To Cooperate or to Compete in the Gig Economy? Endorsements and the Performance of Freelancers in Online Labor Markets

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Abstract

Online labor markets connect buyers with gig workers across several task categories. A buyer evaluates workers' quality based on their past performance encapsulated in ratings and reviews. However, these ratings can be inflated and arguably fail to assess workers' true quality. Literature shows that worker characteristics like skills, experience, and heuristic cues can measure worker quality. In this study, we explore how gig workers' personality traits in terms of Social Value Orientation (SVO) affects their performance on an online labor platform. We measure SVO from peer endorsements among workers on an online labor platform. Our results show that a cooperative SVO, where gig workers endorse each other, is more beneficial to the stakeholders of online labor platforms than competitive and individualistic SVO.

Keywords: online labor markets, social value orientation, cooperation, competition, endorsements, social network analysis, gig economy

1. Introduction

Online labor markets like Freelancer, Upwork, Fiverr, and PeoplePerHour among others are pervasive among digital gig workers. These digital platforms connect buyers with sellers (contract workers or freelancers) irrespective of their location across several categories of tasks. These platforms have grown significantly in the last decade. Around 59 million Americans (36% of the total US workforce) are engaged in some sort of freelancing activities and 36% of these freelancers do such gig work full-time[1]. Furthermore, as a result of the Covid-19 pandemic, 53% of the businesses are willing to employ freelancers because of the increasing adoption of remote work[2].

In an online labor market, workers (freelancers) bid on projects posted by buyers. Given that online labor platforms work like 'experience goods', one cannot assess the true quality of the task outcome in advance (Nelson 1970). Online reputation systems can resolve this uncertainty by using the past performance of workers as a predictor of task outcome quality (Dellarocas 2003). So, the quality of work performed in prior projects captured in a reputation system helps workers get more projects in the future.

However, such reputation systems can fail to capture the real worker quality because of highly skewed maximum rating values (Hu et al. 2012). Instead, multiple aspects such as workers' skillsets, educational background, work experience, and expertise could reflect their actual quality (Kokkodis and Ipeirotis 2016). Thus, workers' characteristics may be leveraged to assess worker quality and reduce uncertainty for buyers.

Buyers in online labor markets evaluate the workers usually through examining their profile information: ratings and review by the reputation system or self-declared credentials like skills and other technical expertise (Chan and Wang 2018; Yoganarasimhan 2013). Literature has presented how online labor markets can manage the shortcomings of reputation systems and dynamic reskilling in the labor market (Kokkodis and Ipeirotis 2016). Prior studies have also shown factors such as gender affect hiring decisions in online labor markets. (Chan and Wang 2018). However, to the best of our knowledge, no study focuses on workers' personality traits and their impact on their performance (or hiring decisions) in the online labor markets.

[1] https://www.upwork.com/documents/independent-workforce-report

[2] https://www.upwork.com/research/future-workforce-report

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In this study, we examine how a worker's social value orientation (SVO) affects their performance in an online labor market. SVO deals with the "weights" that an individual may place on others' welfare versus his or her own welfare (van Lange 1999). There are four categories of SVO: altruistic, cooperative, individualistic, and competitive.

We measured workers' SVO from their endorsement activity in an online labor market. Endorsements are a special type of user-generated content (UGC) that allows workers (full-time or freelance) to acknowledge the presence of specific skills of their peers. Buyers can evaluate workers by analyzing their past gig performance and observing which skills have been acknowledged or endorsed by the workers' community.

Skill endorsements are done with the help of an endorsement system, where each user can endorse another user's skills or can receive endorsements from other users. Workers in an online labor market compete against each other to get more work for themselves, and at the same time, also often endorse each other's skills. Thus, gig workers who compete on online platforms can also be seen endorsing each other, which we conceptualize as one form of cooperation across gig workers. This cooperative behavior of competing gig workers is an interesting empirical phenomenon we further examine in this study. In this study, we examine this endorsement behavior of gig workers using the theoretical framework of SVO.

We collected worker profile data and determined their SVO based on their endorsement activities. We observed that altruistic workers who sent endorsements at the beginning of the year got endorsed eventually. So, we filtered only those workers who were consistent in the SVO and categorized them as individualistic, cooperative, and competitive based on their endorsement activity. Then, we measured the impact of these orientations on freelancers' future gig performance by using propensity score matching. We observe that cooperative workers have the highest yield in terms of completing new projects and working with new buyers followed by competitive and individualistic workers respectively.

