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Xiao Ma, Lara Khansa & Sung S. Kim

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XIAO MA, LARA KHANSA, AND SUNG S. KIM

XIAO MA (xma@bauer.uh.edu; corresponding author) is an Assistant Professor of Business Analytics in the C. T. Bauer College of Business at the University of Houston. He graduated with a Ph.D. in Business from the University of Wisconsin-Madison, concentrating on information systems and management. His research focuses on the problems of online gambling behavior and smartphone usage and proper interventions, participation behavior in online labor and knowledge communities, and the roles of habit relating to IT artifacts. His research has appeared or is forthcoming in premier information systems journals, including *Journal of Management Information Systems, Information Systems Research*, and *Journal of the Association for Information Systems*.

LARA KHANSA (larak@vt.edu) is Associate Dean for Undergraduate Programs and Associate Professor of Business Information Technology in the Pamplin College of Business at Virginia Tech. She received her Ph.D. in information systems from the University of Wisconsin-Madison. Dr. Khansa's research interests include human–computer interaction, online user behavior, online information privacy, and healthcare analytics. Her work has been published in *Journal of Management Information Systems, Decision Sciences, Communications of the ACM, Decision Support Systems*, and other journals.

SUNG S. KIM (skim@bus.wisc.edu) is the Peter T. Allen Professor of Operations and Information Management in the Wisconsin School of Business at the University of Wisconsin-Madison. He holds a Ph.D. in information technology management from the Georgia Institute of Technology. His primary research focus is on automaticity in IT use, online consumer behavior, information privacy, and philosophical and methodological issues. His work has appeared in *Management Science, Information Systems Research, Journal of Management Information Systems, MIS Quarterly, Journal of the Association for Information Systems*, and *Decision Sciences*.

ABSTRACT: Crowdworkers, such as Mturk workers, face challenging work conditions, including low pay and unfair treatment. To overcome a lack of means to share information with other workers, they often self-organize in independent online communities, for example, TurkerNation. Although prior research has explored both the crowdwork and online community contexts, it has largely ignored crowdworkers' dual-context roles. This research provides evidence for the dual-context

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phenomenon. We propose three theory-driven mechanisms—embeddedness, cross-influence, and moderated heuristics—that, together with the conventional model and the sequential-update mechanism, explained up to 72% of key behavioral outcomes in both contexts. Moreover, crowdworkers' active participation in online communities had a persistent mitigating effect on their desires to quit working in the crowdworking environment. These findings add to a richer understanding of crowdworkers' integrated and evolving psychology within the dual-context environment. From a managerial perspective, our findings suggest that crowdwork platforms can better retain their workers by facilitating—and actively engaging with—their discussions in an embedded online community.

Key words and phrases: crowdwork, Amazon Mechanical Turk, Mturk, online communities, crowdworking turnover, turnover intention, two-wave panel, embeddedness, moderated heuristics, co-creation.

Introduction

Online crowdworking marketplaces, such as Upwork (formerly Elance-oDesk) and Amazon Mechanical Turk (Mturk) [29], hire a flexible and scalable mass of workers who are physically scattered worldwide and who are likely drawn from diverse ethnic and cultural backgrounds. These workers are paid to complete work requests put forth on Mturk by employers dubbed requesters [6]. With over 500,000 registered workers globally [2], Mturk is among the most popular and highly frequented online crowdworking marketplaces [29]. Mturk hires workers on behalf of requesters to complete "Human Intelligence Tasks" (HITs) that encompass psychological experiments, academic surveys, creative writing, market research, etc. It has been widely reported that crowdworkers are paid poorly and treated unfairly [55], which could explain why Mturk and other online labor platforms have been plagued by high dropout rates of their active workers [73, 82]—a situation that could jeopardize their long-term sustainability [12]. Ross et al. [73] found that 69% of surveyed Turkers had been with Mturk less than six months; another study by Sun et al. [82] also reported similarly low worker retention rates (i.e., less than 10%) at comparable crowdwork platforms in China (e.g., Taskcn.com).

By design, crowdworking labor platforms do not allow direct communication among crowdworkers from within the platform. As a way to circumvent this hindrance to open communication, crowdworkers have organized themselves into independently operated online crowdworking communities (e.g., Turkopticon and Turker Nation) that serve as platforms for workers to vent their work-related frustrations, seek work-related advice, or simply socialize [12, 54]. For example, through initiating the crowdwork community Turkopticon in 2008, Turkers were able to use word-of-mouth collectively and join forces to single out and expose unethical requesters [77, 78]. Turkopticon and other crowdwork communities have been reported anecdotally not only to benefit crowdworkers but also to benefit crowdworking platforms through sustaining workers' commitment toward their crowdwork [24, 55]. Although Mturk and prominent crowdwork communities have co-existed since at least 2005,[1] existing research has focused on either the crowdworking side or the community side, but not on both.

Substantial research has been conducted separately within each of the crowdwork (see e.g., [81]) and online community (see e.g., [65]) literature streams. The extant crowdwork research established that crowdworkers suffer from poor working conditions, and unfair treatment and compensation [12, 13, 17, 52, 54] and that the crowdwork industry has been plagued with high rates of worker dropout [12]. On the online community side, the literature has mainly explored the motivations behind member participation in online communities [35, 36, 38, 46, 48, 51, 68, 72, 85]. However, no study has combined both literature streams and synthesized their theoretical underpinnings to investigate why and how crowdworkers' participation in online crowdworking communities dynamically interacts with their turnover decision process. By better characterizing the *intertemporal relationship mechanisms* underlying the community-crowdwork relationship, research can help crowdwork platforms like Mturk explore ways to improve their platform design to better retain workers [17]. Furthermore, crowdworkers' community participation and turnover intention are not static but exhibit dynamic characteristics; thus, it is important to incorporate the less explored longitudinal mechanisms underlying the dual role contexts. Despite its significant research and practical implications, the dynamic community participation-turnover intention relationship that characterizes crowdworkers' behavior and psychology has remained largely underinvestigated in the thus far mostly conventional models of crowdwork studies (i.e., [12, 17, 52]).

This research aims at complementing the conventional models and the sequential-update mechanism of crowdworker turnover intention by proposing a three-mechanism conceptual framework of crowdworking behavior. Specifically, our framework first draws on the embeddedness theory to investigate how members' active participation in their communities might diffuse seamlessly to their crowdwork through decreasing their turnover intention, i.e., the embeddedness mechanism. In addition, the proposed conceptual framework builds on social psychology theories and the sequential-update mechanism [40] to further incorporate two novel longitudinal mechanisms—namely, the intertemporal cross-influence mechanism, that is, the lagged influences of different but related perceptions on each other [64, 75], and the moderated heuristics mechanism, that is, the moderating role of prior behaviors in changing the sequential-update from prior beliefs to subsequent beliefs.

Our paper contributes to IS research in several important ways. Addressing a recent call for more boundary-spanning cross disciplinary Information Systems (IS) research [83], our proposed conceptual framework is among the first in the IS literature to theorize the dual community-crowdwork role of crowdworkers, and as far as we know, constitutes the first longitudinal model to examine such a phenomenon. This framework is empirically tested and in large part validated. It improves notably in model fit over conventional models recently published in the literature (e.g., [52]); as such, it demonstrates that accounting for embeddedness and two intertemporal mechanisms, that is, cross-influence and moderated heuristics, is essential in accurately characterizing crowdworkers' turnover decision process. There have been recent calls for research that investigates the consequences of active participation and leadership behavior in online communities [34, 47]. To this end, we theorized and validated that a significant dynamic connection exists between online community behavior and crowdworking behavior and that failure to account for this embeddedness results in a misrepresentation of crowdworkers' behavior over time.

Research Model and Hypotheses

Figure 1 depicts a longitudinal model of crowdworkers' community participation and of these workers' intentions to discontinue their crowdworking jobs. This model consists of two parts. The upper part represents the factors related to online community behavior, and the lower part shows the factors related to crowdwork behavior.

