Crowd Workers' Continued Participation Intention in Crowdsourcing Platforms:
An Empirical Study in Compensation-Based Micro-Task Crowdsourcing

Gabriel Shing-Koon Leung, Hewlett Packard Enterprise, Hong Kong

iD https://orcid.org/0000-0001-8077-007X

Vincent Cho, The Hong Kong Polytechnic University, Hong Kong

iD https://orcid.org/0000-0003-0726-8352

C. H. Wu, The Hang Seng University of Hong Kong, Hong Kong*

iD https://orcid.org/0000-0003-1259-4048

ABSTRACT

The micro-task crowdsourcing marketplace, as a novel platform, has provided firms with a new way to recruit employees at a reasonable cost and with a fast turnaround. This research explores how different types of motivations affect individuals' continued participation intention in compensation-based micro-task crowdsourcing platforms. The theoretical model builds on expectancy theory, self-determination theory, organizational justice theory, and self-efficacy theory. To validate the theoretical model, over 1,000 crowd workers participating in Amazon's Mechanical Turk completed an online questionnaire. Distributive justice and self-efficacy were applied to moderate the relationship between different types of motivations and continued participation intention. The confirmed three-way interaction effects indicated that external regulation and intrinsic motivation on continued participation intention are contingent on distributive justice and the level of self-efficacy. The findings enrich the understanding of MCS communities and provide important guidelines for motivating crowd workers.

KEYWORDS

Compensation-Based Micro-Task Crowdsourcing, Continued Participation Intention, Expectancy Theory, Organizational Justice Theory, Self-Determination Theory, Self-Efficacy

1. INTRODUCTION

In 2005, Jeff Howe and Mark Robinson, editors at Wired, coined the term 'crowdsourcing' to denote the practice by which an organisation or individual broadcasts a request to the public, soliciting contributions from volunteers in the form of an open call (Howe, 2006). Nowadays, organisations need to be dynamic, agile and focused on coping with the ever-changing environment such as COVID-19 (Piscini, Hyman, & Henry, 2016). In this regard, organisations are leveraging crowds' wisdom to perform various Human Intelligence Tasks (HITs), such as submitting novel ideas about new products/services and providing market feedback on existing products/services. Specifically, crowdsourcing

*Corresponding Author

allows organisations to expand their business without hiring dedicated staff to perform routine tasks. The varieties of crowdsourcing applications include crowdfunding (e.g., Kiva.org), competition-based crowdsourcing, knowledge sharing (e.g., Wikipedia), innovation communities (e.g., Dell's IdeaStorm), and compensation-based crowdsourcing (e.g., Amazon's Mechanical Turk, oDesk, and Rent-a-coder). This trend would be a stepping stone for building the next area of computing (Cook, et al. 2020).

In the past decade, crowdsourcing activity has grown dramatically and evolved noticeably in the forms of micro work (Howe, 2008; Deng et al., 2016). A compensation-based micro-task crowdsourcing (MCS) splits the problem into much smaller tasks that multiple crowd workers address independently in return for a reward. The unique low cost, low entry barrier and crowd wisdom leveraging MCS characteristics help companies equip themselves with new competencies (Maiolini & Naggi, 2011). A World Bank report estimated that Amazon's Mechanical Turk (MTurk), the world's largest compensation-based micro-task crowdsourcing, has about 500,000 registered crowd workers (Turkers) worldwide (Kuek et al., 2016). MTurk.com offers crowd workers who want to utilise their own skills and earn money by searching for interesting tasks for completion. However, if crowd workers do not believe that they can provide solutions and earn the money they deserve, they would not consider participating in an MCS platform.

Most crowd workers consider MCS as offering insecure jobs (Ross et. al., 2010) because the pay varies according to the task complexity, and the earnings are not stable. Moreover, some crowd workers may not claim payments because requesters may give micro-tasks to thousands of crowd workers and have the discretion to reject work from the crowd workers who deliver low-quality or incorrect work. Requesters often reserve the right to refuse payment even when completed work meets the requirements. As a consequence, crowd workers face inequality for distributive fairness (Deng et al., 2016). Research shows that crowd workers allocate an average of 23.2% of their capacity on tasks without payment (Berg, 2016). Due to MCS platforms' nature, namely, the lack of in-person interaction, crowd workers may refuse to participate if they perceive the payout from the system is unfair because no personnel are assigned to handle or settle any disputes.

The crowd workers who are rejected for their submitted work may leave crowdsourcing platforms entirely (Franke, Keinz, & Klausberger, 2013). While initial participation is an important first step toward realising MCS success, a platform's eventual success and long-term viability depend on participants' continued participation rather than their first-time use. Especially when most participants are part-timers to MCS platforms at all times, turnover is a major challenge. As such, understanding of participation motivation and continued participation intention is crucial to many MCS platforms' success. For example, Taskcn.com had over 2.8 million registered crowd workers in 2010, but fewer than a mere 10% of them (0.24 million) were paid more than once regardless of the number of completed tasks (Sun et al., 2012). In addition to the monetary incentive, factors such as work schedule flexibility, the autonomy to choose the tasks in which one is interested, and job satisfaction may promote continued participation (Taylor & Joshi, 2018).

To an extent, crowd workers' continued participation is the key to MCS platforms' success (Roberts, Hann, & Slaughter, 2006). The theoretical framework for understanding the crowd workers' continued participation enables us to layout the commercial strategies for a crowdsourcing platform. The underlying factors for crowd workers' continued participation are covered in this study. In this regard, investigation of the underlying motivations that affect crowd workers' continued participation is important to future MCS workforce development. We examine whether crowd workers' self-efficacy and payout fairness are relevant and equally important to sustaining continued participation in an MCS platform. More importantly, our research question is as follows:

Will there be any contingent situation among those factors (motivations, fairness and self-efficacy) for crowd workers to continue to participate in an MCS platform?