Our research makes several significant contributions to theory and practice. We contribute to the body of knowledge related to UGC and online labor platforms. To the best of our knowledge, this is the first study of its kind that analyzes the importance of social value orientation in the digital gig economy. We also study a novel type of UGC, i.e., peer endorsements, in the context of online labor platforms and adapt social value orientation theory as our theoretical framework to examine endorsement behavior among competing workers in such a labor market. The findings of our study have practical implications for digital platform owners on leveraging peer endorsements to engage workers continuously while developing a cooperative worker community. A cooperative worker community would benefit workers by landing them more gigs and contributing to the platform revenue. Additionally, online labor platforms generally employ reputation systems to evaluate worker quality, which can be unreliable. The buyers can evaluate workers by observing workers' endorsed skills and social value orientation in the labor market along with the workers' technical expertise.

2. Literature Review

2.1. Online Labor Platforms

Digital platforms have transformed the operations of various industries like ride sharing, household services, food delivery, shopping, freelancing among others (Kathuria et al. 2020). Online labor platforms are one category of digital platforms that connect buyers who need specific services (e.g., digital marketing, software programming, website, and mobile app development, consulting, photo editing, among others) to professionals (gig workers) who possess the appropriate skills to provide these services. Many online labor markets have emerged in the recent years, namely platforms such as Freelancer, Upwork, Fiverr, and PeoplePerHour, and have attracted millions of skilled professionals across the world to compete for jobs posted by the buyers. Online labor markets offer varied types of connections and interactions between buyers and workers. (a) Workers can bid on "projects" (task requirements) posted by buyers; (b) Buyers can respond to "offers" (promoted bundled work packages) posted by the workers on the platform; (c) Buyers can connect directly with workers through the platform.

Online labor markets have attracted considerable research interest. Early empirical studies on online labor markets show how gig-work (Upwork, Freelancer, PeoplePerHour) differs from traditional work based on work category, work structure, communication, delivery mechanism, and managing tasks (Deng and Joshi 2016; Irani and Silberman 2016; Kuhn and Maleki 2017; Petriglieri et al. 2019). Digital technologies enable workers to create worker profiles, bid for tasks and accept work easily and remotely (Burtch et al. 2018; Deng and Joshi 2016; Kuhn and Maleki 2017).

UGC generated on online labor platforms has attracted considerable research interest. The past performance of workers (reputation) has been shown to affect their probability of being hired in the future (Moreno and Terwiesch 2014). Like e-commerce or other marketplace platforms, online labor markets also offer reputation systems that enable a buyer to provide feedback to the worker on the completed tasks. The reputation scores received over multiple tasks are aggregated to determine the worker's rating on the platform (Rahman 2018). The accumulated scores and the reviews gathered by the reputation system reduce the information asymmetry between workers and buyers and impact hiring choices and worker earnings (Gandini et al. 2016; Pallais 2014; Yoganarasimhan 2013).

However, the employed reputation systems can arguably fail to capture the dynamic and multidimensional nature of tasks in an online platform (Kokkodis 2021), and the reputation scores (ratings) tend to be overly positive and inflated (Filippas et al. 2018). To be competitive in the labor market consistently, workers continuously reskill or upskill themselves to keep up with the shifting labor market demands (Oliver 2015). Prior studies have determined that workers' expertise given a set of skills and attributes like gender may affect hiring decisions (Chan and Wang 2018; Kokkodis and Ipeirotis 2016).

Yet, there are gaps in our understanding of how workers' behavioral attributes (like peer endorsements) affect their future gig performance. Also, there are gaps in our understanding of the factors like worker location, gig category, reputation, and skills, that affect a worker's endorsement behavior.

2.2. Peer Endorsements & UGC

User-generated content (UGC) is an important feature of the Internet, affecting the behavior of individuals or organizations on digital platforms. Research has focused on the effects of UGC like product sales (Hu et al. 2014; Zhu and Zhang 2010), venture capital financing (Aggarwal et al. 2012), and firm competition (Kwark et al. 2014). Second, studies have also focused on the antecedents of UGC attributes like rating (Godes and Silva 2012), review helpfulness (Zhou and Guo 2017) and, review text (Tripathi et al. 2021). However, very few studies have focused on the skill endorsements (a type of UGC) in online labor platforms (Tripathi et al. 2021, Tripathi et al. 2022).

