirical Analysis of Task Selection on a Crowdsourcing Platform

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Crowdsourcing platforms such as Amazon Mechanical Turk (MTurk) and Prolific have become vital sources of income for workers due to their accessibility and low barriers to entry. While prior research has primarily focused on optimizing worker behavior from the requester's perspective, this paper shifts focus to explore how workers strategically engage with these platforms to maximize income. Using a multi-armed bandit framework, we analyze the exploration-exploitation trade-offs in a dataset of over 3 million tasks completed on MTurk between July 2014 and December 2017. Our findings reveal that workers' exploration rates stabilize over time, with task preferences remaining relatively consistent. Moreover, workers tend to gravitate towards tasks offering higher rewards, demonstrating sophisticated strategies that differ from typical multi-armed bandit outcomes. These insights highlight how workers collectively adapt to task selection systems, offering important implications for the design of fairer and more effective crowdsourcing platforms.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: Amazon Mechanical Turk, Multi-Armed Bandits, Crowdsourcing, Empirical Research

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1 INTRODUCTION

The growing prominence of digital labor platforms has transformed the nature of collaborative work, offering individuals flexible opportunities to earn income without traditional employment barriers [11]. Crowdsourcing platforms such as Amazon Mechnical Turk (MTurk) and Prolific enable workers to select from a variety of short, task-based assignments, commonly referred to as *Human Intelligence Tasks (HITs)*. This autonomy empowers workers to manage their schedules and select tasks independently, but it also presents decision-making challenges. Workers must navigate a dynamic task environment with limited information about task duration or long-term earning potential, often resulting in inefficiencies in task selection strategies. In fact, "workers earned a median hourly wage of only $2/hour, and only 4% earned more than $7.25/hour. While the average requester pays more than $11/hour, lower-paying requesters post much more work" [15].

Even with knowledge of each task's reward, workers often lack information about how long tasks will take to complete, complicating task selection. Moreover, pay trends and requester behavior vary over time, adding additional uncertainty (see Figure 1 and 2). To succeed, workers need to quickly learn which tasks are most profitable, while also identifying trustworthy requesters and refining their task selection strategies. These complexities present a classic exploration-exploitation dilemma, where workers must explore new tasks to learn which ones are efficient while exploiting familiar tasks to maximize their earnings.

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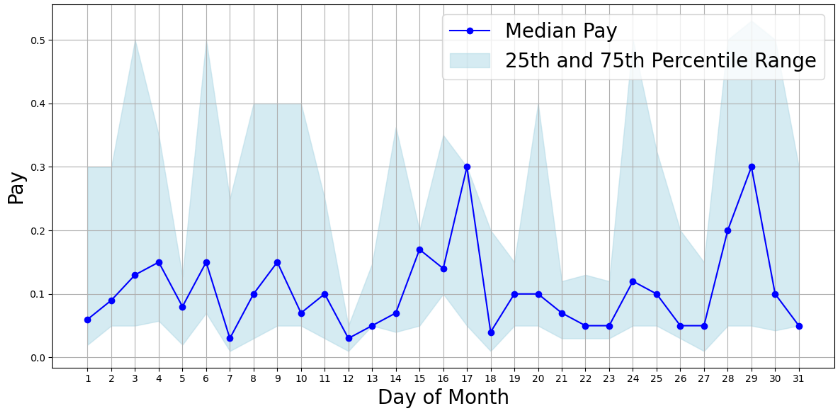

Fig. 1. Median pay for days in March 2017

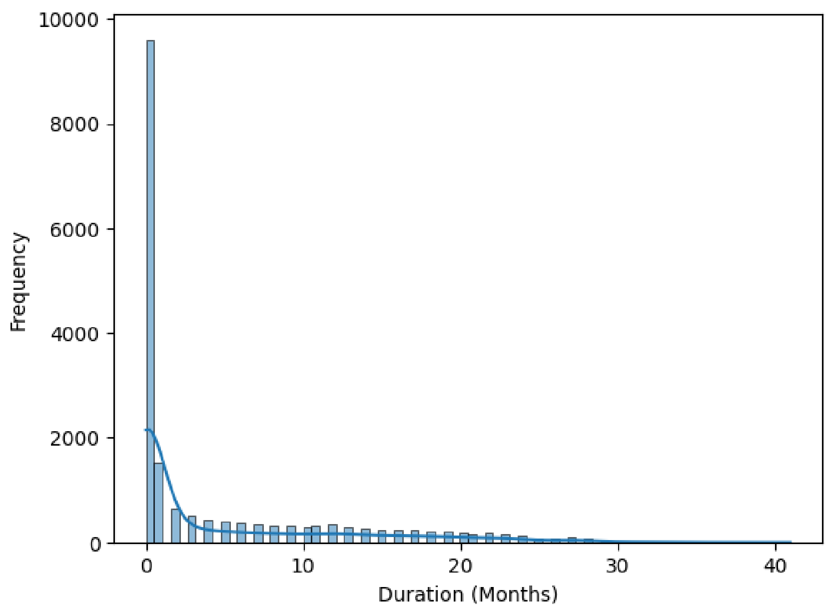

Fig. 2. Distribution of requester durations on MTurk

We frame this decision-making process using the multi-armed bandit (MAB) model, which captures the exploration-exploitation trade-off. In this framework, workers must explore different categories of tasks to learn about their potential while exploiting familiar tasks to maximize earnings based on their accumulated knowledge. Although MAB models have been applied in crowdsourcing platforms from the requester's perspective–such as identifying reliable workers [36]–there is limited research on how workers navigate these trade-offs themselves.