First, the model proposed in this study builds on the traditional framework that suggests that active participation in an online community is a function of affective commitment and continuance commitment and that turnover intention in the crowdwork platform is affected by fairness of rewards and crowdworking satisfaction. Second, this model incorporates the sequential-update mechanism in which the factors at t = 1 influence the same factors at t = 2. Third, the embeddedness mechanism reflects the effect of online community behavior on crowdwork behavior. Fourth, the cross-influence mechanism posits that affective commitment and continuance commitment influence each other over time, and so do fairness of rewards and crowdworking satisfaction. Finally, moderated

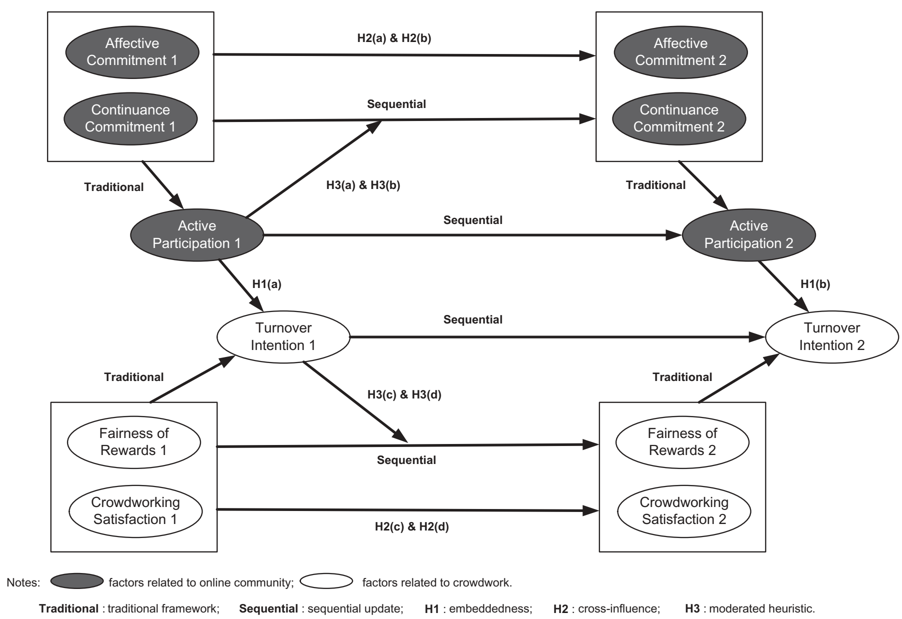


Figure 1. Two-wave panel model of online community and crowdwork.

heuristics imply that active participation and turnover intention moderate the sequential updating of their antecedents.

Table 1 further summarizes the conceptual associations between our research hypotheses and the main overarching theories. We begin by discussing the conventional model [4, 38, 52, 71, 74] that describes the cross-sectional characteristics of online community participation and those of turnover intention. We then discuss sequential updating that reflects how a certain variable affects the same variable at a later stage [10, 26]. Next, we expand the basic model by incorporating three additional theory-driven mechanisms—namely, embeddedness, cross-influence, and moderated heuristics. Overall, our proposed model and hypotheses highlight the evolving relationships between the roles of crowdworkers as community members and workers.

Conventional Model

Active participation is defined as the degree to which a member engages in the mutual exchange of information and knowledge in the community [4]. The online community literature has established that both affective commitment and continuance commitment have positive relationships with active participation [4, 43, 71].[2] Affective commitment depicts such a tie between an individual and a community representing "the strength of [this] individual's identification with and involvement in [the community]" [69, p. 604]. The identification process often strengthens a member's identity perception consistent with others' [85]. Empirical research has shown that affective commitment leads to positive engagement [71], interaction [4], and prosocial behavior such as volunteering one's time and expertise for the benefit of fellow members [22]. Meanwhile, continuance commitment refers to an individual's connection with a community in such a way that the individual is bound to it because of a high level of switching costs [4]. Members with high continuance commitment tend to focus on taking advantage of a community with a minimal amount of interest in its long-term growth [7, 28, 33]. Thus, community members with high continuance commitment are less likely to actively contribute to their community but instead try to benefit from it simply through lurking [43].

Second, prior research (e.g., [52, 74]) has shown that fairness of rewards and crowdworking satisfaction are essential conditions for work continuation. Social exchange theory posits that for a relationship to be sustained, it must facilitate a fair exchange among interacting parties [9]. Crowdworkers provide services to requesters, and in return they expect to be compensated fairly, that is, proportionately to the effort they exerted to complete the agreed upon tasks. This also accords with distributive justice theory, which proposes that rewards ought to be commensurate with the complexity of the task, the skills and experience of the employees completing them, the quality of their work, and the amount of effort they put into completing the work [62, 70]. If employees are not rewarded fairly, they tend to perceive higher inequity and are thus likely to exhibit higher turnover intention [19].

Table 1. Hypotheses and Relevant Theories

Hypothesized Mechanisms	Hypotheses	Causal Paths	Theories
Traditional Framework		AC (t=1) → AP (t=1)	Cross-sectional community-crowdwork model [4, 38, 52, 71, 74]
		CC (t=1) → AP (t=1)	
		FR (t=1) → TI (t=1)	
		WS (t=1) → TI (t=1)	
		AC (t=2) → AP (t=2)	
		CC (t=2) → AP (t=2)	
		FR (t=2) → TI (t=2)	
		WS (t=2) → TI (t=2)	
Sequential Update		AC (t=1) → AC (t=2)	The theory of belief updating [10, 26]
		CC (t=1) → CC (t=2)	
		FR (t=1) → FR (t=2)	
		WS (t=1) → WS (t=2)	
		AP (t=1) → AP (t=2)	
		TI (t=1) → TI (t=2)	
Embeddedness [45, 60]	H1(a)	AP (t=1) → TI (t=1)	Embeddedness theory
	H1(b)	AP (t=2) → TI (t=2)	
Cross-Influence	H2(a)	AC (t=1) → CC (t=2)	The model of interdependent beliefs and attitudes (e.g., [75])
	H2(b)	CC (t=1) → AC (t=2)	
	H2(c)	FR (t=1) → WS (t=2)	
	H2(d)	WS (t=1) → FR (t=2)	
Moderated Heuristics	H3(a)	AC*AP (t=1) → AC (t=2)	Elaboration likelihood model [67]
	H3(b)	CC*AP (t=1) → CC (t=2)	
	H3(c)	FR*TI (t=1) → FR (t=2)	
	H3(d)	WS*TI (t=1) → WS (t=2)	

Notes: AC = online community affective commitment; CC = online community continuance commitment; FR = fairness of rewards; WS = crowdworking satisfaction; AP = online community active participation; TI = crowdworking turnover intention.

Meanwhile, satisfaction with one's work has also been previously identified in the turnover literature as a requirement for job continuation [74, 86]. Dissatisfied employees are more likely to quit and move on to more satisfying opportunities (e.g., [25, 31, 74]). In the specific case of crowdworking marketplaces, insufficient worker compensation makes crowdworking satisfaction an even more critical requirement for retention. Taken together, both fairness of rewards and crowdworking satisfaction have been shown to be negatively related to turnover intention.[3] Overall, we propose that the cross-sectional causal links between affective commitment and continuance commitment, on the one hand, and active participation, on the other, remain true in a longitudinal setting; this is also expected for the relationships between fairness of rewards and crowdworking satisfaction and turnover intention. Thus, we consider the traditional model as the theoretical basis for developing our proposed longitudinal model.

Sequential Update

When characterizing the determinants of continued decision-making such as continued community participation and sustained work intention, it is important to factor in past evaluations and decisions that carry important information critical for subsequent evaluations and decisions [37, 40]. This is because, according to the theory of belief updating [10, 26], decision-making carried on over time is seldom done in isolation. Instead, it often starts with prior judgments known as anchors that are adjusted thereafter with "succeeding pieces of evidence" [26, p. 8]. This sequential updating mechanism has been documented in studies on continued IS use [37, 40] and in marketing studies investigating changes in customer attitudes [11], customer satisfaction [10, 61], and purchase intention [44, 61]. Because crowdworkers gain knowledge and experience over time in the course of their crowdworking and participation in related online communities, we expect that preceding behavior and evaluations serve as bases for future ones. Therefore, based on this sequential updating mechanism, we propose that prior instances of all six factors — affective commitment, continuance commitment, fairness of rewards, crowdworking satisfaction, active participation, and turnover intention at $t = 1$ — are positively related to their subsequent instances at $t = 2$. We thus expect that the sequential-update mechanism will continue to work in our research setting.

Embeddedness

On top of the causal links established above and based on embeddedness theory [45, 60], we contend that there is a linkage between the contexts of community and crowdwork. This embeddedness phenomenon could refer to situations in which employees stay in their jobs to remain in close proximity to their families or to continue reaping corporate benefits [27]. Generally, embeddedness accounts for nontraditional determinants of turnover that do not stem from job attitudes or perceived alternatives [27]. In organizational settings, it represents "a broad constellation of influences on employee retention" [60, p. 7] connecting "an employee ... in a social, psychological, and financial web that includes work and non-work friends, groups, the community ... in which he or she lives" [60, p. 8]. In other words, when two contexts are embedded, active behavior in one context translates automatically into a similarly engaged behavior in the other. Applied to our crowdwork context, active participation in the crowdwork community is expected to diffuse seamlessly into the crowdwork context and transpire into a similarly high level of engagement and less likelihood of leaving Mturk [45, 60]. The embeddedness between active participation and turnover intention could result from the support that active members furnish to crowdworking colleagues through their community engagement [71]. Specifically, helping others could help them realize how good they are, and this energy and appreciation of oneself further propels their work energy and efficacy. Further, the desire to continue helping others in the community may serve as a motivator of their furthering their worker role so as to keep exploring the solutions to emerging challenges and unknowns in the crowdwork environment. Embeddedness sparks active members' creativity and improves their ability to see new linkages and possibilities, both of which are instrumental in completing crowdwork tasks more effectively, leading in turn to a higher likelihood of crowdwork continuance. This same embeddedness phenomenon has been observed in the contexts of open source systems [23] and entrepreneurship fundraising [84]. Overall, we expect active members' community engagement to reflect positively on their crowdwork and in turn lead to lesser likelihood of their quitting their jobs. Therefore,

> *Hypothesis 1 (a): Active participation at time $t = 1$ has a negative relationship with turnover intention at $t = 1$.*

> *Hypothesis 1 (b): Active participation at time $t = 2$ has a negative relationship with turnover intention at $t = 2$.*

Cross-Influence

Ryan [75] empirically demonstrated an *interdependence* between different types of beliefs. Ryan's cross-influence mechanism suggests an ongoing belief-changing scenario in which a type of beliefs evolves gradually under the influence of another type of beliefs. Although reflecting a psychological connection between the member and the community, affective commitment and continuance commitment represent different facets of this connection [58]. As discussed earlier, affective commitment results from an emotional feeling of belongingness [69]. In contrast, continuance commitment captures a sense of being locked in the relationship [4]. Building on these definitions of the two commitments and on the time-lagged theoretical foundation of crossover-effects between beliefs and attitudes discussed earlier, we thus expect, from Time 1 to Time 2, a positive influence of affective commitment on continuance commitment and a positive influence of continuance commitment on affective commitment.