Past studies of MCS focused on the system design to enrich the function, features and performance of the crowdsourcing intermediate platform to enhance participants' motivation (Amrollahi & Ahmadi, 2019; Franzoni & Sauermann, 2014; Boudreau, Lacetera, & Lakhani, 2011; Zheng et al.,

2011). Bayus (2013) and Zheng et al. (2011) also analysed whether task design would affect crowd workers' intrinsic and extrinsic motivation to engage in an MCS platform.

In terms of quality control, Hu et al. (2020), adopting the zero-determinant strategy, proposed two incentive algorithms of adjusting the monetary reward for improving the job quality. Alabuljabbar and Al-Dossari (2019) suggested a dynamic approach for selecting the most suitable quality control mechanism based on requesters' feedback. Shi et al. (2019) relied on a partially observable Markov decision process to identify those crowd workers with a good performance given a valid answer for a crowdsourcing problem. The selected workers will be assigned with tasks for solving problems with unknown answers.From the perspective of crowd workers, their participation contributes to MCS platforms' success (Ye & Kankanhalli, 2017; Deng et al., 2016; Sauerman & Franzoni, 2015). Specifically, the quality of outcomes stems directly from work schedule flexibility, self-challenge, payment security, and autonomy over task selection (Taylor & Joshi, 2018; Litman et al., 2015). However, most of these studies lack a holistic consideration of crowd workers' continued participation in an MCS platform.

To expand upon the literature, this study leverages expectancy theory (Vroom, 1964) as the backbone, combined with self-determination theory (SDT) (Deci & Ryan, 1985, 2000); organisational justice theory (Thibaut & Walker, 1975); and self-efficacy theory (Bandura, 1977) to explore how intrinsic and extrinsic motivation, fairness, crowd workers' efficacy and the three-way interaction among these factors enhance crowd workers' continued participation. The model incorporated the results of an online survey of 1,040 crowd workers through the MTurk platform and was vastly supported.
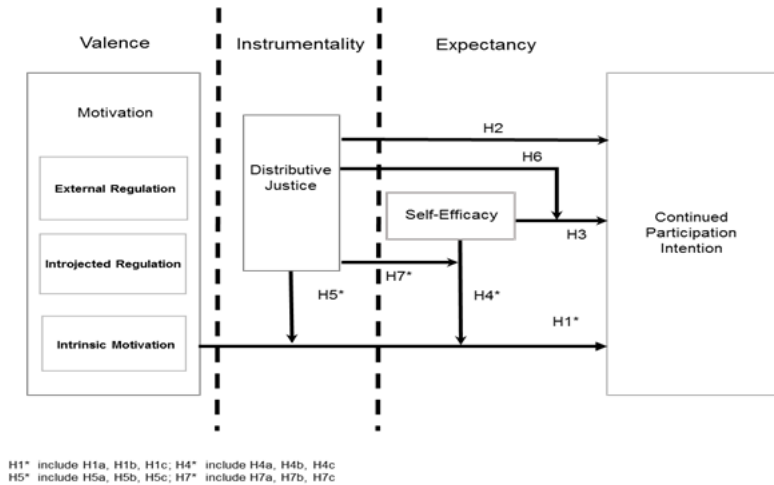
The following sections provide the rationale that underlies our framework and the development of our theoretical arguments that support each of the hypothesised relationships. We use the expectancy theory, which consists of valence, instrumentality and expectancy (VIE), as an overarching logic to demonstrate how the three basic psychological motivations of SDT, distributive justice from organisational justice theory and self-efficacy from self-efficacy theory to explain crowd workers' continued participation in compensation-based MCS. Finally, we conclude with theoretical contributions to the crowdsourcing literature and provide insight to practitioners on where MCS designs could benefit further from enhancing fairness and transparency in the use of the platforms and, most importantly, on how best to sustain crowd workers' continued participation.

2. FRAMEWORK BACKGROUND & HYPOTHESIS DEVELOPMENT

Expectancy theory (Vroom, 1964) has been a core theory for numerous motivation researches over the past decades. This theory's key logic is that, when people decide to take on a task, they undergo a cognitive cycle that involves VIE. Valence is considered as the source of motivation (Sanchez, Truxillo, & Bauer, 2000), and different types of motivation derive different forms of valence based on self-determination theory (Ryan & Deci, 2000a). Organisation justice theory is applied because it reflects instrumentality that is fairly or unfairly distributed. Self-efficacy has been viewed as one of the most popular forms of expectancy belief in applied psychology studies (Latham & Pinder, 2005) and indicates the expectation for an individual to complete the necessary tasks and achieve certain performance levels (Olson, Roese, & Zanna, 1996). In this study, we propose that VIE constitute the three key motivators that determine crowd workers' continued participation intention in an MCS platform according to the following relevant factors: intrinsic motivation, external regulation, introjected regulation, distributive justice and self-efficacy. The research model is shown in Figure 1.

Valence, in which an individual's assessment of the value or desirability of the reward associated with a given behaviour (Vroom, 1964), describes the importance of the potential participant's rewards. Since the reward can be intangible such as happiness and satisfaction, or tangible such as money return, many scholars used extrinsic and intrinsic motivations to address these valence-relevant factors (values), which are considered as key concepts in SDT (Bandura, 1977; Vroom, 1964; Deci et al.,

Figure 1. Model Framework

H1* include H1a, H1b, H1c; H4* include H4a, H4b, H4c
H5* include H5a, H5b, H5c; H7* include H7a, H7b, H7c

1999; Ryan & Deci, 2000b). That is whether the valance is tangible or intangible be assessed by the intrinsic or extrinsic motivation behind.