Our research investigates the following questions: What strategies do MTurk workers employ when selecting tasks? How do workers balance exploration and exploitation over time? To what extent can MTurk workers' behavior be explained by empirical and theoretical multi-armed bandit models?

Using a dataset of 1.2 million tasks, we categorize tasks into 11 distinct types (e.g., Surveys, Transcription, and Labeling) and further divide them into pay-based quartiles, resulting in 44 task categories or "arms." For each task selection, we classify worker behavior as either *exploration* or *exploitation* and analyze their earnings relative to the best available task choices.

Our findings reveal several important patterns in worker behavior. First, workers tend to gravitate toward higher-paying tasks even when they are not the most time-efficient. Second, exploration rates stabilize over time, suggesting that workers refine their strategies as they gain experience. However, the limited shifts in task preferences indicate a potential under-exploration problem, where workers may miss opportunities to maximize earnings. These insights offer practical recommendations for improving platform design and task recommendation systems, helping workers make more informed decisions and achieve better outcomes over time.

In summary, this paper makes three key contributions. First, we extend the multi-armed bandit framework to study task selection from the worker's perspective, filling an important gap in the crowdsourcing literature. Second, we provide empirical evidence on how workers balance exploration and exploitation, with implications for crowdsourcing platform design. Finally, we propose practical strategies for improving personalized recommendations and learning tools that support sustainable worker engagement on MTurk and similar platforms.

1.1 Related Work

Our study draws on two primary streams of research: crowdsourcing worker behavior and multi-armed bandit models for decision-making.

The MTurk ecosystem has been extensively studied and under scrutiny as it falls under the unconventional yet rising work category of crowdsourcing work. Common complaints among workers have included rejected and abandoned tasks [14, 28] in addition to issues with proper compensation [24, 28]. We also see that bad relationships occur between MTurk workers and requesters. Similarly, Piecework serves as a historical example which points to workers becoming "game efficiency experts," leading to bad relationships with their managers [3]. The anonymity of the worker-requester relationship in MTurk contributes to requesters taking advantage by rejecting tasks and not compensating workers [19]. Conversely, from the requester point of view, workers can take advantage by submitting low-quality tasks to earn money more efficiently [2, 35, 36]. However, crowdworkers are eager for good relationships with requesters in order to avoid potential disputes or non-payment [19].

Additional challenges help build this tension between workers and requesters. Uncertainty in the compensation workers may receive may be due to transparency tending to be lower in algorithmic management than traditional management [9, 29]. Harsh and missing evaluations in crowdsourcing work serves as an example of a lack of transparency, which badly affects worker wellbeing [6, 13]. Another challenge is managing flexibility: workers have to be self-motivated and find time on their own to do tasks on MTurk. This means workers often overwork in order to reach their earning goals [22]. In addition, MTurk's system has several inefficiencies such as non-standardized task descriptions and variable pay rates [18].

Due to the aforementioned challenges, workers must find some way to make MTurk work a worthwhile endeavor. They are incentivized to do so by some significant pros to MTurk work, including being an online and anonymous work environment [17], large flexibility in work hours, and tasks to complete. On the other hand, many workers struggle to transition out of MTurk due to financial constraints and a lack of career guidance [31]. One way that workers make ends meet on MTurk are by finding the tasks that match their preferences so that doing work is more enjoyable [26]. Previous work on MTurk has focused on helping workers match through a task recommendation system which has positive benefits for both workers and requesters [11].

It has been shown that higher monetary rewards are associated with a large increase in quantity of tasks done [30]. However, with such low wages, a worker must aim to be optimal about what tasks they complete. Furthermore, MTurk tasks are only shown with the reward that a worker will receive, meaning workers must estimate how long the task will take to achieve efficient work periods. Work such as the crowd-workers.com plug-in have attempted to solve this problem by providing a measure of the expected hourly pay [7].

Some strategies that have already been explored in the MTurk literature involve goal-setting, as workers already set intrinsic and extrinsic goals intrinsically [1]. Experiments have been run that train crowdsourcing workers to set different goals, but show no effect on learning or performance [30].

Ideally, an optimal MTurk earnings strategy should incorporate some patterns that have already been observed. First, crowdsourcing workers are able to quickly pick up and complete tasks when tasks are relevant are similar to each other [11]. Second, workers should stop spending too much time browsing for tasks and looking for matches [25, 26, 37]. Third, the most productive workers tend to follow specific requesters [8]. This is the case since the phenomena of loyalty can be linked to relationships , and “instead of embracing new, valuable exchanges with strangers whose propensity to cooperate is uncertain, individuals may prefer to preserve recurring ties with familiar actors [21].” Fourth, diverse tasks receive the highest ratings from workers. This corresponds to the wide variety of tasks available on MTurk that workers can take advantage of. A workplace study shows that the learning rate of workers in a general context has been shown [33] to increase alongside greater variance of tasks completed.

The aforementioned results and other studies [32] discuss worker habits that can lead to better task performance. However, a guide for allowing new workers to learn efficiently about the MTurk ecosystem while doing tasks has not yet been researched. One way to approach optimal worker learning is to study workers' exploration and exploitation patterns for task selection. We introduce the multi-armed bandits framework to fill this gap in MTurk strategy literature.