In an endorsement system, each user can endorse another user's skills or can receive endorsements from their acquaintances present in a social network. For example, a business analytics professional can endorse skills (like data mining, data science, natural language processing) to their colleagues or acquaintances in LinkedIn. Prior studies on endorsement systems have focused on the endorsements received by full-time workers who participate in professional networking platforms like LinkedIn or ResearchGate. Skill endorsement recognizes the skills of a user from their peers and effectively helps in building a professional network (Wu et al 2018). Skill endorsements of Information Technology (IT) professionals can recommend IT jobs for Informatics Engineering graduates (Kumalasari and Susanto 2019). A study by Rapanta and Cantoni (2017) used a survey to determine the motivation behind endorsement behavior on LinkedIn and found that most professionals receive and provide endorsements without calculating the epistemic weight of knowledge authority attribution. Furthermore, studies on endorsements in online platforms applied survey-based methods performed on full-time workers and survey-based methods arguably suffer from limitations stemming from the self-reported nature of this information. Prior studies have focused less on the actual endorsement behavior among gig workers of an online labor market. Tripathi et al. (2022) applied the decision tree induction method to extract the worker attributes that influence endorsement decisions across all worker categories.

In an online labor market, the purpose of an endorsement system is to showcase the expertise level of workers based on endorsements received from their acquaintances. Endorsements can also help prospective buyers evaluate the workers and make hiring decisions. The acquaintances or endorsers in an online labor market can be buyers a given worker worked in the past, other workers in the labor market, or other people outside of the labor market. The endorsers generally review the workers' profile before providing endorsements to the listed skills of a specific worker. Our study focusses on the endorsements generated by the workers of the labor platform. Here, workers compete against each other by bidding on a specific set of listed projects in the online labor market. Yet, skill endorsements from competitive workers can help their peers get more projects is an interesting phenomenon and such behavior can be conceptualized as a cooperative action. This cooperative behavior in a competitive environment like online labor markets can be best explained by Social Value Orientation theory.

2.3. Social Value Orientation

Social value orientation (SVO) indicates an individual's relative priority focuses on his welfare and that of others (van Lange 1999). SVO theory assumes that individuals maintain a diversified preference for combinations of outcomes as they relate to the benefits derived by themselves and others. The diversified preference results in four categories of orientation: (a) Altruistic - Maximize others' outcomes at the cost of your own outcomes, (b) Cooperative - Maximize others' outcomes and your own outcomes, (c) Individualistic - Maximize your own outcomes and not outcomes of the others and (d) Competitive: Maximize own outcomes at the cost of other's outcomes (Fiedler et al. 2013).

A worker endorsing other peer workers' skills can arguably support others' welfare in terms of higher gig opportunities. Endorsements received by a worker's peers reinforce the presence of their skills from a buyer's perspective. Then a buyer entrusts this worker to work on the gig activity which results in the worker completing more gig work. A worker maximizes their peers' outcomes (in terms of more gig work) by endorsing their peers' skills and may receive endorsements from their peers, which maximizes their outcome. In the context of endorsements among competitive online labor market workers, an altruistic worker will only endorse other workers without receiving any endorsements. A cooperative worker will receive endorsements and endorse other workers. However, pure altruism is difficult to sustain as an altruistic worker may get endorsed eventually by another altruistic worker. So, all altruistic workers have cooperative SVO in the long run. A competitive worker will only receive endorsements and not endorse anyone. Individualistic workers are not concerned about others' welfare and will neither send nor receive endorsements. In this study, our research objective is to understand how multiple types of SVO (in terms of receiving or sending endorsements) impact a worker's future gig performance.

3. Hypothesis Development

3.1. Cooperative vs Individualistic.

The objective of an endorsement system is to enable workers to help their peers to acquire more gig opportunities. Endorsing the listed skills of a worker by their peers shows the worker's expertise level in those skills. Literature on offline, full-time labor workforce also shows that pro-social behavior helps raise workers' productivity (Rotemberg 1994). These observations can also be extended to online labor platforms. Workers acquire more gig opportunities by receiving help (in the form of skill endorsements) from peers than by not receiving such aid. So, we maintain that cooperative workers (pro-social through their behavior of endorsing others and receiving endorsements from others) will perform better than workers who don't send or receive endorsements (individualistic SVO). Accordingly, we hypothesize:

H1: *Cooperative workers have higher output than workers with an individualistic social value orientation.*

3.2. Competitive vs Individualistic.

We posit that competitive workers (pro-self through their behavior of only receiving endorsements) will perform better than their individualistic peers. This is because competitive workers are receiving endorsements from their peers, which makes buyers realize the presence of endorsed skills in the worker and trust them with completing the project. So, accordingly, we hypothesize:

H2: *Competitive workers have higher output than workers with an individualistic social value orientation.*

3.3. Competitive vs Cooperative.

Cooperative goal structures will result in higher achievement than competitive goal structures (Roseth et al. 2008). Also, prior studies have shown that competition motivates progress, but cooperation is essential for development and cohesive growth (Bacaria 2007). Furthermore, Johnson et al. (1981) reviewed 122 studies and found that the measures related to cooperative behavior were more effective than that of individualistic behavior for effectively achieving productivity goals. Broadening this theoretical explanation in the context of online labor markets, pro-social (cooperative) workers endorse the skills of their peers and seek unified success of the worker community whereas pro-self (competitive) workers aim to maximize their wealth and not endorse back their peers. In other words, workers with cooperative behavior will complete more gig activities than workers with competitive behavior. So, we hypothesize:

H3: *Competitive workers have lower output than workers with cooperative social value orientation.*

3.4. Altruistic vs Others.

Altruistic SVO relates to pro-social behavior, where a person assigns higher weights to others' outcomes. When an altruistic person endorses the skills of another altruistic person, the recipient endorses the skills of the sender as the recipient also assigns higher weights to peers' outcomes. We observed this behavior over the entire year in this online labor platform where all altruistic workers eventually got endorsed and turned into cooperative SVO. So, we have not hypothesized the outcomes of altruistic workers with respect to other SVOs.

4. Empirical Context and Data

We collected endorsements data from an online labor platform that helps buyers hire workers across multiple task categories such as technology and programming, language and translation, design, photo-video-audio, social media, etc. This platform uses English language for the mode of communication where the workers hail from 150 countries across the globe. This platform employs a reputation system along with an endorsement system to help buyers meet and select the best gig workers for their tasks or jobs. The dataset used in this analysis was collected in two phases: one at the end of May 2021 and another at the end of May 2022. The dataset consists of approximately 15K workers actively participating on the platform in the last 60 days. For each worker, we collected data on worker characteristics (location, category, prizes, certifications obtained, response time, etc.), endorsements received by the worker from their peers, endorsements sent by the worker to their peers, and the worker's gig history on that platform (number of completed tasks, number of buyers worked with, average rating). We collected the same worker data in both phases. Table 1 presents the descriptive statistics of the workers' data.

Table 1: Descriptive Statistics

Variable	Mean	Std.Dev	Min	Max
Rating	3.85	2.04	0	5
Log Hourly Rate	3.15	0.65	2.23	7.24
New #Projects	2.10	1.62	0	8.94
New #Buyers	0.47	0.84	0	6.25
Listed Skills	10.81	3.78	1	15

5. Constructs

5.1. Outcome Variable.

We test the hypotheses estimating the effect of a specific SVO on the future gig performance of the worker as compared to another SVO. Thus, the dependent variable is a worker's future gig activity based on the new number of projects completed in one calendar year. Since workers can complete repeated projects with the same buyer, this creates an inherent trust. So, we also use the new number of buyers worked with in the same calendar year as our alternate outcome variable.

5.2. Focal Variable.

The focal variable of interest is the SVO of the worker based on their endorsement activity. If a worker has not sent or received endorsements, we label them as individualistic. If a worker has sent and received endorsements, they are labeled as cooperative, whereas if the worker has only received but hasn't sent any endorsements, they are labeled as competitive. We observed that workers who only sent endorsements (altruistic behavior) in May 2021 eventually got endorsed by their peers within a year. So, we labeled such workers as cooperative. In summary, there were 4651 workers who are individualistic, 3573 cooperative and 6814 competitive workers who retained their SVO throughout the entire year.

5.3. Treatment and Control Groups.

For H1, our treatment group was cooperative workers whereas the control group was individualistic workers. For H2, our treatment group was competitive workers whereas the control group was individualistic workers. For H3: treatment was competitive workers whereas the control group was cooperative workers.

5.4. Control Variables.

A worker's future gig performance may be influenced by the reputation earned before May 2021 (platform achievements, prizes, and ratings), listed skills, work category, response time to buyers, geographical location, industry experience, and hourly rate charged. We measured these covariates from the worker profile data collected at the beginning of May 2021 and rescaled all nominal variables to logarithmic form.