According to SDT, there are five different regulations: intrinsic regulation (also known as intrinsic motivation), identified regulation, integrated regulation, introjected regulation and external regulation. Intrinsic motivation is defined as the willingness to undertake a task because of a person's interests and values (Ryan & Deci, 2000a). When intrinsically motivated, a person engages fully in an activity for enjoyment and excitement. Vallerand et al. (1994) stated that it is challenging to distinguish integration from identification psychometrically. Similarly, Gagne et al. (2010) cited the same difficulty to separate integrated regulation from identified regulation and intrinsic motivation. According to the past studies, these three motivations (intrinsic motivation, identified regulation, and integrated regulation) seem indistinguishable. Thus, we also only consider intrinsic motivation instead of identified regulation and integrated regulation in this study.

Extrinsic motivation refers to motivation resulting from external factors such as tangible rewards or social recognition for completion of uninteresting tasks that are not in line with one's personal goals and inspirations. SDT divides extrinsic motivation into two kinds of motivation: external regulation and introjected regulation. External regulation is based on rewards or punishments for controlling people's behaviour; those who experience introjected regulation, in contrast, are pressured to act due to feelings of guilt, and their core sense of self does not internally endorse this behaviour (Deci & Ryan, 1985).

Past literature demonstrated that monetary reward (Sun et al., 2012; Adabduljabbar and Al-Dossari, 2019), profit sharing (Horton & Chilton, 2010) and job opportunities (Bayus, 2013; Brabham, 2010) drive crowd workers to participate in MCS (Stewart et al., 2010). In this vein, crowd workers who are externally regulated often continue to participate in MCS as long as the rewards and incentives are attractive. Therefore, we propose the following hypothesis:

H1a: External regulation is positively related to continued participation intention.

Nevertheless, when participants are in the state of introjected regulation, their fears of being rejected, unable to sustain their reputation and disqualified from consideration as high performers are dominant. It has happened to those accounting students participating in the low-stakes test (Helm and Warwas, 2018) or university student in selecting an elective physical education activity (Kim

2018). Relatively few participants can both be selected for a task and receive compensation after their work. When such pressure builds up, participants more frequently feel less desire to join an MCS platform. Blau (1964) stated in social exchange theory that people behave in ways that maximise their benefits and minimise their social exchange costs. In this regard, when crowd workers believe the chance of obtaining the reward is less than the cost of completing an MCS task, they are highly likely to discontinue their participation. Therefore, we propose the following hypothesis:

H1b: Introjected regulation is negatively related to continued participation intention.

From the intrinsic motivation perspective, crowd workers participate in activities because of the challenge that the activities entail, generating enjoyment and excitement (Ryan & Deci, 2000a). When participants successfully accomplish the tasks, their innate psychological needs are satisfied, confidence in their abilities expands and self-efficacy increases (Gagné & Deci, 2005). Recent reviews of MCS also confirmed that crowd workers with intrinsic motivation react positively to the opportunity to express creative ideas freely (Battistella & Nonino, 2012). Some crowd workers even develop addictions to MCS and emotional attachments to the MCS community (Estellés-Arolas & González-Ladrón-de-Guevara, 2012). Some crowdsourcing platforms provide gamification artefacts to satisfy crowd workers and drive crowd workers intrinsically to participate in the platforms (Feng et al. 2018). Hence, we propose the following hypothesis:

H1c: Intrinsic motivation is positively related to continued participation intention.

According to expectancy theory, instrumentality refers to the subjective probability assessment that a given performance level will lead to a reward (Hann et al., 2007). Organisational justice plays a critical role in reflecting such instrumentality and comprises four dimensions: distributive justice, procedural justice, interpersonal justice and informational justice (Colquitt et al., 2001; Colquitt et al., 2013). Distributive justice concerns resource allocation fairness among different individuals, procedural justice refers to the fairness of processes that lead to outcomes, informational justice relates to the information for justice-related events, and interpersonal justice concerns the fairness of interpersonal interactions. Generally, both informational and interpersonal justice are often grouped together under interactional justice.

Based on the nature of the MCS environment, both interactional and procedural justice were excluded from this study. Most often, the procedural details and specification of a task will be posted clearly in the crowdsourcing platform, and hence, crowd workers do not need to interact with the requester (Brawley & Pury, 2016; Franke et al. 2013). In this regard, interactional justice and procedural justice do not play a role in the crowdsourcing practice.

Concerning distributive justice (Adams, 1965), individuals tend to evaluate their input (e.g., effort) and outcome (e.g., reward) and to compare their outcome-to-input ratio. When the outcome-to-input ratio of an individual is equal to others, the individual perceives distributive justice. Understandably, workers would perform best if the awards were fair and proportional to their performance (Franke et al., 2013). Previous studies (Colquitt et al., 2001) have demonstrated that workers are more willing to take up more responsibilities and challenges when these tasks are associated with positive organisational justice. The success of crowdsourcing platform does not only relies heavily on both the quality and quantity of the crowds (Bayus, 2013; Sun et al., 2012) but also incorporates fairness and trust to help sustain participation in transactional virtual communities (Stewart & Malaga, 2009).

Franke et al. (2013) found that participants' expectations on distributive fairness affect their willingness to contribute to MCS communities. Boudreau et al. (2011) demonstrated that uncertain compensation dilutes participants' motivation to improve their performance; this reduced motivation is because requesters may distribute micro-tasks among thousands of crowd workers and reserve the

right to refuse accepting work from the crowd workers who deliver poorly done or incomplete work. Requesters may even decline to pay crowd workers for completed tasks that meet the requirements. Consequently, crowd workers face inequality rather than distributive fairness (Deng et al., 2016), and MCS participants may be positively motivated by fair distribution of rewards. Therefore, we propose the following hypothesis:

H2: Distributive justice is positively related to continued participation intention.

