Toward a Contextual Theory of Turnover Intention in Online Crowdworking

Completed Research Paper

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Abstract

Online crowdworking marketplaces represent an emergent labor market. Despite the ample recent literature on crowdworking marketplaces, we still lack a clear understanding of the antecedents to worker turnover behavior in such labor markets. This paper integrates the extant crowdworking literature with traditional theories of worker turnover intention, boundary spanning, and online communities to develop a Contextual Model of Turnover Intention in online Crowdworking (COMTIC). Conceptually, COMTIC complements the traditional organizational turnover perspective with a contextualized boundary spanning perspective and illustrates how the two theories work together to more accurately depict the crowdworker turnover intention. The model is tested using partial least squares structural equation modeling and is largely confirmed by the results. We discuss the theoretical implications of the proposed COMTIC framework and offer practical insights for existent and future crowdworking marketplaces.

Keywords: contextual theory, turnover intention, online crowdworking, emergent labor market, Amazon Mechanical Turk, boundary spanning, knowledge brokerage, online communities

Introduction

Workers’ turnover intention refers to their intention to switch over to another organization. For instance, information technology (IT) professionals’ turnover intention entails a desire to move from their current employer to another within the IT field (Joseph et al. 2012). A large stream of research in the information systems (IS) literature studied the etiology of IT professionals’ turnover intention (Ahuja et al. 2007; Armstrong et al. 2015; Bakker et al. 2005, Blau 2007, Moore 2000; Rutner et al. 2008). It has been found that exhaustion, i.e. being “emotionally overextended and depleted” (Maslach 1998, p. 69), and workload (Bakker et al. 2005) are among the major factors behind such an intention. Another significant factor is perceived unfairness in job compensation (Moore 2000, Rutner et al. 2008), e.g., as a result of unjustified
pay gap (Joseph et al. 2015). In addition, lack of job satisfaction was shown to significantly contribute to turnover intention (Guimaraes and Igbria 1992, Tett and Meyer 1993).1

Despite the extant research studying the behavior of IT professionals in the general sense, we lack understanding of workers’ behavior in emerging IT platforms, e.g., online crowdworking marketplaces (Martin et al. 2014, Schulze et al. 2012). An “online crowdworking marketplace” represents an online labor platform accessible via online crowdsourcing websites (Howe 2006) where workers are paid for their work.2 Online crowdworking marketplaces (or platforms) offer a diverse, “flexible,” and “scalable” mass of “workers” (hereafter, “crowdworkers”) who complete work requests for “requesters” (hereafter, “Requesters”), i.e., individuals or firms who post job requests (Bergvall-Kåreborn and Howcroft 2014). By doing so, online crowdworking marketplaces constitute an example of an important emergent labor market that has been shown to be very helpful to firms and researchers especially those in the fields of psychology and computational human behavior (Buhrmester et al. 2011, Karger et al. 2014, Steelman et al. 2014). These crowdsourcing sites offer online platforms for the execution of transient employer-employee contractual agreements that define the specifications of micro-tasks (Brawley and Pury 2016).

Crowdworkers’ turnover intention thus refers to their intention to stop working in the current crowdworking marketplace and possibly seek alternative choices. Theoretically, it is important and urgent to study this technology-enabled emergent labor market (Corley and Gioia 2011, Gosling and Mason 2015, Stone and Deadrick 2015). Crowdworkers are spot workers and part of the gig economy. Thus, their perceptions of what constitutes a proper work relationship may be different. In this paper, we focus our attention on a prominent online crowdworking marketplace, namely Amazon Mechanical Turk (hereafter, “Mturk”). Mturk is among the most popular and highly frequented online crowdworking marketplaces worldwide (Difallah et al. 2015).

This research aims to develop a contextual model of turnover intention in online crowdworking and empirically test it by collecting survey data about Mturk workers (hereafter, “Turkers”). We argue that to gain a better understanding of turnover intention in online crowdworking, we should begin with examining the applicability of turnover models in traditional organizational settings, i.e., the literature of IT professionals’ turnover intention. Moreover, given the contextual uniqueness of the online crowdworking labor market, we stipulate that the IT turnover literature may not capture a holistic view of crowdworkers’ work attitudes and intention. Specifically, many Turkers often participate in online communities that are related to, but nevertheless independent from, Mturk (Irani and Silberman 2013, Martin et al. 2014). They interact with one another in online communities to exchange important information related to their work on Mturk (Irani and Silberman 2013). As a result, this gives rise to the opportunity of engaging in “boundary spanning”, i.e., crossing the knowledge boundaries of distinct work areas and playing a role of knowledge broker across those boundaries. In our context, an online community facilitates boundary spanning because crowdworkers who specialize in certain types of tasks (e.g., audio transcription, psychological experiments) freely exchange suggestions and expertise with those who specialize in other tasks. Such boundary spanning enables the transfer and application of experiences learned from online communities onto the Turker’s process of doing actual tasks in Mturk.

No prior work has attempted to examine whether a boundary spanning perspective may integrate well with and contribute to a traditional organizational view of turnover intention in the crowdworking context. We integrate the literatures on crowdsourcing marketplaces, IT professionals’ turnover behavior, traditional boundary spanning, and online communities, and develop a Contextual Model of Turnover Intention in Crowdworking (COMTIC). It is important to note that we do not aim at studying the motivation to work in online crowdworking; rather, this paper examines work continuance, or equivalently, turnover intention, and its antecedents. As would be expected, there are critical differences between intention to start working and intention to continue working in the long term. Although there may not be a mature literature for this difference in the organizational literature, the literature on initial technology adoption and continued use of IT has established well that the antecedents of initial adoption are very different from those of continued IT use (e.g., Li et al. 2013, Limayem et al. 2007). Similar to the case of technology use, the initial acceptance

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1 We refer readers to Joseph et al. (2007) for a comprehensive review of distal factors that affect job satisfaction and organizational commitment such as role stressors (i.e., role ambiguity, role conflict), job performance, fairness rewards, and social support, among others.

2 Therefore, behavior in other crowdsourcing phenomena including open-source software projects is not part of the scope here, although their literatures are informative to our theory development, hence they have been included in our literature review.
of online crowdworking may be driven by various motivations (e.g., to simply try it out, procure much needed money quickly, etc.), but the enduring work intention/behavior remains largely driven by the variables we include.

This research expects to have several important contributions. Our research is one of the first IS studies to theorize and empirically test the possible linkage between member participation in online communities and their work behavior. As such, the results of this pioneering study could shed light on the facilitating role of online communities in cross-boundary knowledge transfer beyond the context of regular work. Overall, we make both theoretical and empirical contributions to the literatures on online crowdworking, worker turnover intention, boundary spanning, and online communities, by contextualizing organizational turnover and boundary spanning theories in an important and emerging area of industrial economy.