6. Matching

Our dataset is observational, where self-selection of treatment could impact the estimate of a causal effect between treatment and control groups. Factors affecting a worker's propensity to be competitive, cooperative, or individualistic might simultaneously affect their future gig performance on the online labor platform. To mitigate this concern, we employ a matching method based on propensity scores (Rosenbaum and Rubin 1983). We identified variables that could position a worker to be competitive, individualistic, or cooperative: ratings, location, response time, and prior gig performance, among others. Next, we determined propensity scores using logistic regression and applied a one-to-one nearest neighbor matching. However, not all observations were matched one-to-one and there was class imbalance among treatment and control groups. So, we applied weights to the control observations who exactly matched with multiple treatment observation. This creates three matched samples of cooperative vs. individualistic (8224 observations), competitive vs. individualistic (11465 observations), and cooperative vs. competitive workers (10384 observations).

7. Model Specification

We specify the worker's future gig performance as a function of the worker's SVO while controlling for the worker's hourly rate, listed skills, ratings, response time, gig performance certifications received from the platform, work category, geographical location, and industry experience. Since we determined weights for control group observations who matched with multiple treatment group observations, we estimate this model by weighted ordinary least squares (OLS) regression with robust standard errors on the matched sample datasets:

$$Log(Projects\ /\ Buyers)_i = \alpha + \beta_1\, SVO + \gamma Controls_i + \varepsilon_i$$

8. Results

Table 2 presents the estimation results of the regression models for the research question on the effect of a certain SVO. Here, the dependent variable is the number of new projects completed and new buyers worked with (both transformed into the log), the treatment and control groups are varied for each hypothesis. The numbers in parenthesis denote the standard error and the estimated coefficient indicates how a certain SVO as compared to control SVO performed in the online labor market for an entire year. For example, a cooperative worker completed 24.2% more projects than individualistic workers. The estimated treatment effect of cooperative vs. individualistic and competitive vs. individualistic orientations are significant at a 1% level across all dependent variables.

So, the effect of having cooperative and competitive SVO positively affects the future number of projects completed. This positive effect is also observed for the new buyers these workers worked with in the future. We observed that the estimated effect of cooperative workers is higher than that of competitive for both future projects completed, and new buyers worked with as compared to workers with individualistic SVO. So, H1 and H2 are supported.

The treatment effect of competitive workers with respect to cooperative workers is negative and significant for both dependent variables. This indicates that competitive workers completed less gig activity and worked with fewer new buyers as compared to cooperative workers. So, H3 is supported.

In summary, we observed that cooperative workers generate higher output in terms of completing more projects and working with more buyers than competitive followed by individualistic workers. Now, online labor markets charge a service fee on workers' earnings and this charge usually constitutes the major component of their revenue. So, cooperative behavior among workers can get higher revenue for the gig platform. In the next section, we analyze how such cooperative behavior (endorsements) manifests in the online labor market and how platform stakeholders can exploit such phenomenon to their benefit.

Table 2. SVO Impact Results

DV	Treatment	Control	Estimated Coeff.
Number of Projects	Cooperative	Individualistic	0.242*** (0.019)
	Competitive	Individualistic	0.095*** (0.009)
	Competitive	Cooperative	-0.047*** (0.010)
Number of Buyers	Cooperative	Individualistic	0.202*** (0.017)
	Competitive	Individualistic	0.079*** (0.008)
	Competitive	Cooperative	-0.040*** (0.009)

Note *: p < 0.1, **: p <0.01, ***: p<0.001

9. Discussion

We have used peer endorsements among online gig workers to determine multiple categories of SVO: individualistic, cooperative, and competitive. By comparing the gig performance of similar workers having a specific category of orientation, we observed that workers having cooperative behavior have higher output in terms of completing gig projects and working with new buyers. This is followed by workers having competitive and then individualistic workers. This demonstrates that cooperation (in terms of endorsing skills of peers) is more beneficial for workers as well as the labor platform. Workers in an online labor platform compete against each other to get more gig projects from buyers. Yet, we observed that cooperative behavior among workers is more beneficial.

9.1. Theoretical Contributions

We broaden social value orientation theory to understand peer endorsements among workers in an online labor market. We categorize workers as cooperative, competitive, and individualistic based on their receiving and sending endorsement statistics. Next, we compare the gig performance of the 3 SVO categories and observed that cooperative workers have more output in terms of completing gig projects and working with new buyers. This is followed by competitive and individualistic workers. Prior studies have not explored the impact of behavioral attributes of gig workers on their performance in the online labor platform.