The multi-armed bandit problem (MAB) is a popular kind of decision-making problem where a decision maker chooses among a fixed set of "arms" which have unknown properties. Backed by probability and reinforcement learning theory, one can track how often the decision maker "exploits" the best arm versus "explores" in order to build a larger information set, as well as update beliefs about various "arms". This is deemed the exploration-exploitation trade-off which pertains to many decision making problems [27]. Numerous human applications of MAB include allocating COVID-19 tests [4, 5], identifying reliable crowdsourcing workers [36], and making managerial decisions [10]. These applications indicate positive effects when applying MAB algorithms on data and may help MTurk workers select tasks effectively.

In summary, the MTurk platform provides many new challenges about work and workers must be strategic about how they spend their time. While goal setting has been a popular strategy and area of research, optimizing task selection on MTurk requires a long-term treatment of the exploration and exploitation trade-off. In addition, although uses of MAB have been prevalent in crowdsourcing work from the perspective of picking out reliable workers, there has yet to be results from the worker's perspective. Our approach builds on insights from the MTurk literature and human applications of Multi-armed bandits by introducing the MAB framework to MTurk task selection. In this manner, we hope to improve the existing information base on how to succeed in MTurk and other forms of crowdsourcing work.

2 METHODOLOGY

We analyze a dataset of over 3 million tasks completed by MTurk workers from July 2014 to December 2017 collected by [7, 16]. For each task completed, we associate an arm pull (task category choice) associated with the task, categorize the task as an instance of exploration or exploitation, and compute the "loss" that a worker incurred from selecting the task over the best alternative. Explanations of these computations are as follows.

2.1 Task Categorization (*Arms*)

We first filter our dataset for workers that didn't do tasks within the first or last 30 days of our dataset. This allows for us to assume that the entire work span of these workers is completely shown in our dataset.

Next, we categorize each task based on two criteria: pay percentile and task title. We chose these criteria based on findings from a questionnaire which asked workers on the Microworkers crowdsourcing platform to rank criteria for recommendation systems based on importance [34]. From the study, the top 3 criteria were "most money,", "payment per time", and "similar", the latter signifying a grouping of tasks based on similar characteristics. Since the study finds that workers care significantly about task pay and characteristics, these two factors are the basis for distinguishing tasks from one another.

In our implementation, we define an arm as a task group with a unique task reward and unique category description. For our first arms component, we divide the possible rewards into 4 groups based on percentile to keep track of which tasks are low or high paying. So, for the task reward category, each task falls within the 0th to 25th percentile, 25th to 50th, 50th to 75th, or 75th to 99th percentile (labeled as 100) groups.

We compare each task based on the last 500 tasks completed on the site. This is a valid assumption since for the first task in our dataset, we can use the previously filtered 30 days of tasks for comparison. In this manner, we remove the long-term time effect on task reward evolution. Thus, the percentile group the task completed falls into is based on its percentile relative to these 500 tasks.

For our second task component, task description, we categorize tasks into 11 groups: *'Survey'*, *'Transcription'*, *'Evaluation & Assessment'*, *'Categorization & Labeling'*, *'Information Collection'*, *'Analyzation & Verification'*, *'Writing Work'*, *'Communication Work'*, *'Experiment & Game'*, *'Other'*, *'Unknown'*. 'Other' signifies tasks that didn't have keyword to fit under one of the 9 other groups and 'Unknown' tasks are those with no description. The task categories other than 'Other' and 'Unknown' are self-explanatory.

We do so by using keywords and inspecting the descriptions of each task. For example, a worker may see certain words such as "fill", "questionnaire" that allow them to determine that a task is, in fact, a survey. So using keywords can model the categorization tasks in a worker's mind, allowing for a simpler decision making process. We note that our use of keywords is subjective as many tasks that fall under 'Other' may be of another category. However, we are confident that we have used enough keywords such that 64% of tasks in our dataset are not categorized under "Other."

Pairing categories from these 4 reward groups and 11 title groups allows us to create 44 different "arms" in which workers "pull", as is consistent with the multi-armed bandits framework. Now, we can associate each task with one of the 44 arms.

2.2 Exploration and Loss

Exploration typically means in the context of MAB to pull a different arm, while exploitation means to pull the best arm. To replicate these ideas, for each worker we create a dictionary of arm performance by pay per hour which changes over time.

To fill this dictionary, we iterate chronologically through all tasks that a worker has completed by averaging the associated pay per hour metric. First, for each task, we calculate its pay per hour. We then use the arm the task is associated with to track our findings. If the arm has not been pulled, that arm is now associated to that task's pay/hour. If the arm has already been pulled, we take the average among all pay/hour values it has been associated with, including the current task. For example, suppose an arm has been pulled twice and has averaged a pay/hour of \$6, and our current task is associated with that arm which has a pay/hour rate of \$3. Then, that arm now has an average of \$6 + \$6 + \$3 divided by 3 tasks, since the task that has been pulled is the 3rd one. So, that arm now has an average of \$5 pay per hour associated with it.

To determine if a worker exploits at time t, we look at the arm they have pulled. If the arm that has the highest average per hour at time $t-1$ is the same as the arm they have pulled, the worker exploits. If not, the worker explores. As a default setting, we have set the first task for every worker to be an instance of exploration.