**Literature Review**

*Crowdworking Labor Market and Worker Turnover*

As a job market platform (Brawley and Pury 2016, Kaufmann et al. 2011, Martin et al. 2014, Paolacci and Chandler 2014), a crowdworking marketplace (e.g., Mturk) is in many ways similar to traditional IT contracting jobs that represent a significant portion of the IT labor market (Bidwell and Briscoe 2009). Table 1 summarizes these similarities including the trend of job outsourcing, worker autonomy, and the evaluation of work performance. In spite of the similarities, crowdworking is characterized by unique contextual differences in work processes, including a high reliance on such IT artifacts as the Internet and online communities, and a low level of control over task requirements. Table 1 highlights these differences.

There has been an upsurge in research that has studied crowdworking marketplaces, in general, and Mturk in particular. One such stream of research focused on the technicalities of crowdworking platforms and investigated ways that Requesters can better exploit the labor market to optimize job design. Within this research stream, Karger et al. (2014) developed a model of optimal task assignment to minimize total costs given a target reliability level. Similarly, Ambati et al. (2011) proposed and implemented a recommendation engine that suggests tasks to Turkers based on their skillset. Their proposal was shown to result in more successful task completion rates for workers as well as an increase in the overall quality of completed tasks.

A second literature stream has focused on the worker side. The majority of research in this research stream analyzed worker demographics (Martin et al. 2014), which is particularly important given that the Amazon-managed private platform, Mturk, does not openly reveal the number of active Turkers at a particular time (Irani and Silberman 2013). Such research includes work by Paolacci et al. (2010) and Paolacci & Chandler (2014) who presented detailed demographic data about Turkers and recommended ways to capitalize on Turkers as a subject pool to conduct more rigorous research in psychology. Related work that adopted a Turker’s perspective includes Martin et al. (2014) who conducted an ethnomethodological analysis of the text archive of an online community and unveiled ways in which community members behaved as economic actors, e.g., through sharing useful information and tactical strategies, and rating and reviewing specific Requesters.

Despite the increased number of crowdworking-related studies, only few (i.e., Brawley and Pury 2016, Martin et al. 2014, Schulze et al. 2012) examined ways to extend crowdworkers’ tenure. Meanwhile, a problem that has haunted the long-term prosperity of the crowdworking industry is workers’ high dropout rates. As argued in Brawley and Pury (2016), little research has focused on the worker experience on Mturk, and such a lack of understanding is bound to exacerbate the trend of shrinking crowdworker tenure. There are mainly two critical ingredients to crowdworkers’ experience, namely, their motivation to engage in crowdworking, and their reasons for turning-over. On the one hand, research has uncovered both extrinsic (e.g., immediate payoffs, delayed payoffs, social motivation) and intrinsic (e.g., task autonomy, skill variety) motives behind the amount of time spent on Mturk in a week (Kaufmann et al. 2011) — keeping in mind that those findings were based on preliminary analyses (e.g., frequency and correlations). Other research has explored factors that may influence worker intention. Within this line of research, Schulze et al. (2012) proposed a structural model of work intention as predicted by fits along the demands-abilities and needs-supplies dimensions. The authors drew theoretical support from the person-job fit theory, but they have not collected empirical data to validate their model. Although informative about factors that motivate crowdworkers to initiate their crowdworking, the extant literature oncrowdworker motivation falls short of offering insights into factors affecting crowdworker retention in the long run. Understanding turnover...
intention is more critical insofar as the sustainability of the labor market lies in longer crowdworker tenure. Yet, we are aware of only one study (i.e., Brawley and Pury 2016) that has tackled crowdworker turnover intention. Brawley and Pury (2016) applied principles from industrial-organizational psychology to understand factors that influence workers’ intention to quit working for one Requester and switch to another. Note that this “switching-over” to a different Requester within Mturk does not fall under our definition of turnover behavior, which refers to crowdworkers’ intention to leave the current crowdworking platform (i.e., Mturk in our empirical context). Although a large stream of research in the management literature has studied the determinants of voluntary turnover intention (e.g., Aquino et al. 1997, March and Simon 1958, Moore 2000, Rutner et al. 2008, Wright and Cropanzano 1998), this extant research stream only considered worker behavior in an organizational context; yet, such a context enabling face-to-face interactions differs significantly from the online crowdworking context. In sum, research studying the nomological network and potential determinants of turnover intention in online crowdworking is scarce. This particular study serves to examine this important but nevertheless neglected research topic.

<table>
<thead>
<tr>
<th>Traditional Organizational Setting (e.g., IT contract jobs)</th>
<th>Online Crowdworking Setting</th>
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</thead>
<tbody>
<tr>
<td>More jobs and tasks are being outsourced (Niederman et al. 2006)</td>
<td>Workers are able to select the projects they wish to work on and have better control over their work schedule (Kaufmann et al. 2011)</td>
</tr>
<tr>
<td>Worker performance is often evaluated based on the successful completion of the project</td>
<td>Internet is only a small portion of workers’ resources while on the job</td>
</tr>
<tr>
<td>Workers and employers communicate extensively and reach mutual agreements on project requirements, quality criteria, project schedule, etc.</td>
<td>Workers have little control over project requirements, quality criteria, and deadlines; they only get to decide whether or not to work on certain projects given prespecified requirements; Requesters and workers rarely communicate (Brawley and Pury 2016)</td>
</tr>
<tr>
<td>Except for the research examining software programmers’ behavior, the literature has offered little documentation related to community participation of IT workers</td>
<td>Many Mturk workers often participate in online communities that are related to, but nevertheless independent from, Mturk (Irani and Silberman 2013, Martin et al. 2014)</td>
</tr>
<tr>
<td>Boundary spanners tend to occupy central network positions (Johnson et al. 2015)</td>
<td>Knowledge brokers do not necessarily have to occupy central network positions (Cranefield et al. 2014)</td>
</tr>
<tr>
<td>Boundary spanning is part of the job or role requirements (Fleming and Waguespack 2007)</td>
<td>Boundary spanning is optional</td>
</tr>
<tr>
<td>Boundary spanning focuses on job fulfillment</td>
<td>Boundary spanning focuses on knowledge accumulation</td>
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</table>

**Contextualizing Boundary Spanning**

Crowdworking is characterized by the necessity for ongoing access to the Internet while working. As a socio-technical artifact, the Internet provides a vast repository of potentially useful resources for many IT applications. Thus, boundary spanning across online knowledge domains is convenient. In our context, a salient IT artifact is that provided by online crowdworking communities. It is thus not surprising that some
Turkers also participate heavily in crowdworking communities while simultaneously working on Mturk. Online communities are known to facilitate knowledge exchange and transfer amongst participating members and across relevant practical domains—a characteristic of boundary spanning behavior in workplaces. Therefore, it is important to critically evaluate literatures on both boundary spanning and online communities to properly inform our theoretical development.