On the one hand, a strong affective commitment results in an employee's belief that there are too few alternatives and, as a result, it is too costly to leave the current employer — both of which imply a strong continuance commitment. Indeed, Meyer et al. [59] found a positive causal effect of affective commitment on subsequent continuance commitment. On the other hand, if members believe strongly that they could not perform well without their community, over time they might be inclined to play up their feelings. The rationale is that if community members foresee an ongoing relationship with the community, they would wish to believe that they do so not only because they are bound to the community, but also because they are an integral part of the community, and hence, their inflated affective commitment toward the community [57]. This rationale is supported both theoretically and empirically in the management literature. According to Steers and Porter [80], those who maintain continuance commitment gradually develop an affective tie with their employers. Besides, Meyer et al. [59] also demonstrated a positive causal path from continuance commitment to affective commitment in both cross-sectional and time-lagged settings. Given the above reasoning, we anticipate a positive effect of affective commitment at $t = 1$ on continuance commitment at $t = 2$, and a positive effect of continuance commitment at $t = 1$ on affective commitment at $t = 2$. Thus,

> *Hypothesis 2 (a): Affective commitment at $t = 1$ has a positive effect on continuance commitment at $t = 2$.*

> *Hypothesis 2 (b): Continuance commitment at $t = 1$ has a positive effect on affective commitment at $t = 2$.*

As discussed previously, fairness of rewards tends to be a requirement for crowdworking satisfaction. If employees believe they are rewarded unfairly relative to the work they have provided and in comparison with the rewards that similar workers have received, they tend to become dissatisfied. On the other hand, if crowdworkers perceive their rewards to be fair at $t = 1$, all else being equal, they are likely to be grateful for the benefits the crowdworking marketplace has given them and likely to feel satisfied with their crowdworking at $t = 2$. Similarly, when employees experience feelings of satisfaction at $t = 1$, they are likely to perpetuate their appreciation of, and positive feelings toward, their crowdworking marketplace in subsequent periods. As a result of inferential processing [75], they may tend to believe more strongly that the rewards they have received must be reasonably fair. Thus,

> *Hypothesis 2 (c): Fairness of rewards at $t = 1$ has a positive effect on crowdworking satisfaction at $t = 2$.*

> *Hypothesis 2 (d): Crowdworking satisfaction at $t = 1$ has a positive effect on fairness of rewards at $t = 2$.*

Moderated Heuristics

The elaboration likelihood model (ELM) suggests two routes of decision-making processes: the central and peripheral routes. According to ELM, the central route is chosen when people thoroughly evaluate the pros and cons associated with the situation in question. In contrast, the peripheral route is followed when people make a quick, heuristic decision [8]. People tend to rely heavily on prior judgments in the case of the peripheral route, but they are less influenced by prior judgments in the case of the central route [52]. ELM also posits that people adopt heuristic processing when they have positive attitudes toward a situation [67]. The rationale behind this proposition is that when people are pleased with a current situation, they do not have a strong incentive to scrutinize its benefits and costs in comparison with its alternatives. However, when they have negative attitudes toward a product or service, they tend to engage in conscious processing [67]. This is because to justify continuing the current way of doing things, they want to ensure that the benefits of their current choice outweigh its costs.

ELM sheds light on the issue of how over time prior beliefs are transformed into subsequent beliefs. We argued earlier that prior beliefs would have a positive relationship with subsequent beliefs through the process of sequential updating. The previous discussion on ELM implies that the sequential-updating mechanism will change according to individuals' disposition toward a situation in question. If their disposition is favorable, the sequential-updating mechanism is likely to be stronger because people do not need to exercise a conscious effort to evaluate the current choice. In contrast, when their disposition is negative, people are less likely to base their decisions on prior judgments; thus, the sequential-updating mechanism is likely to be weaker in such a situation. Numerous studies in the IS literature suggest that an individual's behavior is one of the best proxies for estimating his or her disposition [37, 39]. Whereas the peripheral route is followed when people perform a behavior frequently, the central route is chosen if a behavior is performed only occasionally.

The previous discussion leads us to predict the way that active participation moderates the relationship between prior and subsequent judgments. Specifically, if people actively participate in their online community, they are unlikely to spend their mental energy in thoroughly evaluating whether they should stay in the current community. Thus, the positive effect of prior commitment on subsequent commitment is likely to be stronger with an increase in active participation. However, such a heuristic process is less likely if community members are less active in participating in the online community. Then, they have more reasons to engage in the deliberate evaluation of their current situation in their community. Accordingly, the effect of prior commitment on subsequent commitment will be weaker because of community members' deliberate decision-making process. In sum, we expect that active participation, as a proxy of one's disposition toward an online community, will moderate the sequential-updating mechanism.

Hypothesis 3 (a): Active participation at t = 1 strengthens the positive relationship between affective commitment at t = 1 and affective commitment at t = 2.

Hypothesis 3 (b): Active participation at t = 1 strengthens the positive relationship between continuance commitment at t = 1 and continuance commitment at t = 2.

Similarly, in a crowdworking context, turnover intention at t = 1 is likely to moderate the impact that prior beliefs have on subsequent beliefs such as fairness of rewards at t = 2 and crowdworking satisfaction at t = 2. Specifically, turnover intention represents a negative disposition toward a crowdwork platform. Thus, as turnover intention increases, people become more attentive to the pros and cons of staying in their incumbent platform and thereby follow the central route in forming subsequent judgments. In contrast, a decrease in turnover intention suggests a more favorable disposition. Accordingly, it will facilitate the heuristic process as represented by the relationship between prior and subsequent beliefs. Thus, we expect that the positive relationship between fairness of rewards at t = 1 and fairness of rewards at t = 2 will decrease with an increase in turnover intention at t = 1. Similarly, the positive relationship between crowdworking satisfaction at t = 1 and crowdworking satisfaction at t = 2 will be weaker as turnover intention at t = 1 increases. The specific hypotheses are formally stated as follows:

> *Hypothesis 3 (c): Turnover intention at t = 1 weakens the positive relationship between fairness of rewards at t = 1 and fairness of rewards at t = 2.*

> *Hypothesis 3 (d): Turnover intention at t = 1 weakens the positive relationship between crowdworking satisfaction at t = 1 and crowdworking satisfaction at t = 2.*

Research Method

Data Collection

The survey method is ideal for collecting the data needed for testing our theoretical model. Because Mturk is still an emerging subject pool for research, we followed Mason and Suri [56]'s guidelines for collecting survey data in regard to four aspects: generalizability, data security, quality assurance, and requester ethics. Mason and Suri [56] caution that Turkers may not be representative of the population of any geographical areas, and thus survey researchers using Mturk should carefully evaluate the generalizability of their findings based on the Turkers. Because our study specifically focuses on the crowdworker population and Mturk is a representative online labor platform as well as the most popular, we deem it appropriate to sample from Turkers. Moreover, our primary focus is on the behavior of those crowdworkers who are also members of online worker communities. Thus, recruiting Turkers from an established Turkers' community would be reasonable. Pursuant to Mason and Suri [56]'s suggestion, we used externally hosted online surveys (on Qualtrics) and embedded hyperlinks to them in Mturk's interface as a way to ensure the security and privacy of the responses. To ensure the quality of survey responses, we adopted two procedures. In the first, a pilot survey collected feedback on the readability and clarity of the instructions and instrument. This allowed us to improve the overall quality of the main surveys [56]. In the second, to filter out possible spammers and respondents who paid little attention to survey instructions, we added "reverse Turing test" questions that assessed knowledge about Mturk and the selected online community. Only one respondent did not provide satisfactory answers to both questions, and these responses were subsequently removed. Meanwhile, we verified that all the included respondents' self-reported Community usernames matched the data in the Community's database. Together, these measures ensured that spammers or inattentive respondents did not compromise our data. Lastly, conforming to the recommended ethical behavior of requesters [56], we paid respondents $2 for each survey, equivalent to wages of $12 an hour based on the 20 minutes considered necessary to complete both waves of the survey. The results indicated that each wave took about eight minutes for a median respondent to complete, thus amounting to a wage of $4 for 16 minutes, or $15 an hour. Overall, our data collection procedures do not raise significant concerns.