Next, we calculate loss for each task by subtracting the pay/hour for the current task from the pay/hour of the best arm. So, $loss = pay/hour_(current) - pay/hour_(best)$. In this manner, positive values mean that the current task has a greater pay/hour than the best arm, while negative values indicate that the current task is worse.

2.3 Analysis

To analyze our resulting dataset, we filtered for workers that did less than or equal to 1000 tasks (whom make up 66.36% of the workers) 3. This is motivated by the bulk of the distribution falling workers that have done 1000 tasks.

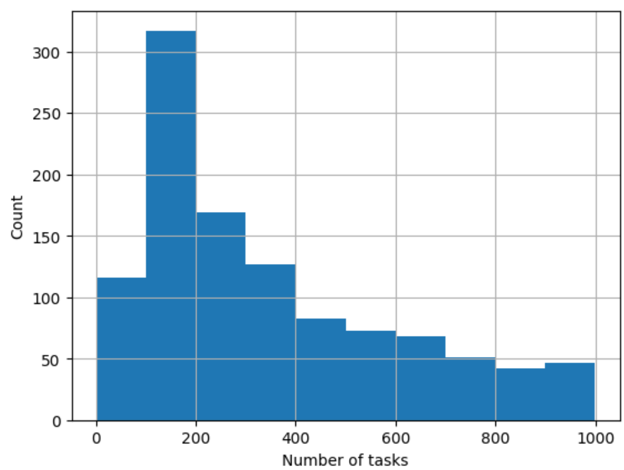

Fig. 3. Distribution of workers with under 1000 tasks completed

3 RESULTS

We discover several patterns that distinguish task selection among MTurk workers from a general multi-armed bandits problem. Using the MAB framework, we are able to get the statistics on loss, how much a worker explores versus exploits, and which task types (arms) are the best. Furthermore, we demonstrate other findings that improve on the existing understanding of the MTurk worker-requester ecosystem.

First, we examine the median exploration ratios over time for all workers. We see in figure 9 there is an initial drop in exploration for the first 10 tasks. This is likely due to MTurk having an initial barrier that restricts new workers to doing few tasks. From around the 10th task on, we see gradual increases in exploration which diminish over time, indicating a convergence of the exploration ratio as shown in figure 12.

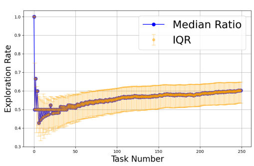

Fig. 4. Exploration rate for tasks 1 to 250

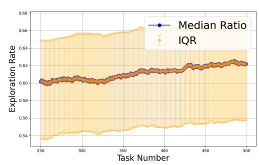

Fig. 5. Exploration rate for tasks 250 to 500

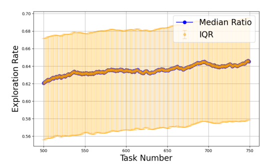

Fig. 6. Exploration rate for tasks 500 to 750

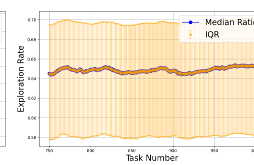

Fig. 7. Exploration rate for tasks 750 to 1000

Fig. 8. Exploration ratio for the first 1000 tasks

We also observe median losses along with their IQR ranges, which collectively appear to have a slight decrease over time.

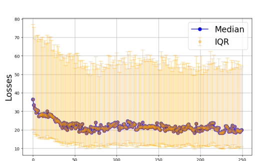

Fig. 9. Median losses for tasks 1 to 250

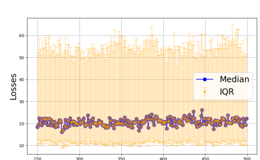

Fig. 10. Median losses for tasks 250 to 500

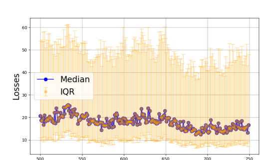

Fig. 11. Median losses for tasks 500 to 750

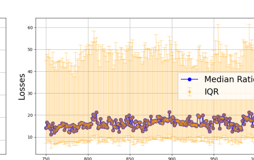

Fig. 12. Median losses for tasks 750 to 1000

Fig. 13. Losses for the first 1000 tasks

Second, we examine the performance of each arm. Figure 14 displays the number of workers for which each arm is their favorite. Arms that are of the 75th-100th percentile type are workers' favorites while arm "75-100-Survey" is the most common favorite for earning. Figure 15 shows the number of workers for which each arm is most visited. In contrast to figure 15, arm "0-25-other" is the most common favorite to pull. Figure 16 exhibits the overall distribution of tasks in our dataset, adding context to figures 14 and 15. We observe that tasks labeled "0-25-other" are the most commonly submitted tasks.