The concept of boundary spanning has spawned from the traditional organizational literature (e.g., Fleming and Waguespack 2007). Certain occupations in the offline organizational setting entail that workers engage in boundary spanning activities, i.e., be in regular contact with personnel in various departments and, in the meantime, acquire knowledge from other departments. 3 However, research is limited about the theoretical and empirical validity of boundary spanning as an antecedent to employee attitude and intention, probably because boundary spanning appears to characterize only few roles (e.g., information center worker is required to interact with many departments but IS personnel are often not; Guimaraes and Igbaria 1992). The limited literature has found mixed results on the effect of boundary spanning (Guimaraes and Igbaria 1992).

Meanwhile, the notion that boundary spanners benefit from playing the role of knowledge brokers, i.e., as conduit of strategic resources across fields, appears appropriate in our context (Au and Fukuda 2002). As such, boundary spanning fits well within the online knowledge domain (Johnson et al. 2015, Levina and Vaast 2005). The main argument is that those members who occupy more central positions in the online social network tend to fulfill a knowledge brokerage role that nourishes information flow across sections of the network; as such, they emerge as leaders of their communities (Johnson et al. 2015). Nonetheless, Johnson et al. (2015) found that online community leaders tend to engage within their own community, but refrain from crossing over boundaries to other communities. Overall, the literature seems to indicate that boundary spanning, either offline or online, is relevant to only a small number of players and its implications are very limited. Contrary to this view, we propose that boundary spanning plays an important role, and we validate this argument in the crowdworking setting. In short, this research stream appears understudied and wanting of additional investigation.

Relevant to the knowledge brokerage role of crowdworkers is the literature on online crowdworking communities. Thus, a review of the online community literature is in order. Ample online community research has looked at the determinants of online community member engagement and continued participation (Bateman et al. 2011, Ray et al. 2014). Although research in this broad area has offered insights into the underlying mechanisms via which online communities attract and promote member participation, a commonality of such research is that online communities have been studied in isolation (i.e., the theories and critical constructs of such research studies have been applied within the context of focal online communities). However, online communities rarely exist in isolation; rather, they almost always fulfill specific functions or purpose for their members — e.g., work skills such as computer programming, hobbies such as entertainment and hedonic travels, or online crowdworking in our context (Ma and Agarwal 2007). As far as we know, except for very few papers (e.g., Algesheimer et al. 2005, Brawley and Purdy 2016, Kim et al. 2008), little research has conceptually or empirically linked online communities with human activities outside the realm of online communities. Within this limited research stream, the central constructs of community satisfaction (Ray et al. 2014)) and community commitment (Bateman et al. 2011) fit with boundary spanning since they carry a strong sense of identification with the online community and, thus, a high degree of knowledge exchange with community members.

Theory of COMTIC and Hypotheses

At the outset, we theorize that, despite the apparent contextual differences between work in the offline organizational setting and online crowdworking, the organizational turnover literature largely applies to crowdworking, except for the effect of perceived workload that is often predefined in the organizational context but largely volitional in crowdworking. Furthermore, we hypothesize that boundary spanning in the online sphere across different exchange contexts benefits the boundary spanner by energizing her or his online crowdworking attitude and intention, and, as such, is expected to complement and interact with the organizational theory perspective. We also propose that a critical community factor (i.e., community continuance commitment) has cross-boundary moderating effects on the role of fairness of rewards. Our

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3 Such knowledge mainly takes the form of domain knowledge and that of organizational culture.
empirical findings are highly consistent with this theory. Figure 1 shows the theoretical components and the hypotheses of the COMTIC model, and the following section explains the mechanisms underlying each of our hypotheses.

Figure 1. A Contextualized Model of Turnover Intention in Crowdworking (COMTIC)

**Hypotheses**

Prior research has found that dissatisfied employees are more likely to turnover from their jobs (e.g., Jackson and Schuler 1985, Joseph et al. 2007, Porter and Steers 1993, Rutner et al. 2008). Porter and Steers (1993) argued that dissatisfaction emanating from employers' not meeting employees' expectations often results in their leaving their jobs. We expect that the importance of satisfaction to job continuance carries through to the crowdworking environment. In fact, given that monetary compensation is generally petty in crowdworking, we expect that satisfaction is especially important to retain workers. Thus,

**H1(a):** Turnover intention (TI) in online crowdworking is negatively influenced by job satisfaction (JSAT).

Crowdworkers provide services to Requesters (i.e., individuals and businesses) in exchange for monetary compensation upon successfully completing projects and meeting Requesters’ expectations. The importance of rewards or compensation is advocated by social exchange theory, which predicts that for a relationship to perpetuate, it has to be mutually rewarding to both parties in question. However, not only are rewards expected, but they more importantly need to be fair, i.e., commensurate with the nature of the job responsibilities, the employees' experience, the amount of effort they put forth, the quality of the work they complete, and the amount of stress and strains required to complete said job (Moorman 1991, Price and Mueller 1986). Dittrich and Carroll (1979) showed that equity perceptions, i.e. perceptions of distributive justice, are strong predictors of turnover intention. In other words, it is important for workers to feel that they have been rewarded fairly for them to continue working for their organization. Turkers are often paid poorly as a base income, so we expect fairness of rewards to be as, if not more, important in the crowdworking context as in the offline context (Silberman et al. 2010). Regardless of the form of reward or the dollar value attached to it, it is important that it be fair, i.e., commensurate with the effort needed to complete the work, and that it be distributed fairly to workers. All in all, we propose that crowdworker perceptions of reward fairness are necessary for them to continue working in the long term.

**H1(b):** TI is negatively influenced by fairness of rewards (FAIR).

Perceived workload (PW), or the perceived quantity of work demands (Moore, 2000), has been shown to be the strongest predictor of exhaustion (i.e., mental, physical, and emotional per Moore (2000)'s definition) and stress (Fischer 1998, Li and Shani 1991) that are, in turn, associated with employee turnover...
Contextual Theory of Turnover Intention

(Bartol and Martin 1982, Goldstein and Rockart 1984, Ivancevich et al., 1983, Jackson et al. 1986, Li and Shani 1991, Leiter 1991, Moore 2000, Pines et al. 1981, Rutner et al. 2008, Sethi et al. 1999, Weiss 1983). The crowdworking context, however, is different in that workers choose the projects they wish to accept, so they are autonomous in deciding on their specific workload and working hours. Because of this flexibility, we do not expect perceived workload to have a significant effect on job satisfaction or turnover intention. Thus,