We initially conducted a pilot survey to get feedback on the quality of our instrument. We placed an advertisement on the target community website to recruit members as participants (henceforth referred to with the pseudonym "Community" to protect the identities and privacy of our respondents; more details about the Community can be found later in this section). Forty-five respondents completed the pilot. Cronbach alpha values were used to help attain acceptable reliability levels. Based on the feedback on the clarity of our survey, several instructions and descriptions were modified. We used a two-wave study design for the main surveys. The two waves of surveys were administered in 2015 and at least two months apart. Each survey was kept open for two weeks. For the Wave 1 survey, we invited participants in the same way we had for the pilot. Three hundred forty-two respondents not included in the pilot survey completed the Wave 1 survey. We subsequently invited all of these respondents to participate in the Wave 2 survey. To lower the dropout rate, we sent four reminder messages to the nonrespondents during Wave 2. Three hundred twenty-six (95.3%) of the 342 respondents gave complete and usable responses to the entire two-wave study. We compared summary statistics on the research and demographic variables as follows: (1) female versus male groups, (2) the drop-outs from Wave 2 survey versus all other respondents. We did not find any significant differences.

The final sample had 58% female respondents and an average age of about 39. Both the gender and age statistics of this sample are consistent with those of the prior and recent samples reported in the literature (see Table 2 for their references and statistics). We noticed that the proportion of Indian workers was much smaller in our sample than in those drawn in earlier years (e.g., [73]). We anticipated such a contrast because starting in mid-2012, only U.S. residents were allowed to register new accounts, and existing non-U.S. Turkers tended to drop out over time. Consequently, the proportions of Turkers outside the United States, including Indians, tended to be much lower in our sample. Thus, the findings of this study are expected to apply more to crowdworkers in the United States than to those in other countries.

Table 2. Comparison of This Sample with Those in the Literature

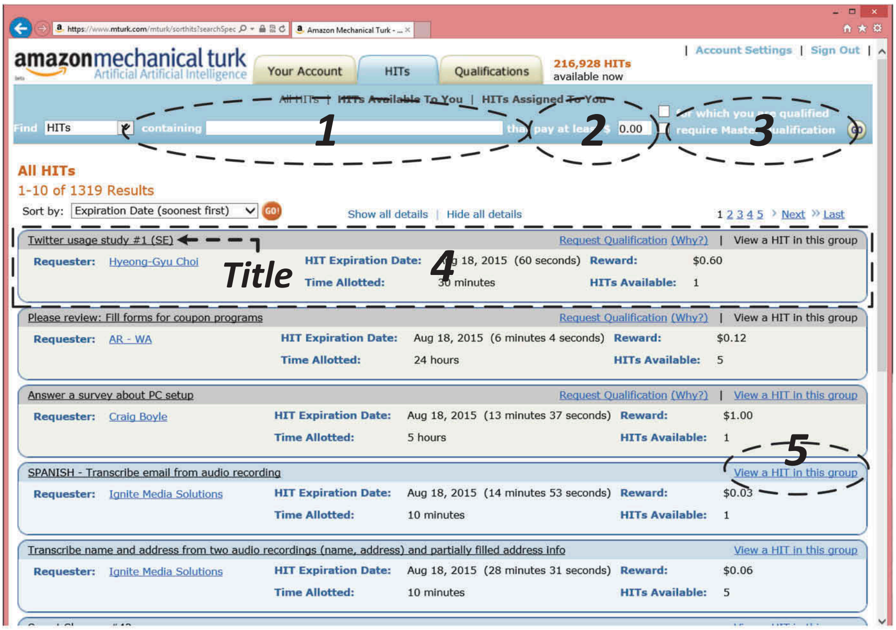
	This Study	Paolacci et al. [66]	Ross et al. [73]	Deng et al. [17]	Ma et al. [52]
Female	58%	65%	55%	52%	57%
Age: Average	39	36	31	35	40
18 – 27	15.1%	–	61%	45%	26%
28 – 37	31.4%	–	19%	22%	26%
38 – 47	26.1%	–	11%	21%	24%
48 – 57	13.9%	–	8%	12%	14%
58 – 71	13.5%	–	1%	0%	10%
Country of Residence					
United States	91%	47%	57%		
India	6%	34%	32%		
Others	3%	19%	11%		

Amazon Mechanical Turk

To test our theoretical framework, we chose Mturk as the research context for crowdwork. Mturk is among the most trafficked crowdworking marketplaces with over 500,000 registered workers worldwide [18]. Research has shown that the composition of this large Turker base is highly diverse and closely resembles the demographics of the U.S. population at large [79]. Another reason Mturk is an appropriate research context is that its interface has remained straightforward and consistent over the past decade. Figure 2(a) is a screen capture of the main page after a worker has signed in. This page lists all tasks (aka HITs) available at a given time. Besides browsing for available HITs, a worker may also search for any HIT whose requester name or description contains specific keywords (Figure 2(a), highlight 1) and whose pay is more than a specified amount (highlight 2) or that is for Master workers only (highlight 3). For each search result, Mturk provides information about various properties of the HIT (highlight 4); each result can also be expanded for more information by clicking the title of the HIT ("Title" in Figure 2(a)). Workers may view the actual content of a HIT by clicking "view a HIT in this group" (highlight 5), which will then display a page similar to Figure 2(b). If workers decide to work on a particular HIT, they will have to "Accept HIT" (Figure 2(b), highlight 1). All in all, the process of selecting and working on HITs on Mturk is unambiguous.

An important aspect of our theory is the time-varying dynamics of worker behavior. To show there are numerous dynamic changes in Turker behavior over time, Figure 3 highlights the workload changes across the two time points of data collection. More specifically, the bars represent the percentages of Turkers whose 30-day numbers of HITs increased (i.e., increased by more than 10%), remained unchanged (i.e., change was within 10%), or decreased (i.e., decreased by more than 10%), by gender and age bracket, respectively, from Time 1 to Time 2. The dark solid bars (in both graphs) indicate the percentages of Turkers whose numbers of completed HITs increased over

(a)



(b)

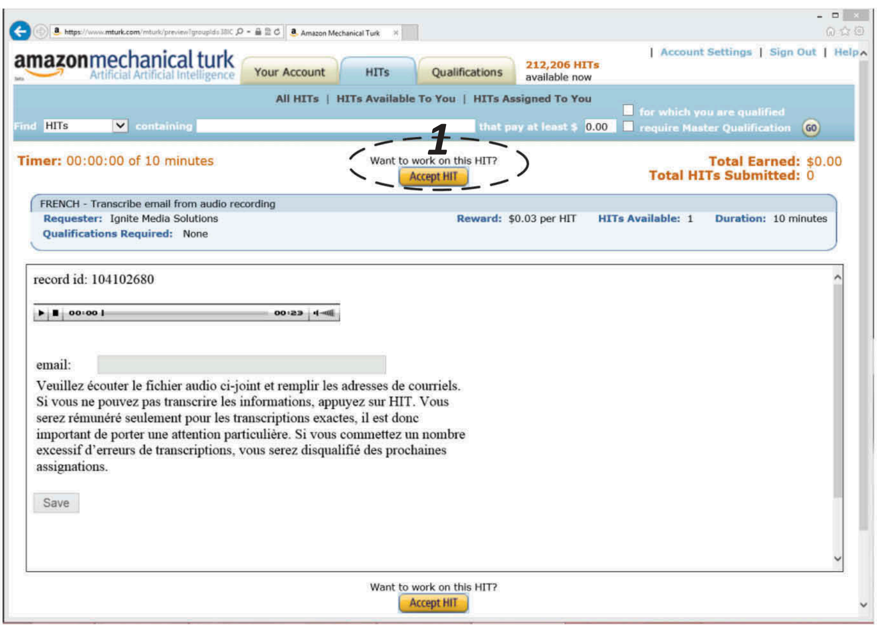


Figure 2. Illustrations: (a) Main page of Mturk after login. (b) Example page of a Human Intelligence Task (HIT).