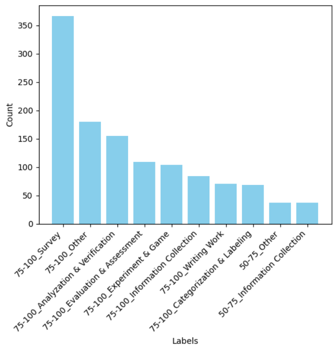

Fig. 14. Top earning arms per worker

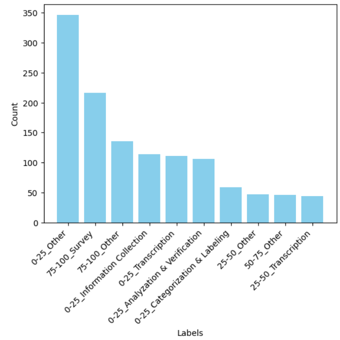

Fig. 15. Most visited arms per worker

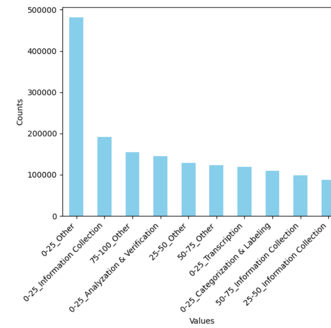

Fig. 16. Top 10 arms pulled

Fig. 17. Arms statistics

To further understand how workers prefer different arms, we devise a ranking system to accurately capture workers preferences. For each worker, using the history of arms they pulled, we first individually rank which ones perform the best on a pay per hour basis. We give the best performing arm a score of 44, the 2nd best performing arm a score of 43, and so on until we reach the worst performing arm. Then, we sum up all the scores for each arm. The top 10 arms ranked by this metric appear in Figure 18, while the bottom 10 arms ranked by this metric appear in Figure 21.

Next, we also weigh the arms so that the scores in figures 18 and 21 are divided by the number of workers that have pulled that arm. We can interpret these weights as average rankings that these arms fall under: e.g. arm "75-100_Survey" has an average ranking of 41.825, meaning that it can be expected to perform highly. The top 10 arms weighted appear in Figure 19 while the bottom 10 ranked arms appear in figure 22. We observe that arms that offer higher rewards are ranked the highest when weighted, supporting evidence from figure 14. Conversely, arms that offer lower rewards are ranked the highest.

75-100_Other	58334.0
75-100_Survey	55879.0
50-75_Other	47288.0
75-100_Analyzation & Verification	45779.0
75-100_Information Collection	42040.0
25-50_Other	41862.0
0-25_Other	40587.0
75-100_Evaluation & Assessment	40544.0
50-75_Survey	35196.0
50-75_Information Collection	33249.0

Fig. 18. Highest ranked arms

75-100_Survey	41.825599
75-100_Other	41.022504
75-100_Experiment & Game	39.818182
75-100_Analyzation & Verification	39.704250
75-100_Evaluation & Assessment	38.947166
75-100_Information Collection	37.468806
75-100_Unknown	36.333333
50-75_Other	36.070175
75-100_Communication Work	35.970414
75-100_Categorization & Labeling	35.685259

Fig. 19. 10 highest ranked arms (weighted)

Fig. 20. Best ranked arms

50-75_Experiment & Game	3612.0
25-50_Experiment & Game	1635.0
0-25_Unknown	1612.0
75-100_Unknown	1090.0
0-25_Experiment & Game	971.0
50-75_Unknown	959.0
50-75_Communication Work	805.0
25-50_Unknown	679.0
0-25_Communication Work	337.0
25-50_Communication Work	255.0

Fig. 21. 10 worst ranked arms

0-25_Categorization & Labeling	28.522207
25-50_Experiment & Game	28.189655
50-75_Writing Work	28.091787
0-25_Evaluation & Assessment	27.817043
50-75_Communication Work	26.833333
25-50_Writing Work	26.798969
0-25_Writing Work	26.071698
25-50_Communication Work	25.500000
0-25_Experiment & Game	22.068182
0-25_Communication Work	18.722222

Fig. 22. 10 worst ranked arms (weighted)

Fig. 23. Worst ranked arms

Third, we track how many shifts in preference workers undergo. We define a shift in preference by a change from one arm being scored the highest to a different arm being scored the highest. In this manner, an "arm shift" measures how often workers' favorite type of task changes. We isolate for workers that have done 0 to 1000 tasks, since this group makes up a significant group (66.36%) of workers and is thus most representative. In addition, we display 4 graphs: one isolating workers having done 100 to 250 task 24, the second isolating workers having done 250 to 500 tasks 25, third 500 to 750 26, and lastly 750 to 1000 27.

We notice that for all workers having done less than 1000 tasks, most have less than 15 shifts in preference. We surprisingly also observe that a large amount of workers in all cases shift less than 5 times.