Self-efficacy refers to the confidence in the individual's perceived ability to achieve the intended results for a particular task (Bandura, 1982). Past studies found that self-efficacy has a positive relationship with different motivations and outcomes, such as self-set goals, acceptance and commitment to high standards, and persistence in the face of adversity (Latham & Pinder, 2005). Ng and Lucianetti (2016) asserted that self-efficacy is related to adopting new technology, participation in online activities and engagement in creative activities. In general, crowd workers with high self-efficacy can complete tasks tend to have a high likelihood to continue to participate in an MCS platform. Therefore, we propose the following hypothesis:

H3: Self-efficacy is positively related to continued participation intention.

Moderation Effect of Self-efficacy on Motivation and Continued Participation Intention
Shah and Higgins (1997) demonstrated that, when the task is considered a job and its attainment only bring responsibility fulfilment, those with high self-efficacy would only use minimal effort to complete the task. Mann and Eland (2005) also argued that people with high self-efficacy tend to spend less time practising a newly learned task than those with low self-efficacy. This is because self-efficacy is related to directing resources positively toward unattained goals but negatively toward attained goals. Along these lines, Bandura (1977) uncovered that a positive relationship exists when individuals perform because individuals with high self-efficacy endeavour to demonstrate their competence. On the contrary, when individuals are in a participating state, a negative relationship exists; the individuals with high self-efficacy would do what was needed to meet the requirements.

To a certain extent, when external regulation motivates MCS crowd workers' participation, economic/monetary reward becomes these workers' prime focus. Because winning is a job fulfilment rather than an accomplishment, the 'negative relationship' applies (Vancouver et al., 2008), in which high self-efficacy crowd workers tend to spend even less effort and time than what is minimally required (Shah & Higgins, 1997). As such, we propose the following hypothesis:

H4a: The positive effect of external regulation on continued participation intention is weaker when self-efficacy is high.

When individuals with high self-efficacy experience introjected regulation, they tend to demonstrate their ability for going above and beyond in their work (Brabham, 2010; Zheng et al. 2011). MCS participants who consider themselves as having high self-efficacy are more willing to participate because they believe that they can complete tasks and receive rewards. Vancouver et al. (2008) considered these high self-efficacy crowd workers can achieve more. Therefore, we propose the following hypothesis:

H4b: The negative effect of introjected regulation on continued participation intention is weaker (less negative) when self-efficacy is high.

To a certain extent, self-efficacy is relevant to crowd workers' sense of competence in judging the probability of succeeding in tasks. Intrinsic motivation can influence participation intention, especially when crowd workers with high self-efficacy believe that they will understand tasks and when their perceived competence and enjoyment is satisfied through success on a given task. The accomplishment mode and the 'positive relationship' apply where crowd workers with high self-efficacy have a stronger desire to participate when intrinsically motivated. Therefore, we propose the following hypothesis:

H4c: The positive effect of intrinsic motivation on continued participation intention is stronger when self-efficacy is high.

Moderation Effect of Justice on Motivation and Continued Participation Intention

In general, peoples' perceptions of fairness predict a wide variety of attitudinal, behavioural and health outcomes (Colquitt et al., 2001; Robbins, Ford, & Tetrick, 2012). Distributive justice injects various impacts on crowd workers' motivation towards their continued participation intention in an MCS platform. When crowd workers are externally regulated, their goal is purely to obtain the rewards. Distributive justice is essential and catalytic because it ensures that their efforts are fairly rewarded, strengthening crowd workers' desire to continue to participate. As such, we propose the following hypothesis:

H5a: The positive effect of external regulation on continued participation intention is stronger when distributive justice is high.

Nevertheless, when crowd workers are capable of introjected regulation, their continued participation motivation is based upon the fear of losing and failing to sustain their reputation. The promotion of fairness in crowdsourcing platforms may help lessen this fear; if participants believe that everyone has an equal chance of receiving the same reward for completing a task, they feel encouraged to consider participation. Hence, we argue that fairness in reward distribution would weaken the negative effect of introjected crowd workers' regulation on continued participation intention, and we propose the following hypothesis:

H5b: The negative effect of introjected regulation on continued participation intention is weaker (less negative) when the distributive justice is high.

When crowd workers are intrinsically motivated, their continued participation motivation stems from their innate psychological need for autonomy and competence. However, crowd workers' intrinsic motivation could become suppressed if compensation were performance-based. Deci et al. (1999) examined the negative effects of extrinsic rewards on intrinsic motivation and proved that tangible or expected rewards could reduce free-choice intrinsic motivation. In the case of MCS, if distributive justice is highly emphasised, crowd workers' intrinsic motivation is likely undermined because their focus is diverted to external rewards rather than self-enjoyment and satisfaction. As a result, their continued participation intention through intrinsic motivation is lessened, and we propose the following hypothesis:

H5c: The positive effect of intrinsic motivation on continued participation intention is weaker when distributive justice is high.

Moderation Effect of Justice on Self-efficacy and Continued Participation Intention

Bandura (1986) suggested that self-efficacy is situational and can be affected by environmental factors such as task nature and complexity. When crowd workers perceive that distributive justice is present, they feel that the crowdsourcing platform is safe and secure. They are thus willing to participate in the related task, especially when they view themselves as capable and confident (Zou et al., 2015). Therefore, we propose that distributive justice has a positive impact on the relationship between crowd workers' self-efficacy and their continued participation intention in MCS as follows:

H6: The positive effect of self-efficacy on continued participation intention is stronger when distributive justice is high.

Three-Way Synergetic Effect of Motivation, Self-efficacy and Justice on Continued Participation Intention

Although many scholars in various domains have widely studied and applied expectancy theory, VIE's interaction effects are not yet understood (Vroom, 1964). By building upon the previous hypotheses, we intend to explore the three-way synergetic effects of motivation, self-efficacy and justice on continued participation intention.