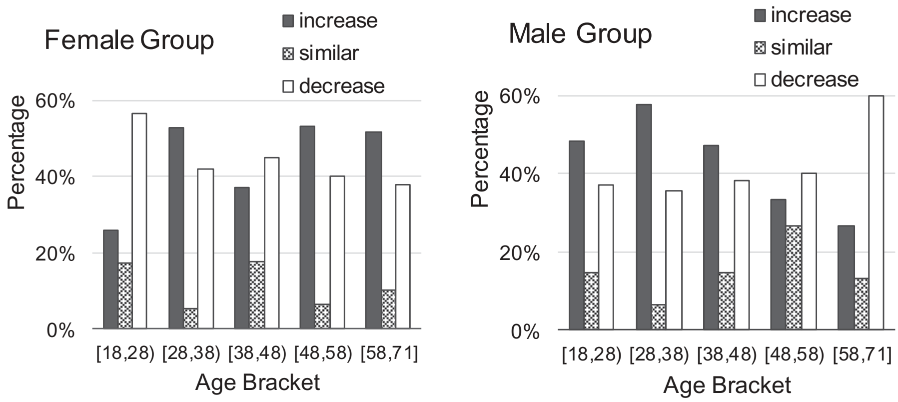


Figure 3. Change of workload between two data collections by gender and age bracket. *Notes*: The bars represent the percentages of Turkers whose 30-day numbers of HITs increased (i.e., increased by more than 10%), remained unchanged (i.e., change was within 10%), or decreased (i.e., decreased by more than 10%), by gender and age bracket, respectively, from Time 1 to Time 2. Time 1 and Time 2 were the times during which the corresponding wave of the survey was collected, and the gap between the two times was at least two months. N (Female) = 190. N (Male) = 136.

time. For instance, in the female group (left graph), the dark solid bars indicate that about 25% of female Turkers between the ages of 18 and 28 worked on significantly more HITs between the two time points. The patterned bars denote the percentages of Turkers whose numbers of HITs remained unchanged. The white bars represent the percentages of Turkers who worked on fewer HITs between Time 1 and Time 2. These graphs show that the majority of workers in our sample experienced significant changes in workload over time, while fewer than 20% maintained a similar level of workload over time. Also noticeable is the difference in the trend of change across the age brackets of female and male groups. Whereas older females tend to increase their levels of work activity as time passes, older males are likelier to work less over time. Meanwhile, younger females and males tend to exhibit the opposite trends.

Online Community

Another important reason why we chose Mturk as our crowdworking context is that Turkers have built several prominent online communities independent of Amazon [52, 54]. These online communities provide a means of knowledge sharing among workers about the Mturk interface, quality of HITs, and the ethics of requesters [32]. Workers gather in online communities to exchange wisdom and best practices that rejuvenate their crowdwork activities. Besides discussing serious topics such as “Is this requester trustworthy?” and troubleshooting specific issues that arise while using Mturk, members in these communities often discuss nonwork-related topics such as lifestyles [32].

Figure 4 illustrates several leading communities. A common feature of Mturk communities is that they allow members to register their unique accounts and create their own community profiles (Figure 4, enlarged in magnifiers). Account registration is required before users can post information, access valuable content, or initiate private conversations with fellow community members. Although these communities share primary design architecture, each one has placed emphasis on certain topics and has developed its own particular culture that includes appropriate communication etiquette (e.g., humor level), expected moderator roles (e.g., how much moderation is most acceptable), etc.

Target Community

For the purposes of this study, we collected data from one of the established Mturk communities depicted in Figure 4. The Community is open for account registration by any Turker or potential worker. By the time of this writing, the Community had been in existence for over five years and had over 15,000 registered workers and 200,000 posts.

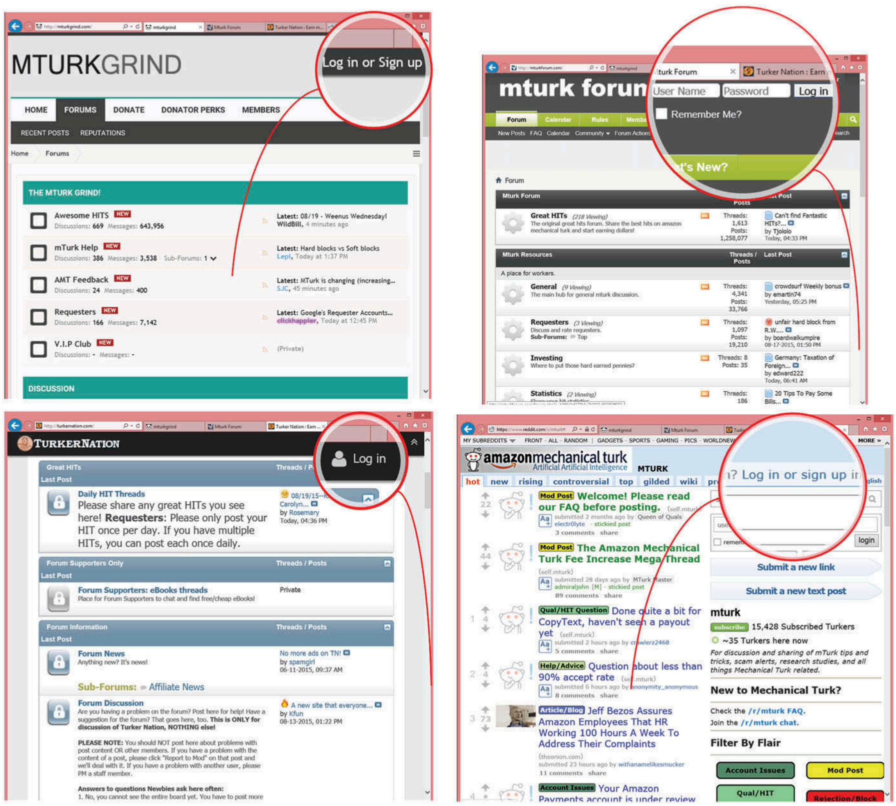


Figure 4. Illustrations: Four leading online communities of Mturk workers.

Measures

The appendix shows the specific items used in this study. We borrowed from existing well-established scales and adapted them for the new crowdworking and online community contexts. First, to measure online community affective commitment, we used four items from [4]. Online community continuance commitment was measured with three items from [4]. Second, we measured fairness of rewards using four items adapted from [16]. Third, crowdworking satisfaction was measured with three items adapted from those of the job satisfaction measure in [74]. Fourth, we measured active participation by using four items adapted from [1] and [15]. Finally, to measure turnover intention, we used four items adapted from [74]. All of the items mentioned previously were measured in both Survey 1 and Survey 2.

Meanwhile, the scale of fantasizing was used as a marker-variable in this study [49, 53]. Fantasizing is defined as the extent to which one has a vivid imagination [63]. This marker-variable is thought to be unrelated to online community and crowdworking behavior; thus, it was included in this study to control for common method bias [49, 53]. We measured this variable only once in Survey 1 and used three items from [63].

Data Analysis

Measurement Model

To assess the psychometric properties of the measurement items, we performed a confirmatory factor analysis (CFA). Several fit indices were examined to evaluate different aspects of model fit. We used four measures commonly used in the literature [14, 21, 41]: the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), the comparative fit index (CFI), and the nonnormed fit index (NNFI). The measurement model that we tested included 12 research variables with 44 indicators. A unique feature of this model was that the errors of the same items between Survey 1 and Survey 2 were allowed to correlate [40]. We ran a CFA, and the results showed that the model fit the data satisfactorily: χ^2 (814) = 1444.73 ($p < 0.001$), RMSEA = 0.049, SRMR = 0.044, CFI = 0.99, NNFI = 0.99, AGFI = 0.80. Table 3 shows the means, standard deviations, composite reliabilities, and the average variance extracted (AVE) of the variables.

Based on the results of the measurement model, we evaluated the reliability, convergent validity, and discriminant validity of the constructs. First, reliability was assessed by composite reliability (CR) and average variance extracted (AVE); reliability is considered adequate if CR $\geq$ 0.70 and AVE $\geq$ 0.50 [3, 5]. As Table 3 shows, the CR and AVE values exceed the cut-off, which suggests a satisfactory level of reliability (i.e., CRs > 0.85 and AVEs > 0.65). Next, we checked convergent validity through item loadings [3, 20]. We found that item loadings were greater than or equal to 0.83, which exceeds the cutoff value of 0.60 and thus indicates an adequate level of convergent validity [3]. Finally, we evaluated discriminant validity

Table 3. Properties of Measurement Scales

					Correlation											
	ME	SD	CR	AVE	1	2	3	4	5	6	7	8	9	10	11	12
1. AC1	4.51	1.56	0.95	0.83	1											
2. CC1	5.37	1.39	0.85	0.65	0.64	1										
3. FR1	4.27	1.77	0.97	0.88	0.17	0.18	1									
4. WS1	4.69	1.52	0.96	0.90	0.27	0.27	0.65	1								
5. AP1	5.24	1.47	0.96	0.87	0.72	0.61	0.13	0.31	1							
6. TI1	2.04	1.38	0.94	0.80	−0.23	−0.32	−0.38	−0.54	−0.36	1						
7. AC2	4.51	1.63	0.96	0.86	0.78	0.60	0.27	0.32	0.61	−0.33	1					
8. CC2	5.22	1.56	0.89	0.73	0.55	0.78	0.14	0.21	0.49	−0.26	0.68	1				
9. FR2	4.15	1.80	0.98	0.91	0.11	0.14	0.70	0.57	0.11	−0.36	0.25	0.18	1			
10. WS2	4.71	1.49	0.96	0.89	0.15	0.16	0.53	0.73	0.18	−0.46	0.29	0.16	0.63	1		
11. AP2	5.16	1.42	0.97	0.88	0.66	0.56	0.17	0.28	0.75	−0.30	0.76	0.63	0.18	0.25	1	
12. TI2	2.07	1.43	0.94	0.80	−0.21	−0.29	−0.26	−0.38	−0.27	0.77	−0.32	−0.26	−0.33	−0.46	−0.37	1

Notes:

- ME = mean; SD = standard deviation; CR = composite reliability; AVE = average variance extracted.
- AC = online community affective commitment; CC = online community continuance commitment; FR = fairness of rewards; WS = crowdworking satisfaction; AP = active participation; TI = turnover intention. Numbers indicate the waves of survey.

by comparing a model in which a pair of factors was allowed to freely correlate and an alternative model in which the correlation was restricted to unity [76]. We found from a series of chi-square difference tests that the two models in each pair of the factors were statistically significant, which provides evidence of discriminant validity. Given the levels of model fit, reliability, convergent validity, and discriminant validity, our research variables were shown to exhibit psychometrically desirable properties.