**H1(c):** TI is not influenced by perceived workload (PW).

Prior work has shown that fairness of rewards is necessary for job satisfaction (Clem et al. 2008, Howard and Cordes 2010). Howard and Cordes (2010, p. 411), in particular, noted that experiencing unfairness on the job "consumes and drains valuable emotional energy, thus depleting emotional and cognitive resources and contributing to emotional exhaustion." Yet, inequities in pay or promotion have been shown to exist in the IS profession, in general (Allen et al. 2004, Ball 2013, Armstrong et al. 2015). We expect the importance of fairness of rewards in the IS field to carry through to the crowdworking context. Given that crowdworkers are generally not well paid, their expectation for fair compensation is an even more important requirement for their job satisfaction. Thus,

**H2(a):** JSAT is positively influenced by FAIR.

Following the same argument in H1(c), and given that crowdworkers can choose the kind of tasks they want to work on and are well aware ahead of time of the job difficulty and workload, we expect perceived workload to not be a significant factor in how satisfied they feel about crowdworking. Thus,

**H2(b):** JSAT is not influenced by PW.

Community satisfaction (CSAT) indicates that members are satisfied with their interaction and information exchange with other members. It also implies that they are able to receive beneficial information and resources that help them improve their crowdworking. Because of these benefits, crowdworkers are likely to be more successful at what they do. This, in turn, implies they are more likely to be satisfied with their jobs (Au and Fukuda 2002, Joseph et al. 2007) and less likely to turnover from it. Thus,

**H3:** Community satisfaction (CSAT) (a) negatively influences TI and (b) positively influences JSAT.

Community continuance commitment (CCC), or need-based commitment, is a bond that community members develop with their online communities because they feel a need for their communities' indispensable and irreplaceable resources and benefits (Bateman et al. 2011, Whitener and Walz 1993). Crowdworkers’ participation in their communities is discretionary, as discussed earlier. Thus, if workers are committed to their community, they are likely to also be satisfied with their community. As such,

**H4:** Community continuance commitment (CCC) positively influences CSAT.

Crowdworkers who exhibit CCC are likely to be receiving valuable information from their community that helps them improve their crowdworking, else they would not be committed to continuing their membership. These boundary spanning crowdworkers are likely to benefit from the valuable job-related information exchanged within crowdworking communities and become more productive at performing their work as a result. A perception then follows that they can successfully complete more work and earn more rewards in less time. These crowdworkers will thus tend to believe they are reaping more rewards than others. As such, we expect that the perceived fairness of rewards plays a lesser role for crowdworkers with high CCC.

In addition, boundary spanning crowdworkers are information brokers who acquire valuable information at no cost from their fellow members. Higher CCC implies higher perceived value of the knowledge gathered from community membership. Such high perceived informational value can, in turn, make fairness of monetary rewards less of a determining factor in crowdworkers' job attitudes and intentions. Thus,

**H5(a):** CCC weakens the effect of FAIR on JSAT, so that if CCC is high, the positive effect of FAIR on JSAT becomes less positive.

**H5(b):** CCC weakens the effect of FAIR on TI, so that if CCC is high, the negative effect of FAIR on TI becomes less negative.
Method

Measures

Table 2 presents the measures that have been used in this study. We did not develop new constructs because that is beyond our research objective. We believe that adapting measurement items from existing well-established scales in the literature is appropriate. We do so by slightly modifying the wording to fit our research context. Specifically, we used scales from Rutner et al. (2008) to measure TI, JSAT, FAIR, and PW. We reverse coded the items for TI in Rutner et al. (2008) to mitigate common method bias. To measure CSAT, we used the scales from Ray et al. (2014). We measured CCC using the scales in Bateman et al. (2011). We used single-item controls for demographic variables such as AGE, GENDER, and TENURE. Finally, we adapted the items from Armstrong et al. (2015) to measure work exhaustion (EXH) as a control variable. We treated work exhaustion as a control variable because, unlike in the traditional IS profession context, the role of work exhaustion is marginalized in the online crowdworking context following a rationale akin to the one previously used to justify the lack of influence of perceived workload. However, prior literature in IS (Armstrong et al. 2015) has shown the significance of exhaustion. In order to clarify the contextual differences empirically, we controlled for work exhaustion in our model.

All scales are considered to reflectively measure the latent constructs of interest (Chin 1998).

Data Collection and Sample

There are at least seven popular online communities for Turkers that operate as online forums (Reddit “Mturk Communities” 2016). We selected our sample from one of these forums (pseudonym “the Forum” in order to anonymize our respondents). The Forum has existed for at least four years and has amalgamated over 10,000 registered members to date. Overall, the Forum is representative of the kind of online communities in our context.

Survey is the ideal method for collecting data needed to test our theory. We recruited our sample in March 2015. One of the authors posted an advertisement in the Forum that was only visible to members after they have logged in. The ad promised an incentive consistent with the average reward level of academic research available on Mturk. We kept the survey open for three weeks. A total of 311 respondents clicked into the study hosted on Qualtrics, among whom 285 fully completed the survey. We used their self-reported usernames in the Forum to verify that each respondent was a unique member, and used their self-reported Mturk IDs to verify their unique worker identification. Thus, we can reasonably believe that each respondent in our sample corresponds to a unique person. About 57% of the respondents are female. Respondents distribute widely in age brackets, i.e., 24.4% in 20-29, 26.5% in 30-39, 23.7% in 40-49, 14.1% in 50-59, 9.9% over 59, with a small percentage fitting in the 18-19 age bracket. It is difficult to quantify the true response rate because we could not observe how many members saw the ads. Based on the number of members who clicked on the ad, we computed a response rate of 91.6%.

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4 Following Rutner et al. (2008), we used two items to measure FAIR. Although it is generally advisable to use at least three items to measure a latent factor, this is not a big concern in our study because, as will be discussed in the Measurement Model of the Results section, the results of both the EFA and the CFA were beyond the satisfactory level. We also verified that the two items of FAIR met the sufficiency condition of measurement for a latent construct according to the guidelines in Kenny et al. (1998).
Table 2. Reflective Measurement Items and Factor Loadings