Externally regulated crowd workers aim for monetary rewards in MCS. When distributive justice is fair and emphasised, it enhances and strengthens the positive external regulation impact onto continued participation intention, as mentioned above. When applied to crowd workers with low self-efficacy, their participation intention is further enhanced; participation becomes an accomplishment when they surpass the crowd workers with high self-efficacy, especially when knowing that the rewards and payout are fair. As such, we argue that externally regulated crowd workers have a strong desire to continue to participate when they consider that they have low self-efficacy but high distributive justice:

H7a: There is a three-way synergistic effect of external regulation (ER), self-efficacy (SE) and distributive justice (DJ) on continued participation intention (CP), such that the effect of ER on CP will be at its greatest when DJ is high and SE is low.

Crowd workers with introjected regulation tend to be more motivated on participation when they consider themselves to have high self-efficacy. The belief in their high capabilities helps lessen their fear or even convert this belief into a higher chance of accomplishing tasks to regain and sustain their reputations on MCS platforms. With the emphasis on fairness in distributive justice, crowd workers' continued participation intention is further strengthened. Therefore, we propose that introjected regulated crowd workers have a strong desire to continue to participate when they consider themselves as having high self-efficacy and distributive justice:

H7b: There is a three-way synergistic effect of introjected regulation (IR), self-efficacy (SE) and distributive justice (DJ) on continued participation intention (CP), such that the effect of IR on CP will be at its greatest when both SE and DJ are high.

Intrinsically motivated crowd workers seek enjoyment and fulfil their basic psychological needs – autonomy, competence and relatedness – through completion of MCS tasks. Hence, the crowd workers with high self-efficacy undoubtedly have a strong desire to continue participating because they believe that they are capable of doing that. Nonetheless, to enhance these crowd workers' continued participation intention, distributive justice must decrease, so the crowd workers are not distracted by the rewards or payouts. Hence, we suggest that intrinsically motivated crowd workers

have a strong desire to continue to participate when they consider that they have high self-efficacy but low distributive justice:

H7c: There is a three-way synergistic effect of intrinsic motivation (IM), self-efficacy (SE) and distributive justice (DJ) on continued participation intention (CP), such that the effect of IM on CP will be at its greatest when SE is high and DJ is low.

3. RESEARCH METHODOLOGY

In order to empirically verify the theoretical model, two pilot surveys and a mass online survey were conducted. A separate offline and online pilot survey was executed to obtain adequate preliminary data to justify the research design. The offline pilot survey was conducted in a local (Hong Kong) 'co-working space' facility within January 2017. Fifteen valid questionnaires were collected from a group of experienced practitioners with more than 12 months of experience with MCS and who had participated in MCS activities more than 3 times within the previous 12 months. The respondents' average age was the mid-30s, and most of the respondents had a bachelor's degree or above. Based on the pilot study, the wording of the questionnaire was slightly modified according to the respondents' input during face-to-face interactions to ensure that the final questionnaire would be relevant and meaningful to participants in the mass survey.

In addition, we conducted an online pilot survey via MTurk on February 21, 2017. Twenty valid data sets were collected from respondents whose average age and MCS experience were comparable to those of the offline survey respondents. A preliminary testing of all construct measures' validity and reliability was completed and confirmed, and we identified no major errors before we proceeded to the mass survey.

In the online mass survey, we posted a task on MTurk called 'Motivations of sustained participation in online crowdsourcing platforms'. All survey respondents, who participated in crowdsourcing activities in the past, were redirected to a Google Form to fill in a questionnaire consisting of 45 questions and 3 'test questions'. An estimated completion time of 10 to 15 minutes was indicated. To avoid selection bias, data were collected from MTurk users over different timeframes. Like those sampled from the first batch, these respondents had been involved in at least one crowdsourcing activity on MTurk or any other MCS platforms (e.g., Taskcn.com).

A total of 1307 responses were collected from the online mass survey; this total does not include the pilot surveys' data. The respondents who are crowd workers on MTurk were asked to spend at least 10 minutes on completing the survey (Barger, Behrend, Sharek, & Sinar, 2011), and we invalidated the questionnaires of participants who spent far less than 10 minutes on the survey or who failed to answer the test questions. After screening, 267 responses were discarded. As a result, only 1040 usable responses, with a response rate of 79.6%, were obtained. This was in line with the quality control measures on MTurk (Downs, Holbrook, Sheng, & Cranor, 2010).

The demographics of the respondents are presented in Table 1. Around 61.73% of the respondents were male, and 83.56% of them were under 40 years old. Approximately 74.71% of the respondents held a bachelor's degree or above. Their annual incomes were relatively low; 60.87% of them earned less than US$40,000 annually. More than 68.71% of the respondents had less than 18 months of crowdsourcing experience, and 57.88% of them spent less than 10 hours per week on crowdsourcing activities. This profile is comparable with our offline and online pivots.

3.1 Measurements

All the constructs were measured by a self-reported questionnaire using a 7-point scale ranging from 'highly disagree' (1) to 'highly agree' (7). The items used to operationalise the variables were adapted from prior studies. Changes in wording from the original questions were made to reflect the specific micro-task crowdsourcing context.

Table 1. Descriptive Statistics of the Respondents

Gender: Male (642, 61.73%), Female (398, 38.27%)	Age: 18–25 (212, 20.38%) 26–30 (331, 31.83%), 31–40 (326, 31.35%), 41–50 (98, 9.42%), 51 or above (73, 7.02%)
Education: No schooling/pre-primary (3, 0.29%), primary (13, 1.25%), secondary (54, 5.19%), diploma/higher diploma (193, 18.56%), degree (584, 56.15%), postgraduate (193, 18.56%)	
Annual income: Below US$20,000 (339, 32.60%), US$20,001–40,000 (294, 28.27%), US$40,001–60,000 (206, 19.81%), US$60,001–80,000 (114, 10.96%), US$80,001–100,000 (50, 4.81%), US$100,001 or above (37, 3.56%)	
The number of months that the respondents participated in crowdsourcing activities: Less than 6 months (260, 25.00%), 6–12 months (283, 27.21%), 13–18 months (171, 16.44%), 19–24 months (113, 10.87%), 25–30 months (61, 5.87%), more than 30 months (152, 14.62%)	
Average time spent on crowdsourcing activities per week: Less than 10 hours (602, 57.88%), 11–20 hours (216, 20.77%), 21–30 hours (112, 10.77%), 31–40 hours (56, 5.38%), 41 hours or above (54, 5.19%)	