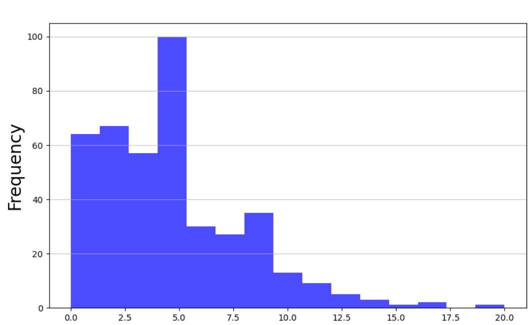

Fig. 24. Shifts in preference for workers that have done 100 to 250 tasks

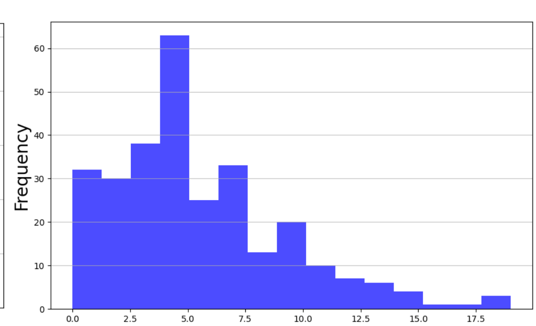

Fig. 25. Shifts in preference for workers that done 250 to 500 tasks

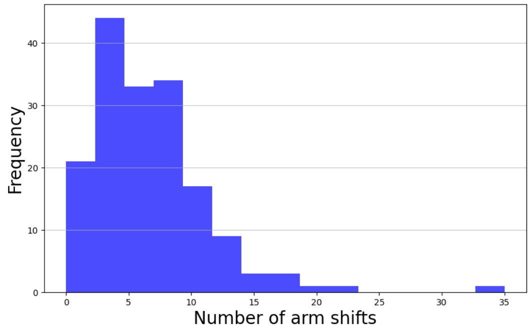

Fig. 26. Shifts in preference for workers that have done 500 to 750 tasks

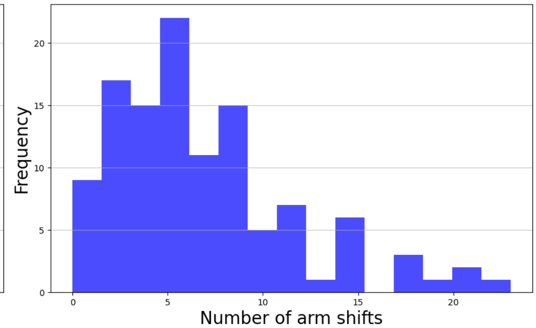

Fig. 27. Shifts in preference for workers that have done 750 to 1000 tasks

Fig. 28. Shifts in preferences

Lastly, we attempt to find if high losses may serve as a rationale for quitting MTurk. We analyze the last 20 tasks completed of each worker and compare that against the difference between average loss for the last 20 tasks and all tasks. In this manner, a positive difference means that a worker loses more on average in their last 20 tasks than for all tasks. Figure 29 shows a normally distributed loss difference that is centered around a slightly negative loss difference value, which doesn't support our hypothesis that workers quit due to receiving high losses.

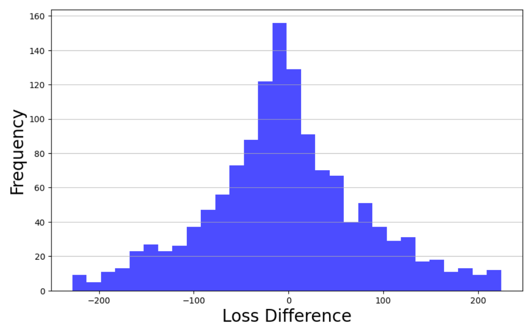

Fig. 29. Distribution of differences between the average loss of last 20 tasks versus all

4 DISCUSSION

Our empirical analysis of MTurk worker behavior using multi-armed bandits revealed several patterns that workers can exploit in their strategies. Our key findings are that workers' exploration rates tend to converge over time while losses slightly decrease, tasks with high rewards are ranked highest in relation to pay/hour while tasks with low rewards are ranked the lowest, workers' top preferences do not shift much, and that losses do not appear to have an effect on worker quitting.

First, our results demonstrate exploration rates stabilizing over time 13. This aligns with previous research on multi-armed bandits where algorithms converge over time [12], as well as an optimal exploration rate [20]. Our findings suggest that workers slowly are able to find an ideal exploration rate, which our data shows to be around 65% for the median worker, and ranging from 58% to 0.70%

between the first and third quartiles. This exploration may be a helpful baseline for new workers to keep in mind as

We note that this exploration rate is also affected by our choice of arms. We divided MTurk tasks into 44 distinct categories (arms) but it is possible to have created arms based on one of task description or reward. In those cases, the exploration rate would most likely be less due to the greater number of tasks within each category.

Second, we observe that although tasks that fall under the "0-25_Other" arm category are most frequent in our dataset and are the most common to be most visited among workers, they do not perform the best 17. Instead, the top earning arms are most commonly from arms with the "75-100" label. Furthermore, these popular tasks perform the worst according to our ranking of arms based on each worker's relative preferences 23, while the arms with high rewards ("75-100_") labels are ranked highest 20.

This relationship between high reward and high efficiency (pay per hour) is possibly unsurprising. Requesters are prone to pay out as little as possible for workers and an easy way to do so is by charging small amounts for hard tasks. Conversely, it is harder to give a high reward for a task and expect an equally high proportion of time, as serious concerns about task quality and a task's ability to be completed may arise.

Another potential explanation for this relationship is that workers may be more incentivized to complete tasks that have a higher reward, regardless of the time it may take. This hypothesis is supported by an article which suggests workers respond stronger to rewards aggregated over many tasks than rewards per task.

This data also brings into criticism the flexibility of tasks to complete on MTurk. If so many tasks are of low reward and they also are not a good investment of time, there must be a shortage of good tasks to complete for workers to consider doing these tasks.

Third, our figures 28 show that workers' top preferences do not change much over time. While it is possible that this is due to workers exploiting their highest paying arm, only 8% of workers have the same arm as their highest pay per hour category and most pulled or selected category.

Lastly, we notice that there isn't a noticeable difference in loss between the last 20 tasks workers' complete on MTurk versus all that they complete. So, loss cannot be concluded to be an important factor for leaving MTurk. Recalling that we compute loss by comparing a task's pay per hour results versus the pay per hour from the best arm in a worker's history, it seems that workers are earning from tasks at a similar rate throughout their lifetime. It is possible that workers may leave based on other reasons than a surprisingly low-paying batch of tasks.