<table>
<thead>
<tr>
<th>Construct</th>
<th>Scale</th>
<th>Factor Loadings</th>
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<tbody>
<tr>
<td>CCC1</td>
<td>If I stopped coming to the Forum, it would take me a long time to find a community that could replace it.</td>
<td>.880</td>
</tr>
<tr>
<td>CCC2</td>
<td>There are very few other places where I could find the kind of useful content and services that I get from the Forum.</td>
<td>.780</td>
</tr>
<tr>
<td>CCC3</td>
<td>The content of the Forum is too valuable for me to stop coming back.</td>
<td>.885</td>
</tr>
<tr>
<td>CSAT1</td>
<td>In general, I am satisfied with the benefits of coming to the Forum.</td>
<td>.950</td>
</tr>
<tr>
<td>CSAT2</td>
<td>Overall, the benefits of coming to the Forum meet my expectations.</td>
<td>.961</td>
</tr>
<tr>
<td>CSAT3</td>
<td>I am content with what I get from coming to the Forum.</td>
<td>.959</td>
</tr>
<tr>
<td>CSAT4</td>
<td>What I get from coming to the Forum meets what I expect from this type of community.</td>
<td>.939</td>
</tr>
<tr>
<td>EXH1</td>
<td>I feel emotionally drained from my work at Mturk.</td>
<td>.916</td>
</tr>
<tr>
<td>EXH2</td>
<td>I feel used up after completing my tasks at Mturk.</td>
<td>.911</td>
</tr>
<tr>
<td>EXH3</td>
<td>I feel fatigued when I get up in the morning and have to face other tasks at Mturk.</td>
<td>.936</td>
</tr>
<tr>
<td>EXH4</td>
<td>I feel burned out from my work at Mturk.</td>
<td>.913</td>
</tr>
<tr>
<td>FAIR1</td>
<td>I think my level of pay at Mturk is fair.</td>
<td>.969</td>
</tr>
<tr>
<td>FAIR2</td>
<td>Overall, the rewards I receive at Mturk are quite fair.</td>
<td>.969</td>
</tr>
<tr>
<td>JSAT1</td>
<td>Generally speaking, I feel satisfied with the work at Mturk.</td>
<td>.946</td>
</tr>
<tr>
<td>JSAT2</td>
<td>Overall, I feel satisfied with the kind of work I do at Mturk.</td>
<td>.931</td>
</tr>
<tr>
<td>JSAT3</td>
<td>In general, I feel satisfied with the work at Mturk.</td>
<td>.975</td>
</tr>
<tr>
<td>PW1</td>
<td>I feel rushed to execute the requested work on time at Mturk.</td>
<td>.771</td>
</tr>
<tr>
<td>PW2</td>
<td>I feel pressured at Mturk because I have too much work to do in too little time.</td>
<td>.750</td>
</tr>
<tr>
<td>PW3</td>
<td>I feel that the amount of work I do at Mturk interferes with how well it is done.</td>
<td>.642</td>
</tr>
<tr>
<td>PW4</td>
<td>There is an extreme time pressure at Mturk.</td>
<td>.869</td>
</tr>
<tr>
<td>PW5</td>
<td>There are unrealistic expectations about productivity at Mturk.</td>
<td>.894</td>
</tr>
<tr>
<td>TI1_r</td>
<td>I will continue to work at Mturk two years from now.</td>
<td>.981</td>
</tr>
<tr>
<td>TI2_r</td>
<td>I intend to continue to work at Mturk this time next year.</td>
<td>.941</td>
</tr>
<tr>
<td>TI3_r</td>
<td>I plan to continue to work at Mturk for the next three years.</td>
<td>.957</td>
</tr>
<tr>
<td>AGE</td>
<td>What is your age in years? (integer values)</td>
<td>**</td>
</tr>
<tr>
<td>GENDER</td>
<td>What is your gender? (1 = Male; 2 = Female)</td>
<td>**</td>
</tr>
<tr>
<td>TENURE</td>
<td>How many years have you spent working at Mturk?</td>
<td>**</td>
</tr>
</tbody>
</table>

Notes.

In the actual survey, “the Forum” was replaced with the real name of the online community. Items for TI are reversed. All multi-item scales used a seven-point Likert scale with “Strongly Disagree” and “Strongly Agree” as extremes and “Neutral” as the middle. * indicates use of the scale: 1 = Less than a year; 2 = 1 to less than 2 years; 3 = 2 to less than 3 years; 4 = 3 to less than 4 years; 5 = 4 to less than 5 years; 6 = 5 to less than 6 years; 7 = 6 or more years. ** indicates single-item controls.

CCC = Continuance Community Commitment; CSAT = Community Satisfaction; EXH = Work Exhaustion; FAIR = Fairness of Rewards; JSAT = Job Satisfaction; PW = Perceived Workload; TI = Turnover Intention

Table 2. Reflective Measurement Items and Factor Loadings

Results

Measurement Model

We first conducted descriptive analyses using SPSS 22. Table 3 reports the means, standard deviations, and correlation matrix of the constructs. Except for the correlations between CSAT and CCC (.56, p<.01), PW and EXH (.61, p<.01), and JSAT and FAIR (.54, p<.01), all correlations we found in the medium to low range. To investigate the concern of multicollinearity, we examined the variance inflation factor (VIF) of the constructs in all three models for the endogenous variables (i.e., JSAT, CSAT, and TI). The interaction term (CCC and FAIR) was also included in the analyses by following the procedure in Chin (1998). The
maximum VIF across all models was 1.75, and the average VIF scores for the three models were 1.33, 1.07, and 1.35, respectively, which were well below the widely accepted threshold of 5 (Hair et al. 2014).

<p>| Table 3. Descriptive Statistics and Measurement Model Results |
|---------------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|</p>
<table>
<thead>
<tr>
<th>CCC</th>
<th>CSAT</th>
<th>EXH</th>
<th>FAIR</th>
<th>JSAT</th>
<th>PW</th>
<th>TI</th>
<th>AGE</th>
<th>GENDER</th>
<th>TENURE</th>
</tr>
</thead>
<tbody>
<tr>
<td>.85</td>
<td>.95</td>
<td>- .13**</td>
<td>- .13*</td>
<td>.92</td>
<td>- .29**</td>
<td>- .26**</td>
<td>.54**</td>
<td>.95</td>
<td>- .08</td>
</tr>
<tr>
<td>T</td>
<td>.96</td>
<td>- .41*</td>
<td>- .22**</td>
<td>.09</td>
<td>- .32**</td>
<td>- .39**</td>
<td>.09</td>
<td>- .01</td>
<td>---</td>
</tr>
<tr>
<td>AGE</td>
<td>.00</td>
<td>- .11</td>
<td>- .13*</td>
<td>- .15*</td>
<td>- .16**</td>
<td>- .12*</td>
<td>.01</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>GENDER</td>
<td>.09</td>
<td>.10</td>
<td>- .11</td>
<td>- .03</td>
<td>.02</td>
<td>- .07</td>
<td>- .08</td>
<td>.12*</td>
<td>---</td>
</tr>
<tr>
<td>TENURE</td>
<td>.08</td>
<td>- .04</td>
<td>.09</td>
<td>- .04</td>
<td>- .08</td>
<td>- .01</td>
<td>- .06</td>
<td>.26**</td>
<td>.08</td>
</tr>
</tbody>
</table>

Mean 5.35 6.01 3.00 3.10 5.06 3.50 2.54 40.03 1.57 2.24
SD 1.35 1.04 1.63 1.56 1.38 1.46 1.39 12.87 .50 1.72
AVE .72 .91 .84 .92 .90 .62 .92 --- --- --- --- --- --- ---
CR .89 .98 .96 .97 .97 .89 .97 --- --- --- --- --- --- ---
Cronbach’s α .81 .97 .94 .96 .95 .87 .96 --- --- --- --- --- --- ---

** p < .01; * p < .05. AVE = Average Variance Extracted. CR = Composite Reliability. Values on the diagonal denote the square root of AVE. Values off the diagonal denote the correlation coefficients.