Motivation Measurement

Nine items were adapted from the Motivation at Work Scale (MAWS) to measure external regulation (ER), introjected regulation (IR) and intrinsic motivation (IM) (Gagné et al., 2010). Based on their recent experience (over the past 12 months), respondents were asked how much they agreed with the following reasons regarding their motivation of participation in crowdsourcing activities. For intrinsic motivation (IM), sample questions included '… because I enjoy crowdsourcing activities very much' and '… because I have fun doing crowdsourcing activities'. For introjected regulation (IR), sample questions included 'Because I have to be the best in crowdsourcing activities; I have to be a winner' and 'Because crowdsourcing activities are very important to me, and I don't want to fail'. For external regulation (ER), sample questions included '… because crowdsourcing activities afford me a certain standard of living' and '… because crowdsourcing activities allow me to make money'.

Distributive Justice Measurement

Four items were extracted from Colquitt (2001) to measure distributive justice (DJ). Respondents were asked to rate the agreement level referring to their crowdsourcing activities' outcome (tangibly measurable), sample questions included 'My crowdsourcing activities' outcome (tangibly measurable) does reflect the effort I have put into my crowdsourcing work' and 'My crowdsourcing activities' outcome (tangibly measurable) is appropriate for the crowdsourcing work I have completed'.

Self-Efficacy Measurement

The general self-efficacy (SE) measurement questions adapted from Chen, Gully and Eden (2001) were used. The reason for using the general self-efficacy questions instead of the task-specific self-efficacy questions used by a previous related online study (Kankanhalli, Tan & Wei, 2005) is because micro-task crowdsourcing covers a wide range of tasks (Saxton et al., 2013). Respondents may have different experiences with various tasks on MCS platforms. Using the general self-efficacy survey questions, crowd workers' self-efficacy levels would be measured comprehensively without the influence of context bias. Eight items were extracted. Based on their recent experience (over the previous 12 months), respondents were asked to what extent they agreed with the following statements regarding their competence levels in handling tasks. Sample questions included 'I will be able to achieve most of the goals that I have set for myself' and 'When facing difficult tasks, I am certain that I will accomplish them'.

Intention To Participate In Crowdsourcing Activities In The Future

For continued participation intention (CP), respondents were asked, based on their recent experience (over the previous 12 months), to what extent they agreed with the following statements regarding

their intention to participate in online crowdsourcing activities in the future. Three items were adopted from Bhattacherjee (2001). Sample questions included 'I intend to continue participating in online crowdsourcing activities' and 'If I could, I would like to continue my participation in online crowdsourcing activities'.

3.2 Control Variables

Past studies of crowdsourcing revealed that individual behaviour may vary due to personal factors such as age, gender and education, which may affect continued participation (Paolacci & Chandler, 2014). Also, community tenure, which is defined as the length of participants' engagement in the MCS marketplace, engenders stronger loyalty and greater familiarity with rules and thus may spark a positive outcome of continued participation intention. Job experience denotes the amount of experience that the participants had in a related field; a more experienced participant usually indicated a higher amount of knowledge in a particular task domain, which is a key component of motivation to participate and was also regarded as a control variable.

When crowd workers judge either their probability of success or the effort required to complete a crowdsourcing task, in addition to their perceived self-efficacy, their assessment of the difficulty or the demand required (Bledow, 2013) was also considered. Hence, task complexity was treated as a control variable.

Crowdsourcing Task Complexity

Three items were adopted from Seijts, Latham, Tasa and Latham (2004). Regarding the general feeling towards the task nature in terms of the difficulty of online crowdsourcing activities, respondents were asked, based on their recent experience (over the previous 12 months), to what extent they agreed with the following statements. Sample questions included 'Completing the tasks of online crowdsourcing activities are challenging to me' and 'I find the tasks of online crowdsourcing activities are very complex'.

Common Method Bias Validation and Test Questions

To eliminate spammers, three multiple-choice test questions were included in the survey, such as 'Who is not the candidate in 2016 United States presidential election? Hilary Clinton, Barack Obama or Donald Trump'. Respondents were required to provide correct answers to all three test questions for their responses to be included in the data sample. Furthermore, five questions for the common method bias test/marker variable test (Lindell & Whitney, 2001) were also included, e.g., 'I participate in crowdsourcing activities because I enjoy listening to music'.

4. ANALYSES AND RESULTS

This section covers the results of two stages, namely (i) data validity and reliability and (ii) hypotheses testing.

4.1 Data Validity and Reliability

We computed the means, standard deviations and bivariate correlations for all the data. To ensure the reliability and validity of this study's instrument, we examined the exploratory factor analysis of the essential constructs: the support for external regulation (ER), intrinsic motivation (IM), introjected regulation (IR), distributive justice (DJ), self-efficacy (SE), task complexity (TC) and continued participation intention (CP). To test the hypotheses, we adopted regression analysis to analyse the framework. We also verified whether the control variables had any significant effects on continued participation intention.

Instrument Reliability and Validity

To ensure reliability, we adopted Cronbach's alpha to measure the internal consistency of the multi-item scales. As shown in Table 2, the Cronbach's alphas of all the constructs were over 0.7, which indicated that the sets of items correlated well with each other. Hence, all of the constructs were deemed reliable. In addition, because all the items in these constructs were adapted from past studies, all the constructs were therefore considered reliable in terms of face validity.