While our research provides several insights to understanding MTurk worker behavior, we must acknowledge that our data involves a short period, July 2014 to December 2017. Since then, efforts and recommendations have been made to improve wages and design tasks for the benefit of the worker, in exchange for higher quality of data. [23]. However, the issues of low pay and matching for tasks still exist, such that our results are still pertinent today.

Furthermore, we have not considered time that a worker may spend searching for tasks. Therefore, our pay per hour numbers are accurate for time spent doing tasks, but are overestimates for time spent in total on MTurk. This is a limitation to our dataset that shows that caution must be exercised when interpreting our results.

Altogether, we infer that workers have several options for improving their task selection strategies via exploration rate or task type, and that there may be limitations that affect workers from selecting best tasks. Further research should explore whether the exploration rate that workers converge towards is actually optimal and the feasibility of completing the top task types that we've listed above. In this manner, we can develop better and applicable suggestions for performing well on MTurk.

5 CONCLUDING REMARKS

Our analysis of task selection among Amazon Mechanical Turk workers has demonstrated patterns in workers' preferences for certain types of tasks and exploration/exploitation behavior. By using the multi-armed bandits framework, we are able to estimate measures of loss, exploration and exploitation, and arm performance, allowing us to gather new findings. Notably, MTurk workers tend to stabilize their exploration rates over time and are most efficient at completing tasks with high rewards.

Future work can build off our work by experimenting with different algorithms for deciding whether tasks are instances of exploration or exploitation. Several methods may improve our method of capturing worker beliefs, as Thompson sampling serves as an example by connecting ideas from Bayesian Inference with human behavior. Furthermore, multi-armed bandits can be further integrated into MTurk task selection by introducing theoretical findings such as the gittins index [10].

REFERENCES

[1] Tahir Abbas and Ujwal Gadiraju. Goal-setting behavior of workers on crowdsourcing platforms: An exploratory study on mturk and prolific. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, volume 10, pages 2–13, 2022.

[2] Ittai Abraham, Omar Alonso, Vasilis Kandylas, and Aleksandrs Slivkins. Adaptive crowdsourcing algorithms for the bandit survey problem. In *Conference on learning theory*, pages 882–910. PMLR, 2013.

[3] Ali Alkhatib, Michael S. Bernstein, and Margaret Levi. Examining crowd work and gig work through the historical lens of piecework. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, page 4599–4616, New York, NY, USA, 2017. Association for Computing Machinery.

[4] Hamsa Bastani, Kimon Drakopoulos, Vishal Gupta, Ioannis Vlachogiannis, Christos Hadjichristodoulou, Pagona Lagiou, Gkikas Magiorkinis, Dimitrios Paraskevis, and Sotirios Tsiodras. Efficient and targeted covid-19 border testing via reinforcement learning. *Nature*, 599(7883):108–113, 2021.

[5] Hamsa Bastani, Kimon Drakopoulos, Vishal Gupta, Jon Vlachogiannis, Christos Hadjichristodoulou, Pagona Lagiou, Gkikas Magiorkinis, Dimitrios Paraskevis, and Sotirios Tsiodras. Interpretable operations research for high-stakes decisions: Designing the greek covid-19 testing system. *INFORMS Journal on Applied Analytics*, 52(5):398–411, 2022.

[6] Janine Berg, Marianne Furrer, Ellie Harmon, Uma Rani, and M Six Silberman. Digital labour platforms and the future of work. *Towards decent work in the online world. Rapport de l'OIT*, 2018.

[7] Chris Callison-Burch. Crowd-workers: Aggregating information across turkers to help them find higher paying work. In *Proceedings of the AAAI conference on human computation and crowdsourcing*, volume 2, pages 8–9, 2014.

[8] Jesse Chandler, Pam Mueller, and Gabriele Paolacci. Nonnaïveté among amazon mechanical turk workers: Consequences and solutions for behavioral researchers. *Behavior research methods*, 46:112–130, 2014.

[9] Bruno Felix, Diego Dourado, and Valcemiro Nossa. Algorithmic management, preferences for autonomy/security and gig-workers' wellbeing: A matter of fit? *Frontiers in Psychology*, 14:1088183, 2023.

[10] Alina Ferecatu and Arnaud De Bruyn. Understanding managers' trade-offs between exploration and exploitation. *Marketing Science*, 41(1):139–165, 2022.

[11] David Geiger and Martin Schader. Personalized task recommendation in crowdsourcing information systems—current state of the art. *Decision Support Systems*, 65:3–16, 2014.

[12] Angeliki Giannou, Emmanouil-Vasileios Vlatakis-Gkaragkounis, and Panayotis Mertikopoulos. On the rate of convergence of regularized learning in games: From bandits and uncertainty to optimism and beyond. *Advances in Neural Information Processing Systems*, 34:22655–22666, 2021.

[13] Kristen L Guth and Daren C Brabham. Finding the diamond in the rough: Exploring communication and platform in crowdsourcing performance. *Communication Monographs*, 84(4):510–533, 2017.

[14] Lei Han, Kevin Roitero, Ujwal Gadiraju, Cristina Sarasua, Alessandro Checco, Eddy Maddalena, and Gianluca Demartini. The impact of task abandonment in crowdsourcing. *IEEE Transactions on Knowledge and Data Engineering*, 33(5):2266–2279, 2019.