Table 3. Descriptive Statistics and Measurement Model Results

We used SmartPLS 2 to evaluate the measurement and path models. SmartPLS is a commonly used software to conduct partial least squares structural equation modeling (PLS-SEM) which is suitable in our context because ours is an exploratory research of the role of online sphere boundary spanning in crowdworking turnover intention (Chin 1998, Hair et al. 2014). We evaluated our measurement model following the guidelines of Hair et al. (2014) and Chin (1998). We examined the reliability of our constructs using composite reliability (CR, reliable if > .7), Cronbach’s α (reliable if > .7), and average variance extracted (AVE, reliable if > .5) (Hair et al. 2014, Chin 1998). The results reported in Table 3 clearly show that all the measures are reliable. For convergent validity, we examined the AVE (valid if > .5) in Table 3, and each factor loading (valid if > .708) of the items reported in Table 2 (Hair et al. 2014). The results of AVE indicate the items converged well onto the intended constructs. Besides, all item loadings were above the threshold except for PW3’s loading that was found at the borderline (.642). According to the procedure offered by Hair et al. (2014), we evaluated the impact of removing this item (PW3) on AVE and CR of the construct (PW). Because the results revealed no clear gains in AVE and CR by removing this item, we kept it in further analyses for maximal asymptotic consistency of our model’s estimates (Chin 1998). Lastly, we examined discriminant validity by following Chin (1998) and Fornell and Larcker (1981). The results are reported in Table 3. For each latent construct, square root of AVE was found to be greater than the construct’s correlation with any other latent construct, thereby establishing satisfactory discriminant validity of the measures (Chin 1998).

Common method bias is a potential concern due to the common method variance in self-reported survey data (Podsakoff et al. 2003). Besides reverse coding the items for TI and assuring our respondents that there are no right or wrong answers in order to eliminate evaluation apprehension (Podsakoff et al. 2003), we used three methods to evaluate the extent of common method variance. First, according to Lindell and Whitney (2001), the smallest correlation among multi-item factors may be a reasonable estimate for the extent of common method variance. Table 3 shows that the common method variance is about .06 (p=n.s.), indicating that common method variance is minimal. Second, we conducted Harmon’s one-factor test by subjecting all items to an exploratory factor analysis (EFA) in SPSS 22 (Podsakoff et al. 2003). The analysis produced seven factors with eigenvalues above 1, and no factor appears to have accounted for the majority of the variance (the largest factor accounted for only 29.5% of the variance). Third, following the procedure of Podsakoff et al. (2003), we used a common method factor test in which, in addition to the existing constructs, we included a common method factor that included all items and reevaluated the measurement
The key is to compare the average variance of the items explained by the substantive constructs to the variance explained by the common method factor. The results indicate that the average variance explained by the substantive constructs is .82, whereas that by the common method factor is only .24, i.e., below the threshold of severe common method variance (Armstrong et al. 2015). In sum, we conclude from these analyses that common method biases should not present a serious concern in our results.

Also of interest to this study is the role of CCC in moderating the effects of FAIR on JSAT and TI. Given that all these constructs are measured as latent factors, it is preferable to treat the interaction term between CCC and FAIR as a latent factor because of the likely measurement error in the items of both constructs (Chin et al. 1996). We followed the procedure in Hair et al. (2014) and evaluated the measurement model including the aforementioned interaction. Specifically, the interaction term consists of six items equivalent to all possible products of the items of CCC and those of FAIR, after each has been standardized (Chin et al. 1996). SmartPLS results indicate that this interaction factor satisfies all validity requirements including reliability (i.e., CR=.95, Cronbach’s α=.94), convergent validity (i.e., AVE=.68, factor loadings>=.78), and discriminant validity (square root of AVE, i.e., .825, is greater than its correlation with any other factor, i.e., highest ρ=.20). All in all, our robustness checks demonstrated that the measurement model for testing the moderating effects of CCC on the FAIR–JSAT and FAIR–TI relationships is valid.

Structural Models

Next we estimated our proposed model, in addition to four other partial (sub) models. The rationale for analyzing these sub models is that because of the explorative nature of the proposed theoretical model, it is a good practice to evaluate the robustness of the path results upon adding additional sets of constructs incrementally. Moreover, we examined the extent to which adding the boundary spanning perspective explains additional variance of the endogenous variables (i.e., JSAT and TI), after the organizational turnover perspective has been accounted for.

Table 4 shows these model results, and highlights the effect of incrementally adding additional variables. Sub model 1 is a baseline model of TI and includes the demographic variables only. Sub model 2 has both JSAT and TI as endogenous variables, includes EXH in both sub-models, and includes JSAT in the TI model, in addition to the demographic variables. Sub model 3 adds FAIR and PW along with the variables previously introduced in Sub model 2. Thus, Sub models 1-3 represent the traditional organizational models of turnover intention. Sub model 4 introduces the additional variable of CSAT in both the models of JSAT and TI. Lastly, in the full model, CSAT is added as an additional endogenous variable as a function of CCC and all the control variables; moreover, CCC and its interaction term with FAIR are introduced to the models of JSAT and TI.

These models demonstrate that the paths of significant interest remain stable when additional sets of constructs are introduced. Specifically, in the organizational behavioral perspective, the effects of JSAT and FAIR on TI remain strong and negative across the models. The effect of FAIR on JSAT also remains strongly positive across the models. All other path results also remain consistent across models except for the effect of EXH on JSAT. EXH had a significant effect on JSAT when only controlling for demographic variables; however, its effect was reduced to a marginal level after including FAIR (Sub model 3) and became insignificant after including both FAIR and CSAT (Sub model 4). This is consistent with the arguments of our theory. Thus, in the full model, we consider EXH as a control variable for both JSAT and TI.