We also examined the possibility of common method bias. As discussed previously, we included the marker variable of fantasizing to assess the extent of common method bias [49, 53]. We reran a CFA with the marker variable and examined the correlation of fantasizing with other variables. The results indicated that the average of the absolute correlations was only 0.04, which is strong evidence that common method bias, if any, is minimal in this study.

Tests of Structural Models

We tested the model proposed in this study as well as two alternative models in which some of the hypothesized relationships were constrained to be nonexistent. As shown in Table 4, Alternative Model 1 represents only the traditional framework [4, 52, 74]. Alternative Model 2 integrates the traditional framework with only the sequential updating mechanism [39]. As such, the proposed model (Figure 1) adds three new mechanisms to the second alternative model. Any difference between the proposed model and the alternative models would imply the efficacy of the longitudinal theory newly examined in our study. To test the competing models, we used a structural equation modeling tool, LISREL 8. Table 4 shows the results of the three models.

Results from Alternative Model 1 indicated this model was not very acceptable. Specifically, the fit of the model was satisfactory in terms of CFI and NNFI but unacceptable in terms of RMSEA and SRMR: χ^2 (1024) = 2632.02 (p < 0.001), RMSEA = 0.070, SRMR = 0.27, CFI = 0.97, NNFI = 0.96. Table 4 shows that most of the paths were significant except for the effect of fairness of rewards on turnover intention at t = 1 (-0.06, p = ns, one-tailed) and at t = 2 (-0.07, p = ns, one-tailed). This model explained 59% of the variation in active participation at t = 1, 62% of active participation at t = 2, 30% of turnover intention at t = 1, and 22% of turnover intention at t = 2. Unsurprisingly, the explained variance between two different time periods was similar because the antecedent factors were the same.

The second alternative model fits the data reasonably well, but the SRMR value (0.093) was outside the acceptable range (acceptable if ≤ 0.08) [30]: χ^2 (1018) = 1886.94 (p < 0.001), RMSEA =0.051, SRMR = 0.093, CFI = 0.98, NNFI = 0.98. As shown in Table 4, all of the paths were significant except for the effect of fairness of rewards on turnover intention at t = 1 (-0.03, p = ns, one-tailed) and at t = 2 (0.01, p = ns, one-tailed). This model explained a large amount of variation in research variables, ranging from 0.29 (turnover intention at t = 1) to 0.71 (active participation at t = 2). Explained variances in active participation (0.71) and turnover intention

Table 4. Results of Structural Equation Models

Hypothesized Mechanisms	Hypotheses	Causal Paths	Alternative Model 1	Alternative Model 2	Proposed Model	Results (Supported?)
Traditional Framework		AC (t=1) → AP (t=1)	0.49***	0.57***	0.55***	
		CC (t=1) → AP (t=1)	0.34***	0.24***	0.27***	
		FR (t=1) → TI (t=1)	–0.06	–0.05	–0.08	
		WS (t=1) → TI (t=1)	–0.51***	–0.51***	–0.42***	
		AC (t=2) → AP (t=2)	0.56***	0.40***	0.39***	
		CC (t=2) → AP (t=2)	0.28***	0.14***	0.15**	
		FR (t=2) → TI (t=2)	–0.07	0.01	0.01	
		WS (t=2) → TI (t=2)	–0.42***	–0.13**	–0.12*	
Sequential Update		AC (t=1) → AC (t=2)		0.77***	0.62***	
		CC (t=1) → CC (t=2)		0.75***	0.72***	
		FR (t=1) → FR (t=2)		0.69***	0.57***	
		WS (t=1) → WS (t=2)		0.71***	0.61***	
		AP (t=1) → AP (t=2)		0.45***	0.44***	
		TI (t=1) → TI (t=2)		0.71***	0.68***	
Embeddedness	H1(a)	AP (t=1) → TI (t=1)			–0.21***	Yes
	H1(b)	AP (t=2) → TI (t=2)			–0.13***	Yes
Cross-Influence	H2(a)	AC (t=1) → CC (t=2)			0.11	No
	H2(b)	CC (t=1) → AC (t=2)			0.19***	Yes
	H2(c)	FR (t=1) → WS (t=2)			0.10*	Yes
	H2(d)	WS (t=1) → FR (t=2)			0.17***	Yes
Moderated Heuristics		AP (t=1) → AC (t=2)			0.05	
	H3(a)	AC*AP (t=1) → AC (t=2)			0.07*	Yes
		AP (t=1) → CC (t=2)			–0.02	
	H3(b)	CC*AP (t=1) → CC (t=2)			0.03	No

(continues)

Table 4. Continued

Hypothesized Mechanisms	Hypotheses	Causal Paths	Alternative Model 1	Alternative Model 2	Proposed Model	Results (Supported?)
		TI (t=1) → FR (t=2)			–0.05	
	H3(c)	FR*TI (t=1) → FR (t=2)			–0.14***	Yes
		TI (t=1) → WS (t=2)			–0.10*	
	H3(d)	WS*TI (t=1) → WS (t=2)			–0.06	No
			Squared Multiple Correlations			
		AP (t=1)	0.59	0.56	0.56	
		TI (t=1)	0.30	0.29	0.32	
		AP (t=2)	0.62	0.71	0.72	
		TI (t=2)	0.22	0.60	0.61	
		AC (t=2)		0.59	0.63	
		CC (t=2)		0.57	0.60	
		FR (t=2)		0.47	0.54	
		WS (t=2)		0.50	0.54	

Notes:
- AC = online community affective commitment; CC = online community continuance commitment; FR = fairness of rewards; WS = crowdworking satisfaction; AP = active participation; TI = turnover intention.
- *p < 0.05, **p < 0.01, ***p < 0.001 (one-tailed).

(0.60) at t = 2 were considerably greater than those in active participation (0.56) and turnover intention (0.29) at t = 1. These results could be attributed to the sequential-updating mechanism. The sequential-updating mechanism was indeed influential in explaining the antecedents of active participation and turnover intention. As indicated in Table 4, this mechanism alone explained 59% of the variation in affective commitment at t = 2, 57% in continuance commitment at t = 2, 47% in fairness of rewards at t = 2, and 50% in crowdworking satisfaction at t = 2.

Subsequently, we examined the results of the proposed model. The fit of this model was generally better than that of the previous model: χ^2 (1004) = 1793.68 ($p <$ 0.001), RMSEA = 0.049, SRMR = 0.054, CFI = 0.98, NNFI = 0.98. Interestingly, the SRMR value (0.054) of this model satisfied the criterion (≤ 0.08) by a large margin. This suggests that the longitudinal theory discussed in this study explains reality better than the alternative model does. Because of the additional predictors, explained variances in these variables improved by 4.5% on average. As Table 4 shows, this model explains 63% of the variation in affective commitment at t = 2, 60% in continuance commitment at t = 2, 54% in fairness of rewards at t = 2, and 54% in crowdworking satisfaction at t = 2. Furthermore, as the proposed model suggests, the connection between online community behavior and crowdworking behavior was shown to exist. We found that the effect of active participation on turnover intention was significant at both t = 1 (-0.21, $p < 0.001$) and t = 2 (-0.13, $p < 0.01$). Overall, the results suggest that the alternative models provide reasonable accounts of the data, but for a fuller understanding of online behavior that evolves over time, a more accurate description is essential as predicted by the proposed model. Figure 5 below depicts the results of the proposed model with only the significant paths.