Means, Standard Deviations, Cronbach's Alpha and Correlation Variables

In Table 2, external regulation (ER), intrinsic motivation (IM), and introjected regulation (IR) have mean values of 5.24, 5.01 and 4.14, respectively, indicating that the respondents were most strongly motivated by external regulation, then by intrinsic motivation and least by introjected regulation. Distributive justice (DJ) has a mean of 4.94, higher than the neutral point of 4, thus indicating that the respondents generally perceived that the crowdsourcing platforms were fair in terms of reward distribution. The mean value for self-efficacy (SE) is 5.70, indicating that the respondents were absolutely confident in their own competence. For task complexity (TC), the mean value is 3.79, lower than the neutral point 4, thereby reflecting the respondents' perception that the crowdsourcing tasks were relatively easy. The mean value for continued participation intention (CP) is 5.68, suggesting that the respondents were likely to continue participating in crowdsourcing tasks. The standard deviations of all constructs have enough variations for the sampled data to represent crowdsourcing users' population.

Table 3 displays the correlations matrix of the constructs, verifying whether the constructs potentially overlap due to their correlations and analysing whether the constructs are independent. If the correlation coefficients between the two constructs are below 0.7, they are deemed independent. Moreover, according to Fornell and Larcker (1981), if the square roots of the average variance extracted (AVE) are all higher than the correlations between constructs, then discriminant validity of all constructs can be assumed. The diagonal elements are shown in Table 3 (reporting the square root of the variance shared between a construct and its measures) are larger than the correlations between the target constructs, without exception. Hence, the discriminant validity of all the constructs in this study is considered acceptable.

The measurement scales' convergent validity was evaluated using two criteria (Fornell & Larcker, 1981). First, all factor loadings of items on their respective constructs should be significant and exceed 0.70. Second, the AVE by each construct should exceed the variance due to the construct measurement errors (i.e., should exceed 0.5). The AVEs of the constructs, as shown in Table 3, were all greater than the variances due to measurement errors. Thus, both conditions for convergent validity were satisfied.

After removing the first item of external regulation (ER1), which was lower than 0.7 in the factor loading in ER and was excluded from the model, ER1 was not considered in later analysis. Table 4 shows the factor loadings of the 26 items, which all had a higher loading value than 0.7 on their respective constructs, thus indicating a high degree of correlation between the results of each construct's measurements using different instruments.

Selection Bias and Common Method Bias

In addition, we employed Lindell and Whitney's (2001) marker variable assessment technique. Five questions (e.g., 'I like reading books') related to marker variables were included in the survey questionnaire, and the results exhibited nonsignificant correlations of 0.18. In summary, none of the significant correlations in the overall model showed insignificance after adjustment, which provided additional evidence against the existence of common method bias.

According to Podsakoff, MacKenzie, Lee and Podsakoff (2003), several common method bias sources, such as the consistency motif and social desirability due to the self-reported surveys, must be addressed. Harman's one-factor analysis was conducted to identify whether common method bias is

Table 2. Descriptive Statistics and Reliability

Variables	Mean*	Std. Dev.
Intrinsic Motivation (IM) (Cronbach's alpha = 0.870)	**5.01**	**1.170**
I participate in crowdsourcing activities because I enjoy crowdsourcing activities very much. (IM1)	**5.01**	**1.313**
I participate in crowdsourcing activities because I have fun doing crowdsourcing activities. (IM2)	**5.06**	**1.294**
I participate in crowdsourcing activities because I enjoy the moments of pleasure that crowdsourcing activities bring me. (IM3)	**4.96**	**1.334**
Introjected Regulation, Extrinsic Motivation (IR) (Cronbach's alpha = 0.841)	**4.14**	**1.513**
I participate in crowdsourcing activities because I have to be the best in crowdsourcing activities; I have to be a 'winner'. (IR1)	**4.38**	**1.691**
I participate in crowdsourcing activities because crowdsourcing activities are very important to me, and I don't want to fail. (IR2)	**4.34**	**1.633**
I participate in crowdsourcing activities because my reputation depends on results. (IR3)	**3.70**	**1.877**
External Regulation, Extrinsic Motivation (ER) (Cronbach's alpha = 0.757)	**5.24**	**1.315**
I participate in crowdsourcing activities because crowdsourcing activities allow me to make money. (ER2)	**5.40**	**1.406**
I participate in crowdsourcing activities because of the pay check. (ER3)	**5.08**	**1.524**
Distributive Justice (DJ) (Cronbach's alpha = 0.837)	**4.94**	**1.012**
My crowdsourcing activities' outcome (tangibly measurable) does reflect the effort I have put into my crowdsourcing work. (DJ1)	**4.96**	**1.265**
My crowdsourcing activities' outcome (tangibly measurable) is appropriate for the crowdsourcing work I have completed. (DJ2)	**4.92**	**1.259**
My crowdsourcing activities' outcome (tangibly measurable) does reflect what I have contributed to the crowdsourcing platform. (DJ3)	**4.90**	**1.206**
My crowdsourcing activities' outcome (tangibly measurable) is justified, given my performance. (DJ4)	**4.99**	**1.209**
Self-Efficacy (SE) (Cronbach's alpha = 0.909)	**5.70**	**0.844**
I will be able to achieve most of the goals that I have set for myself. (SE1)	**5.64**	**1.098**
When facing difficult tasks, I am certain that I will accomplish them. (SE2)	**5.58**	**1.114**
In general, I think that I can obtain outcomes that are important to me. (SE3)	**5.71**	**1.023**
I believe I can succeed at any endeavor to which I set my mind. (SE4)	**5.71**	**1.114**
I will be able to overcome many challenges successfully. (SE5)	**5.75**	**1.059**
I am confident that I can perform effectively on many different tasks. (SE6)	**5.80**	**1.053**
Compared to other people, I can do most tasks very well. (SE7)	**5.67**	**1.117**
Even when things are tough, I can perform very well. (SE8)	**5.70**	**1.062**
Task Complexity (TC) (Cronbach's alpha = 0.846)	**3.79**	**1.449**
I find that completing the tasks of online crowdsourcing activities is difficult for me. (TC1)	**3.43**	**1.686**
Completing the tasks of online crowdsourcing activities is challenging for me. (TC2)	**4.14**	**1.653**
I find that the tasks of online crowdsourcing activities are very complex. (TC3)	**3.81**	**1.631**
Continued Participation Intention (CP) (Cronbach's alpha = 0.852)	**5.68**	**1.026**
I intend to continue to participate in online crowdsourcing activities. (CP1)	**5.63**	**1.174**
If I could, I would like to continue my participation in online crowdsourcing activities. (CP2)	**5.69**	**1.179**
My intention is to continue participating in online crowdsourcing activities. (CP3)	**5.71**	**1.152**