9.2 Practical Implications

The findings of our study have multiple practical implications. First, online labor markets generally employ a reputation system to evaluate worker quality. Reputation systems usually suffer from major biases and are not reliable to measure worker quality. An endorsement system allows a platform to capture the skills expertise of a worker from other workers. This will help buyers make informed decisions about employing a worker on their project. Combining the prior reputation and skill endorsements will reduce the information asymmetry between buyers and workers and build trust among buyers.

Second, we observed that cooperative workers have higher output than competitive and individualistic workers. Digital platform owners can use the endorsement system to develop a workers' community that helps everyone get more gig opportunities. A cooperative worker community would benefit workers by more gigs and then contributing to the platform revenue. Also, a cooperative worker community would help the workers continuously update their skills to compete in the freelancing market.

9.3 Limitations

Our study has several limitations that could be extended to future studies. First, we acknowledge that endorsement systems are not popular among online labor markers as only a handful of such platforms deploy an endorsement system. However, our study analyzes the advantages of skill endorsements and cooperative behavior among gig workers so that they can be implemented across labor markets and benefit all its stakeholders. Second, there might be a dynamic process in workers' SVO where the orientation may change over time. For example, a competitive worker may endorse his peers which changes their SVO category to the cooperative. A future research question could be determining the attributes that influence the change of a worker's SVO over time.

10. Future Research: How does the cooperative behavior manifest itself?

In an endorsement system, users can endorse the skills of their peers or receive endorsements from others. So, an endorsement system of an online labor platform fosters a social network where each node represents a worker and links are represented by endorsements. We plan to apply social network analysis to understand how endorsement links are generated among worker nodes. This would help us examine the factors that influence cooperative behavior among workers. Another future research question could be determining the attributes that influence the change of a worker's SVO over time.

Figure 1 shows an example of the endorsement network formed by 4 workers. The workers are represented by nodes (marked in octagons) and the worker attributes like Country and Category are represented as node properties. The endorsements between workers are represented by links (marked in arrows) and we captured the skills that were endorsed in the network (marked by text for each link). Worker 1 has endorsed worker 3 on Matlab and C++ programming skills. Worker 3 has endorsed back worker 1 back on NoSQL and Python programming skills. Each direction of the link represents the endorser and endorsed worker and the skills that were endorsed.

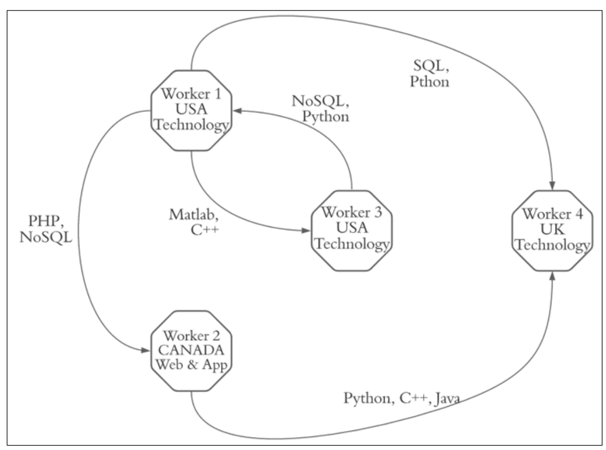

Figure 1: Endorsements among 4 workers

We conducted a preliminary study on the endorsement network data to understand how cooperative behavior manifests among workers. we took a random sample of 2000 workers who have either received or send endorsements before May 2021. We observed that around 5500 new endorsements were generated in 12 months. We created an endorsement network which has 5500 links among 2000 nodes and apply network analysis models to understand what attributes influence the generation of this network. The results of observe that workers reciprocate by endorsing back a worker who has been endorsed in the past. We also found out that popular workers in the gig platform attract endorsements from their peers. Finally, workers sharing the same geographical location and skillsets have a higher chance to endorse each other.

5. Conclusion

In this study, we explore how the behavioral attributes of gig workers impact their future performance in an online labor market. We extend SVO theory to peer endorsements among gig workers and categorized them as cooperative, individualistic, and competitive. Our results corroborate that cooperative workers have completed more gig projects and workers with new buyers followed by competitive and individualistic workers. In other words, cooperative behavior among workers is beneficial to platform stakeholders and platform owners need to encourage such behavior among gig workers. In future, we plan to explore how cooperative behavior manifests among gig workers by understanding the peer endorsement network formation process. Preliminary results suggest that endorsements are generated by three phenomena: reciprocity in cooperation, worker popularity, and homophily in worker location and gig category. We contribute to the literature on online labor markets by focusing on social value orientation behavior which was not studied in the literature.

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