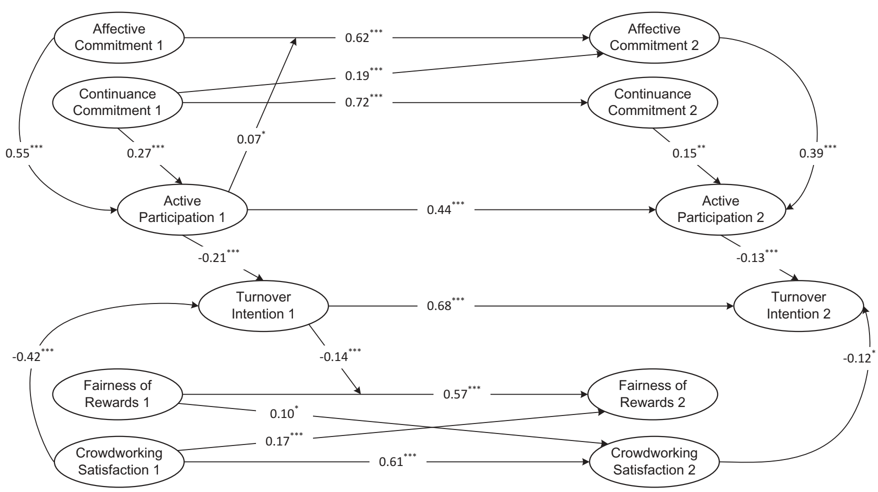


Figure 5. Results of the proposed model.

Results of Research Hypotheses

Table 4 shows the results of the research hypotheses. We first examined H1, which predicts a negative effect of active participation on turnover intention in both time periods. Consistent with the hypothesis, this relationship was negative and significant both at t = 1 (-0.21, $p < 0.001$) and t = 2 (-0.13, $p < 0.001$) (H1a and H1b supported).

H2a and H2b postulate cross-effects in which affective and continuance commitment at t = 1 have a positive effect on, respectively, continuance and affective commitment at t = 2. We found that the effect of affective commitment at t = 1 on continuance commitment at t = 2 was marginal (0.11, $p < 0.10$) (H2a not supported), whereas the effect of continuance commitment at t = 1 on affective commitment at t = 2 was significant (0.19, $p < 0.001$) (H2b supported). H2c and H2d suggest cross-effects between fairness of rewards and crowdworking satisfaction from t = 1 to t = 2 in the context of crowdworking behavior. Consistent with the predictions, fairness of rewards at t = 1 had a positive effect on crowdworking satisfaction at t = 2 (0.10, $p < 0.05$) (H2c supported), and crowdworking satisfaction at t = 1 had a positive effect on fairness of rewards at t = 2 (0.17, $p < 0.001$) (H2d supported).

H3a and H3b predict that active participation at t = 1 strengthens the positive effect of prior commitment on the corresponding subsequent commitment. As Table 4 indicates, active participation at t = 1 is shown to increase the positive relationship between affective commitment at t = 1 and affective commitment at t = 2 (0.07, $p < 0.05$) (H3a supported). However, the relationship between continuance commitment at t = 1 and continuance commitment at t = 2 was not found to be moderated by active participation at t = 1 (0.03, p = ns) (H3b not supported). Meanwhile, H3c and H3d posit that turnover intention at t = 1 weakens the effect of prior beliefs on the corresponding subsequent beliefs. As expected, turnover intention at t = 1 was found to weaken the relationship between fairness of rewards at t = 1 and fairness of rewards at t = 2 (-0.14, $p < 0.001$) (H3c supported). However, the moderating effect of turnover intention at t = 1 on the relationship between crowdworking satisfaction at t = 1 and crowdworking satisfaction at t = 2 was found to be only marginal (-0.06. $p < 0.10$) (H3d not supported).

Overall, seven of 10 subhypotheses were supported, and three were not. Interestingly, the relationship between fairness of rewards and turnover intention that the traditional framework predicted was not significant at either t = 1 or t = 2. Although we do not necessarily have a clear explanation for this lack of significance of fairness of rewards, we speculate that this counterintuitive finding may be rooted in the core message of our paper. Because of the embeddedness that the online support communities provide for crowdworkers, at least for those engaged with the communities, fairness of rewards of the type of crowdwork itself may no longer play a significant role. We urge management researchers keen on gaining an updated understanding of the turnover behavior of crowdworkers to examine more closely whether the role played by fairness of rewards really differs among the workers who participate in the independent support communities vis-à-vis those not engaged in any support communities.

Discussion

The objective of this study was to develop and empirically test a two-wave panel model that illustrates the dynamic process by which the roles of crowdworkers as community members and workers interact and evolve over time. To this end, we drew upon the social psychology literature and identified three additional mechanisms — embeddedness, cross-influence, and moderated heuristics — that best emulate this dynamic interaction. We used structural equation modeling to test our proposed model against data collected in two waves of a survey administered to 326 Turkers who were also members of independent online Mturk communities. Our model was shown to offer a reasonable account of crowdworkers' behavior over time. Importantly, this theory-grounded longitudinal study provides a theoretical account and empirical validation that characterize the evolving, complex causal chains underlying crowdworkers' behavior over time.

Theoretical Contributions

This study is one of the first in IS research to use a unified two-wave theoretical framework to model the dual roles of crowdworkers. We demonstrated that our model remained supported, which takes into account the new relationships epitomizing embeddedness, cross-influence, and moderated heuristics. Of equal importance, we showed that our proposed integrated model explained significantly more variability in both online community participation and crowdworkers' turnover intention. This considerable improvement in model fit suggests that although the conventional cross-sectional model effectively models static behavior, it is incapable of characterizing the dynamic process governing crowdworkers' behavior in the crowdworking environment. Overall, our longitudinal model and analysis demonstrate that failure to account for the three proposed mechanisms could lead to misleading conclusions.

Second, we showed that a significant connection exists between online community behavior and crowdworking behavior at both t = 1 and t = 2. This occurs despite the contextual differences between the online community and crowdworking environments. This embeddedness between on-the-job and off-the-job activities has been studied in the physical settings of work and community (e.g., [42]), but not in the virtual online community context. The revalidation of this embeddedness concept in a virtual online community setting implies that one does not have to actually belong to a physical community that provides physical comfort and physical safety. All in all, our findings echo the importance of simultaneously accounting for embedded roles to gain a fuller understanding of online behavior that evolves over time [83].

Third, our model incorporated cross-influences between affective and continuance commitment on one hand, and fairness of rewards and crowdworking satisfaction on the other. We showed that, at least in our context of a crowdworking ecosystem, crowdworkers behave differently in their community and work contexts despite the connection between these two environments. In the online community context, only the effect of continuance commitment at t = 1 on affective commitment at t = 2 is shown to be significant. However, in the work context, we observe a bidirectional cross-influence between fairness of rewards and crowdworking satisfaction. This could imply a critical difference between the market-based crowdworking environment and the voluntary commitment-based online community context that serves as the boundary condition for the effectiveness of the causal path from affective to cognitive variables. Our findings emphasize the need to revalidate similar cross-influences in seamlessly connected but contextually different IS environments.

Fourth, although prior IS research (e.g., [39]) has drawn upon social psychology theories (e.g., belief updating) to show the existence of a sequential-updating effect, no study has examined how this sequential-updating mechanism could be moderated by behavioral outcomes such as active participation and turnover intention. Our study shows the significant effect of prior beliefs on subsequent beliefs (e.g., affective commitment, continuance commitment, fairness of rewards, and crowdworking satisfaction), which suggests the existence of the sequential-updating mechanism. Moreover, we also found that prior active participation strengthens the positive relationship between prior affective commitment and subsequent affective commitment. Similarly, the moderating effect of prior turnover intention was shown to weaken the relationship between prior fairness of rewards and subsequent fairness of rewards. Excluding these moderated mechanisms from the model would imply that the relationship between prior beliefs and subsequent beliefs is not affected by prior behavioral outcomes, which our results have demonstrated is not accurate. Instead, we have demonstrated that behavioral outcomes strengthen the sequential-updating mechanism in which past beliefs affect subsequent beliefs. This study contributes to IS research by highlighting the moderating role of past behavior in the online community and crowdworking contexts.

Taken together, this work adds to IS research by showing how the three theory-driven mechanisms integrate well with the conventional and the sequential-update mechanisms of crowdwork turnover intention to explain the intertemporal relationships underlying the dual roles of workers in crowdworking marketplaces [83].

Managerial Implications

This research could provide meaningful guidelines for online community managers on how to better retain their actively participating members. Active participation was found to decrease worker turnover intention, and this effect was shown to persist over time. An important takeaway for crowdwork platforms such as Mturk is that by ignoring their crowdworkers' active participation and mutual interactions in the independent online support communities, they risk incurring a high price of losing their highly engaged workers. This potential loss of active workers with a community persona is understandably counterproductive to any platform's market sustainability. Currently, most popular online crowdworker communities are independent from crowdwork platforms such as Mturk. If crowdwork platforms miss the opportunity to engage with their workers' discussions and address their concerns, they risk enduring the continuous loss of their most active workers who, upon exposure to the negative information and opinions in other online communities, might consider switching to alternative work platforms. In the case of Mturk, given its lack of control over and lack of favorability with the majority of independent online worker communities, MTurk could benefit from aggressively promoting and thoughtfully managing its own community site. This suggestion may not be new, but our findings add convincing evidence for Mturk's need for action and for the effectiveness of this approach. Arguably, having their own community provides crowdwork platforms with many opportunities to engage with their workers. These opportunities include, but are not limited to, addressing workers' concerns and complaints upfront and incentivizing more workers to actively participate in the online community in various forms, such as through helping others by answering their questions, asking questions to resolve one's own questions, etc. In turn, this would enable the platforms to maintain a healthy long-term relationship with their workforce [50].