[15] Kotaro Hara, Abigail Adams, Kristy Milland, Saiph Savage, Chris Callison-Burch, and Jeffrey P Bigham. A data-driven analysis of workers' earnings on amazon mechanical turk. In *Proceedings of the 2018 CHI conference on human factors in computing systems*, pages 1–14, 2018.

[16] Kotaro Hara, Abigail Adams, Kristy Milland, Saiph Savage, Benjamin V Hanrahan, Jeffrey P Bigham, and Chris Callison-Burch. Worker demographics and earnings on amazon mechanical turk: An exploratory analysis. In *Extended*

abstracts of the 2019 chi conference on human factors in computing systems, pages 1–6, 2019.
[17] Kotaro Hara and Jeffrey P Bigham. Introducing people with asd to crowd work. In *Proceedings of the 19th International ACM SIGACCESS Conference on Computers and Accessibility*, pages 42–51, 2017.
[18] Panagiotis G Ipeirotis. Analyzing the amazon mechanical turk marketplace. *XRDS: Crossroads, The ACM magazine for students*, 17(2):16–21, 2010.
[19] Lilly C Irani and M Six Silberman. Turkopticon: Interrupting worker invisibility in amazon mechanical turk. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 611–620, 2013.
[20] Zohar Karnin, Tomer Koren, and Oren Somekh. Almost optimal exploration in multi-armed bandits. In *International conference on machine learning*, pages 1238–1246. PMLR, 2013.
[21] Sergio G Lazzarini, Gary J Miller, and Todd R Zenger. Dealing with the paradox of embeddedness: The role of contracts and trust in facilitating movement out of committed relationships. *Organization Science*, 19(5):709–728, 2008.
[22] Vili Lehdonvirta. Flexibility in the gig economy: managing time on three online piecework platforms. *New Technology, Work and Employment*, 33(1):13–29, 2018.
[23] Leib Litman and Jonathan Robinson. *Conducting online research on Amazon Mechanical Turk and beyond.* Sage Publications, 2020.
[24] Leib Litman, Jonathan Robinson, and Cheskie Rosenzweig. The relationship between motivation, monetary compensation, and data quality among us-and india-based workers on mechanical turk. *Behavior research methods*, 47(2):519–528, 2015.
[25] Scott Maier. All the news fit to post? comparing news content on the web to newspapers, television, and radio. *Journalism & Mass Communication Quarterly*, 87(3-4):548–562, 2010.
[26] David Martin, Benjamin V Hanrahan, Jacki O'neill, and Neha Gupta. Being a turker. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, pages 224–235, 2014.
[27] Katja Mehlhorn, Ben R Newell, Peter M Todd, Michael D Lee, Kate Morgan, Victoria A Braithwaite, Daniel Hausmann, Klaus Fiedler, and Cleotilde Gonzalez. Unpacking the exploration–exploitation tradeoff: A synthesis of human and animal literatures. *Decision*, 2(3):191, 2015.
[28] Zahra Nouri, Henning Wachsmuth, and Gregor Engels. Mining crowdsourcing problems from discussion forums of workers. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 6264–6276, 2020.
[29] Xavier Parent-Rocheleau and Sharon K Parker. Algorithms as work designers: How algorithmic management influences the design of jobs. *Human resource management review*, 32(3):100838, 2022.
[30] Amy Rechkemmer and Ming Yin. Motivating novice crowd workers through goal setting: An investigation into the effects on complex crowdsourcing task training. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, volume 8, pages 122–131, 2020.
[31] Veronica A. Rivera and David T. Lee. I want to, but first i need to: Understanding crowdworkers' career goals, challenges, and tensions. *Proc. ACM Hum.-Comput. Interact.*, 5(CSCW1), April 2021.
[32] Jeffrey M Rzeszotarski and Aniket Kittur. Instrumenting the crowd: using implicit behavioral measures to predict task performance. In *Proceedings of the 24th annual ACM symposium on User interface software and technology*, pages 13–22, 2011.
[33] Melissa A Schilling, Patricia Vidal, Robert E Ployhart, and Alexandre Marangoni. Learning by doing something else: Variation, relatedness, and the learning curve. *Management science*, 49(1):39–56, 2003.
[34] Steffen Schnitzer, Christoph Rensing, Sebastian Schmidt, Kathrin Borchert, Matthias Hirth, and Phuoc Tran-Gia. Demands on task recommendation in crowdsourcing platforms-the worker's perspective. In *CrowdRec Workshop*, 2015.
[35] Yiwen Song and Haiming Jin. Minimizing entropy for crowdsourcing with combinatorial multi-armed bandit. In *IEEE INFOCOM 2021-IEEE Conference on Computer Communications*, pages 1–10. IEEE, 2021.
[36] Long Tran-Thanh, Sebastian Stein, Alex Rogers, and Nicholas R Jennings. Efficient crowdsourcing of unknown experts using bounded multi-armed bandits. *Artificial Intelligence*, 214:89–111, 2014.
[37] Alex J Wood, Mark Graham, Vili Lehdonvirta, and Isis Hjorth. Good gig, bad gig: autonomy and algorithmic control in the global gig economy. *Work, employment and society*, 33(1):56–75, 2019.

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