---

5 It is completely normal that the two figures do not sum to 1, because their calculations are separately conducted and only represent best estimates. Results of the common method factor test are not reported to conserve space but is always available upon request.
Table 4. Results of Partial (Sub) and Proposed (Full) Structural Models

<table>
<thead>
<tr>
<th>Construct</th>
<th>Traditional Organizational Models</th>
<th>Traditional Organizational Models integrated with the Theory of Online Boundary Spanning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sub1</td>
<td>Sub2</td>
</tr>
<tr>
<td></td>
<td>Sub4</td>
<td>Full</td>
</tr>
<tr>
<td>AGE</td>
<td>-.037</td>
<td>-.201***</td>
</tr>
<tr>
<td>GENDER</td>
<td>-.081†</td>
<td>.009</td>
</tr>
<tr>
<td>TENURE</td>
<td>-.066</td>
<td>-.007</td>
</tr>
<tr>
<td>EXH</td>
<td>-.287***</td>
<td>-.010</td>
</tr>
<tr>
<td>JSAT</td>
<td></td>
<td>-.407***</td>
</tr>
<tr>
<td>FAIR</td>
<td></td>
<td>.481***</td>
</tr>
<tr>
<td>PW</td>
<td></td>
<td>-.069</td>
</tr>
<tr>
<td>CSAT</td>
<td></td>
<td>.175***</td>
</tr>
<tr>
<td>CCC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R Square</td>
<td>.101</td>
<td>.108</td>
</tr>
</tbody>
</table>

*** p < .001; ** p < .01; * p < .05; † p < .10. Statistical tests based on bootstrapping of 5,000 random samples.

Hypothesis Testing

We use the full model in Table 4 to test our hypotheses. Table 5 summarizes the results of our hypothesis testing, and Figure 2 portrays the full model with estimated paths. TI is negatively influenced by JSAT (-.295, p<.001) and FAIR (-.162, p<.01), confirming H1a and H1b. Consistent with our prediction, the effect of PW on TI is virtually zero (.015, p>.10), confirming H1c. Comparing Sub models 1 and 2 for TI reveals that adding JSAT increases adjusted R square from 0 to .154. Further, comparing Sub models 2 and 3 for TI indicates that introducing FAIR further increases adjusted R square to .168.

As predicted, FAIR has a positive relationship with JSAT (.488, p<.001), while PW exerts no significant effect on JSAT (-.080, p>.10). Thus, both H2a and H2b are confirmed. Upon comparing Sub models 2 and 3 for JSAT, it is shown that adding FAIR increases adjusted R square from .095 to .313.

H3 predicts a negative effect of CSAT on TI (H3a) and a positive effect of CSAT on JSAT (H3b). Both predictions have been confirmed (-.111, p<.05; .183, p<.01; respectively). Moreover, comparing Sub models 3 and 4 reveals that adding CSAT improves adjusted R square of TI from .168 to .176, and that of JSAT from .313 to .340.

H4 predicts that CCC positively influences CSAT. This prediction is strongly supported (.575, p<.001). Lastly, CCC has a significant and negative moderating effect on the FAIR–JSAT relationship (-.165, p<.05), thus confirming H5a. This moderating effect is illustrated in Figure 3. As shown, the slope of FAIR becomes much steeper when CCC is low (one standard deviation below the mean), whereas it is quite flat when CCC is high (one standard deviation above the mean). H5b is not supported, as CCC does not have a significant moderating effect on the FAIR–TI relationship (-.073, p>.10). Comparing Sub model 4 and the full model, we notice that adding the interaction term between FAIR and CCC further boosts adjusted R square of JSAT from .34 to .361; however, adjusted R square of TI is reduced slightly because the main and interaction effects involving CCC are not significant.

In sum, all of the hypotheses except H5b are supported by the full model results. Next we elaborate on these results and discuss their implications.
### Table 5. Summary of Hypotheses Testing Results

<table>
<thead>
<tr>
<th>Hypothesis Statement</th>
<th>Supported?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a TI is negatively influenced by JSAT</td>
<td>Yes</td>
</tr>
<tr>
<td>H1b TI is negatively influenced by FAIR</td>
<td>Yes</td>
</tr>
<tr>
<td>H1c TI is not influenced by PW</td>
<td>Yes</td>
</tr>
<tr>
<td>H2a JSAT is positively influenced by FAIR</td>
<td>Yes</td>
</tr>
<tr>
<td>H2b JSAT is not influenced by PW</td>
<td>Yes</td>
</tr>
<tr>
<td>H3a CSAT negatively influences TI</td>
<td>Yes</td>
</tr>
<tr>
<td>H3b CSAT positively influences JSAT</td>
<td>Yes</td>
</tr>
<tr>
<td>H4 CCC positively influences CSAT</td>
<td>Yes</td>
</tr>
<tr>
<td>H5a CCC weakens the effect of FAIR on JSAT, so that if CCC is high, the positive effect of FAIR on JSAT becomes less positive.</td>
<td>Yes</td>
</tr>
<tr>
<td>H5b CCC weakens the effect of FAIR on TI, so that if CCC is high, the negative effect of FAIR on TI becomes less negative.</td>
<td>No</td>
</tr>
</tbody>
</table>

### Table 5. Hypotheses Testing Results

<table>
<thead>
<tr>
<th>Hypothesis Statement</th>
<th>Supported?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a TI is negatively influenced by JSAT</td>
<td>Yes</td>
</tr>
<tr>
<td>H1b TI is negatively influenced by FAIR</td>
<td>Yes</td>
</tr>
<tr>
<td>H1c TI is not influenced by PW</td>
<td>Yes</td>
</tr>
<tr>
<td>H2a JSAT is positively influenced by FAIR</td>
<td>Yes</td>
</tr>
<tr>
<td>H2b JSAT is not influenced by PW</td>
<td>Yes</td>
</tr>
<tr>
<td>H3a CSAT negatively influences TI</td>
<td>Yes</td>
</tr>
<tr>
<td>H3b CSAT positively influences JSAT</td>
<td>Yes</td>
</tr>
<tr>
<td>H4 CCC positively influences CSAT</td>
<td>Yes</td>
</tr>
<tr>
<td>H5a CCC weakens the effect of FAIR on JSAT, so that if CCC is high, the positive effect of FAIR on JSAT becomes less positive.</td>
<td>Yes</td>
</tr>
<tr>
<td>H5b CCC weakens the effect of FAIR on TI, so that if CCC is high, the negative effect of FAIR on TI becomes less negative.</td>
<td>No</td>
</tr>
</tbody>
</table>

**Notes.**

*** p < .001; ** p < .01; * p < .05; † p < .10. Statistical tests based on bootstrapping of 5,000 random samples.

Solid lines indicate hypothesized effects. Dashed lines indicate hypothesized no effects. Dotted lines indicate controls.

CCC = Continuance Community Commitment; CSAT = Community Satisfaction; EXH = Work Exhaustion; FAIR = Fairness of Rewards; JSAT = Job Satisfaction; PW = Perceived Workload; TI = Turnover Intention.

### Figure 2. Results of the Final Structural Model
Discussion

Theoretical Contributions

Unlike in the traditional organizational setting, our results demonstrated a contextual uniqueness of turnover behavior in the crowdworking context namely, that perceived workload and work exhaustion do not play a significant role in crowdworking turnover. In the organizational literature, especially within the IS context, perceived workload is found to have a direct effect on turnover intention and an indirect effect that is mediated by job satisfaction. This is straightforward because overloaded workers feel injustice as well as emotionally drained, hence becoming dissatisfied with their job. Despite the consistently strong effect of perceived workload in the traditional organizational literature, our results did not reveal a statistical link between perceived workload and either job satisfaction or turnover intention. Perceived workload may appear to be a detrimental factor that could discourage people from entering the job market. Although seemingly contradictory to conventional wisdom, this finding is nevertheless expected. The majority of work in crowdworking consists of micro- to small-tasks with generally clear requirements. Workers have the freedom to select tasks based on a multitude of factors including the amount of work required. They are also free to choose when to pause working at any time of the day. Such flexibility in choosing one’s desired workload level, work schedule, and working hours explains why overall workload does not affect whether or not a worker chooses to abandon the labor market. This lack of influence of perceived workload is among the unique characteristics of crowdworking.