Furthermore, we offer specific examples of how having their own online communities could benefit Mturk and other online labor platforms. One such benefit lies in establishing better feedback collection mechanisms. This is facilitated by the simple fact that, if platform executives managed their own community, they would be able to identify their workers' identities on the community site. Currently, worker identities in independent communities are opaque to labor platforms. As a result, platform managers are unable to set apart accurate reports of system malfunction and useful feedback for improvement, amidst the myriad of less constructive emotional outbursts and unfounded allegations in these communities. If they managed their own community, platform managers might be better equipped to identify their workers' legitimate concerns and engage with them in conversations that would help resolve these issues. Another benefit would be that crowdwork platforms might be in a better position to explore and test alternative design elements to improve their site. Platform managers might also do small-scale experiments by tweaking the interface for only a sample of workers and then unobtrusively observe workers' feedback and respond to them. Ultimately, by adopting better feedback collection mechanisms and adopting a more systematic experimentation approach, managers could continuously improve the platform and further engage workers in interactions on the community site.

Our findings also revealed that community members' participation increases with higher continuance commitment. In an open environment in which members may freely join or leave an online community, without any mandatory commitment, the inability to substitute an online community, as reflected in continuance commitment, ultimately drives members' active participatory behavior. To leverage the effect of community commitment, community managers may embed some lock-in features into the design of the online community to make it more difficult for members to find alternative online communities that can provide the same valuable content and services. For instance, because Mturk does not allow workers to review the tasks available on the platform, online communities may incorporate into their interfaces features that allow the rating of the tasks on Mturk. Once ratings and reviews accumulate, the information they provide to the online community may become indispensable to its members. As a result, members' participation may increase, and their turnover rate may drop.

Limitations and Future Research

Despite its unique contributions, this research comes with some limitations. For example, active participation is operationalized as a future intention of this behavior instead of an observed present behavior. Although intention has often been used as a proxy of behavior in IS literature (e.g., [43]), our findings should be interpreted with caution because they are not necessarily the same. Meanwhile, in explaining active participation, we integrated models from [4] and [71] and characterized active participation as determined by affective commitment and continuance commitment. Although our model explained as much as 56% (t = 1) and 72% (t = 2) of the variances of active participation, it might still have excluded some important variables in the context of online communities. Similarly, the theory of turnover behavior [74] that our model draws upon may not be a perfect fit to serve as a theoretical basis for our crowdworking context. Nonetheless, to the best of our knowledge of the existing literature, Rutner et al. [74] may be the most appropriate model of IT-related work behavior to enlighten our investigation of crowdworking turnover behavior. Our research design sampled Mturk workers from popular online communities; this could raise a potential concern with the nonresponse bias of our findings; that is, those who responded to the surveys likely may be more active in the online community than nonrespondents. We note that given the likely over-concentration of our sample on the higher end of the active participation intention factor, it seems plausible that our results likely captured the lower bound (i.e., less negative end) of the underlying negative relationship between community active participation and crowdwork turnover intention. Had we been better able to attract less active member participants, the result could have been stronger (i.e., more negative coefficients), because these crowdworkers could intend to churn sooner; as such, our data would have captured more variations in the two behavioral factors. Additionally, because the online community chosen in this study is among the most established and popular Mturk communities, our results may not necessarily generalize into newer and niche communities. In the popular community chosen in this study, people interact freely and deeply with each other. Thus, actively participating members become likelier to continue crowdworking as a result of the embeddedness derived from this interaction because they develop a social proximity to fellow Turker members and a heightened level of work energy. In contrast, relatively smaller communities rarely provide full functionality; as such, they may hinder members' interaction and embeddedness. For example, in certain niche communities, people solely generate ratings and short reviews of the requesters. Thus, they are less likely to facilitate the same forms and levels of members' active participation; as a result, active participation may not affect turnover. Therefore, our result on the embedded influence of community members' active participation on lowering their crowdworking turnover intention may not be found in members of niche communities. Moreover, it may be possible that some members of the community had already interacted with one another via other means such as through video or voice chat, phone calls, interaction on social network sites, or face-to-face meetings. The possibility of such offline connections, albeit unlikely, challenges our assumption that online community members are utter strangers and anonymous to one another; thus, it could have influenced our results.

The results of this research present several potentially rich areas of exploration for future research. As with any crowdworking platform, Mturk provides opportunities for workers to choose from a variety of job types (e.g., academic research participation such as online experiments or surveys, innovative machine learning projects such as identifying objects in photos and videos, word processing, online marketing, etc.) or work on multiple types simultaneously. Different job types exhibit different job characteristics; for instance, average reward per task is much higher for academic research (e.g., \$2.00 on average) than it is for online marketing tasks (e.g., \$0.05). Future research may explore whether—and if so, why—the validity of our model changes with specific job types. Moreover, we did not find a direct relationship between fairness of rewards and turnover intention. Note that although the sign of this effect at t = 1 is consistent with our prediction, its magnitude at t = 2 is near 0, which is interesting and could also be an important question to investigate in future crowdwork research, for example, does the effect of fairness of rewards on turnover intention fade over time after taking active participation into account?

Conclusions

Online community behavior and organizational turnover intention have been studied separately in their respective literatures. However, no prior work has combined these two research streams to study how community participation might relate to turnover intention, and how their relationship and their essential antecedents, evolve over time. We are the first to show that three theory-driven mechanisms—namely, embeddedness, cross-influence, and moderated heuristics—help elucidate crowdworkers' complex behavior and psychology over time. Based on these novel findings, we urge researchers to consider incorporating all three mechanisms that we have identified to accurately characterize behaviors across disparate IS contexts.

Notes

The first crowdwork communities (i.e., Turker Nation, mTurk Boards) launched soon after AMT in 2005.

Bateman et al. [4] investigated a third type of commitment, namely normative commitment. However, normative commitment is not typically found to have a significant relationship with active participation (e.g., [43]). Thus, like Ray et al. [71], we did not account for normative commitment, which relates more to one's commitment to a group and less to a member's desire to contribute actively to tasks that are helpful and important to an online community.

Rutner et al. [74] showed that job satisfaction and fairness of rewards are the two most important predictors of turnover intention and that such factors as role conflict, role ambiguity, and autonomy did not have any significant effect on turnover intention. Our intention is not to provide a comprehensive set of determinants of turnover intention, but to depict a reasonable representation of crowdworking behavior, encompassing both online community participation and work continuance in the crowdworking context. Ultimately, our objective is to examine how such a representation evolves over time.

ORCID

Xiao Ma http://orcid.org/0000-0002-9088-9354
Lara Khansa http://orcid.org/0000-0001-7305-5190

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APPENDIX. SURVEY MEASURES

All scale items are on a 7-point scale from "Strongly Disagree" to "Strongly Agree" with "Neutral" in the middle.

Research Variables

Online Community Affective Commitment (AC)

1. I feel like I'm a part of something in this online community.
2. This online community has a great deal of personal meaning for me.
3. I feel a strong sense of belonging to this online community
4. I feel a strong connection to this online community

Online Community Continuance Commitment (CC)

1. If I stopped coming to this online community, it would take me a long time to find a community that could replace it.
2. There are very few other places where I could find the kind of useful content and services that I get from this online community.
3. The content on this online community is too valuable for me to stop visiting.

Active Participation (AP)

1. I intend to be active in communicating with other members of this online community.
2. I will try to participate in discussions in this online community.
3. I will attempt to take an active part in this online community.
4. I will likely contribute information to this online community.

Turnover Intention (TI)

1. As soon as possible, I intend to leave MTurk.
2. I will discontinue to work at MTurk in the near future.
3. I often think about quitting my job at MTurk.
4. I will stop working at MTurk this time next year.

Fairness of Rewards (FR)

1. The rewards that I receive (e.g., reward, bonus) from MTurk reflect the effort I have put into my work.
2. The rewards that I receive (e.g., reward, bonus) from MTurk are appropriate for the work I have completed.
3. The rewards that I receive (e.g., reward, bonus) from MTurk reflect what I have contributed to my work.
4. The rewards that I receive (e.g., reward, bonus) from MTurk are justified, given my performance.

Crowdworking Satisfaction (WS)

1. Generally speaking, I feel satisfied with the work at MTurk.
2. Overall, I feel satisfied with the kind of work I do at MTurk.
3. In general, I feel satisfied with the work at MTurk.

Marker Variable

Fantasizing (FA)

1. I daydream a lot.
2. When I go to the movies I find it easy to lose myself in the film.
3. I often think of what might have been.

Demographic Variables

Age
What is your year of birth? (e.g., type "1970" if you were born on Jan. 1, 1970)

Gender
What is your gender? (1 = male; 2 = female)