Excluding the insignificant effect of perceived workload, the traditional organizational theory of turnover behavior is shown to be largely applicable to the crowdworking context. Specifically, job satisfaction remains a strong proximal predictor of turnover intention. Consistent with prior literature in organizational studies, we found that fairness of rewards both directly and indirectly predicts turnover intention. However, work exhaustion did not appear significant in determining either job satisfaction or turnover intention after accounting for the aforementioned factors, following much the same rationale behind the insignificant effect of perceived workload.

We showed that the perspective of boundary spanning is promising. Different from the prior literature that showed limited and mixed effects of boundary spanning, our findings supported the positive role of boundary spanning in the form of knowledge brokerage in crowdworking. Specifically, satisfaction with online Turkers’ communities, which enable members to engage in extensive knowledge exchange activities, was found to not only enhance their satisfaction with crowdworking but to also directly reduce their intentions to drop out of the labor market. This is in stark contrast with the offline organizational context, wherein boundary spanning has been associated with role ambiguity, conflict, and stress, thus leading to dissatisfaction with one’s job and increased turnover intention.

Meanwhile, existing online community research on boundary spanning has excluded contexts outside the realm of online communities (e.g., Johnson et al. 2015, Levina and Vaast 2005). In this paper, we extended the notion of boundary spanning into an environment where two fields of activities remained separate—i.e., separated with a boundary—but nevertheless interrelated via the shared knowledge domain. The first
involves online communities where crowdworkers exchange knowledge and experience, just as in any other expertise-based community; and the other has to do with working in crowdsourced marketplaces and possibly transferring the knowledge acquired in online communities and turning it into more productive work. In this sense, ours is among the first research to theorize and empirically demonstrate a new form of boundary spanning in the online sphere, specifically the spanning of boundaries between online knowledge exchange and online crowdworking.

Furthermore, we showed how the effect of fairness of rewards, an important factor in determining job attitudes and intentions in both the organizational and crowdworking settings, was dampened upon increasing community continuance commitment. This moderating effect is significant with regard to job satisfaction but not turnover intention. Even though the prevailing underpaid status makes rewards more important to the job attitude of workers, the results imply that crowdworkers may not regard reward as important as long as they continue to have access to useful resources to improve their work productivity. This is an informative finding because technology firms such as Amazon are highly experienced in leveraging computing resources to deliver intelligence to their customers. Therefore, it is reasonable to expect that new tools that can facilitate workers’ boundary spanning or knowledge accumulation may be effective at sustaining the prosperity of crowdworking as an emerging labor market.

**Managerial Implications**

Our research helps inform the practices of crowdworking marketplaces. First, we found that fairness of rewards is a strong predictor of the turnover process. This variable exerts both direct and indirect effects on TI (through JSAT). A fact that is widely known is that crowdworkers are paid poorly, much lower than the U.S. federal minimum wage. In a labor market, workers desire fair compensation in not only the short term but rather the long term. Thus, the underpaying norm in extant platforms (e.g. Mturk) may be a transient state to say the least. We expect that future-generation crowdworking platforms will improve the compensation standard so that crowdworking can transform into a more sustainable form of labor market.

Second, our research revealed that boundary spanning in the form of knowledge transfer may effectively boost the loyalty of crowdworkers toward their labor markets. Workers exchange knowledge in online communities outside the boundary of labor market. Such a knowledge exchange process in turn propels worker engagement in the labor market. Specifically, the more satisfied a worker is with the knowledge exchange community, the more satisfied s/he is expected to be with her/his crowdworking and hence the less likely s/he intends to turn over. In light of the critical role of boundary spanning, we expect that crowdworking marketplaces will benefit from dissolving their boundaries with external knowledge exchange domains. One way that crowdworking marketplaces can achieve this outcome is through cultivating their own knowledge exchange communities and allowing knowledge to flow within and beyond boundaries. For example, Mturk may leverage its technological advantage to design and build a more efficient community to facilitate information exchange among Turkers, requesters, and between the two groups.

Further, efficient knowledge exchange can be argued to increase members’ commitment to their knowledge communities, which, according to our results, indirectly weakens the negative effect of fairness of rewards on worker turnover intention. Thus, in an attempt to alleviate the negative influence of poor rewards, it may be beneficial that extant crowdworking platforms seek to enhance the benefits of knowledge exchange communities above and beyond their efforts to include internal communities.

**Limitations and Future Research**

Although our findings clearly demonstrate the boundary spanning effect of engaging in online communities on crowdworking intention, lingering questions remain related to what motivates some crowdworkers to span their work boundary, and what makes other crowdworkers choose not to. Although these questions appear theoretical, answering them may uncover the underlying causes of the spontaneous boundary spanning of crowdworkers, and can inform a better design of both crowdsourcing and knowledge exchange platforms. In addition, although Mturk may be highly representative of the crowdworking marketplaces, the Forum from where we sampled our members may not be as representative of all boundary spanners in the crowdworking context. As mentioned earlier, there exist at least seven online communities that are related to Mturk. The extent to which the Forum’s members are similar to members of the other.
communities is unclear; thus our findings should be generalized with caution. We encourage future research to sample more widely from members of other communities in order to validate our results.

**Conclusion**

Online crowdsourcing constitutes an emergent labor market. Its ongoing success hinges on crowdworkers’ continued work. Meanwhile, the lack of a balanced power between Requesters and crowdworkers, and pay levels that are well below the United States’ minimum wage rate have plagued the long-term prosperity of crowdworkers and, hence, the sustainability of the emergent crowdsourcing labor market. This research largely confirms the applicability of the organizational view of worker turnover intention to the crowdsourcing marketplace context regarding the roles of job satisfaction and fairness of rewards, but it also reveals that perceived workload does not play a role in determining turnover intention. To complement the organizational view, we build and empirically validate a contextualized theory of boundary spanning in the crowdsourcing context. Boundary-spanning crowdworkers, who voluntarily seek to accumulate information and knowledge in online communities that are outside the crowdsourcing realm, tend to have a lower turnover intention. Further, the more engaged crowdworkers are in boundary spanning, the less likely they will focus on short-term monetary rewards and give up crowdsourcing prematurely. Existent and future crowdsourcing platforms are advised to help their workers more easily cross the boundary of knowledge exchange so as to retain their extant workforce and remain competitive.

**References**