* 1 = strongly disagree and 7 = strongly agree

Table 3. Correlation Matrix

	AVE	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1 IM	0.631	**0.794**						
2 IR	0.638	.548**	**0.799**					
3 ER	0.732	.244**	.315**	**0.856**				
4 DJ	0.579	.492**	.391**	.324**	**0.761**			
5 SE	0.577	.220**	.101**	.223**	.364**	**0.760**		
6 TC	0.707	.250**	.355**	.040	.146**	−.197**	**0.841**	
7 CP	0.623	.321**	.125**	.354**	.394**	.511**	−.185**	**0.790**

** Correlation is significant at the 0.01 level (2-tailed). The numbers in bold in the diagonal row are square roots of the average variance extracted.

a severe concern in this study. The results for the total variance obtained from the exploratory factor analysis of the essential variables indicated that no single factor, with a dominant value of 28.746%, accounts for most of the covariance.

4.2 Hypotheses Testing

Model set 1 – external regulation (ER) × self-efficacy (SE) × distributive justice (DJ)

The first set of the regression result is shown in Table 5. Based on the R^2 coefficient, the increment between Model 1 and Model 0 is 0.397, suggesting that our independent variables' influence is significant in predicting the dependent variable: continued participation intention (CP).

Main Effect

H1a, H1b and H1c are supported because both intrinsic motivation (IM) ($\beta = 0.286***$) and external regulation (ER) ($\beta = 0.287***$) are positively related to CP while introjected regulation (IR) ($\beta = -0.218***$) is negatively related to CP. According to Model 1, the result shows that DJ is positively related to CP ($\beta = 0.181***$), which supports H2, while self-efficacy (SE) significantly boosts CP ($\beta = 0.341***$), which supports H3.

Moderation Effect

The moderation effect between external regulation (ER) and self-efficacy (SE) is significant in Model 2b ($\beta = -0.087***$), Model 2d ($\beta = -0.097***$) and Model 3 ($\beta = -0.085***$). Hence, the results indicate that the level of self-efficacy (SE) moderates the positive relationship between ER and CP. The higher the level of SE, the weaker the direct effect of ER on CP is. Consequently, H4a is supported.

Nonetheless, H5a and H6 are not supported. For the former, the moderation effect between ER and DJ is not significant. For the latter, the results also indicate that the moderation effect between DJ and SE is not significant.

Three-Way Interaction Effect

H7a proposes that there is a three-way interaction among ER, SE and DJ. The result of Model 3 indicates that the three-way interaction effect is significant ($\beta = -0.103***$), and this three-way interaction effect does not significantly influence the effects of other variables when comparing Model 2d and Model 3 in Table 5, thus confirming and supporting H7a.

As shown in Figure 2, the relationships between ER and CP in four different combinations include a reference line to explain the form of the interaction further. High and low SE and DJ levels were plotted, and the high and low points on the graph represent ± 1 SD (Aiken, West & Reno, 1991). Moreover, a reference line without the interaction effect, that is, with both SE and DJ at the mean

Table 4. Factor Analysis

|							
Rotated Component Matrixa							
	Component						
	1	**2**	**3**	**4**	**5**	**6**	**7**
IM1	_.790_	.287	.075	.230	.103	.148	.109
IM2	_.829_	.159	.075	.216	.129	.062	.144
IM3	_.763_	.352	.023	.204	.077	.115	.114
IR1	.242	_.804_	.088	.181	.055	.149	-.002
IR2	.274	_.806_	.093	.150	.025	.125	.045
IR3	.162	_.786_	.076	.164	-.057	.279	-.053
ER2	.119	.102	_.823_	.142	.133	.024	.226
ER3	.023	.112	_.887_	.135	.087	.010	.079
DJ1	.218	.080	.115	_.723_	.127	.057	.076
DJ2	.161	.128	.052	_.761_	.192	.060	.147
DJ3	.148	.128	.125	_.771_	.183	.059	.102
DJ4	.076	.177	.048	_.786_	.184	.058	.135
SE1	.015	.047	.062	.168	_.720_	-.043	.078
SE2	.054	.001	.052	.078	_.777_	-.073	.124
SE3	.009	-.079	.057	.159	_.745_	-.092	.128
SE4	.009	.057	.031	.115	_.769_	-.068	.113
SE5	.054	.004	.028	.117	_.782_	-.050	.145
SE6	.017	.004	.034	.083	_.778_	-.074	.181
SE7	.129	.011	.066	.049	_.738_	-.036	.086
SE8	.103	.024	.019	.076	_.768_	-.018	.135
TC1	.044	.168	.011	.035	-.181	_.819_	-.181
TC2	.142	.152	.008	.110	-.078	_.827_	.063
TC3	.072	.156	.014	.057	-.099	_.875_	-.109
CP1	.121	-.014	.132	.137	.263	-.066	_.811_
CP2	.121	-.023	.116	.167	.316	-.082	_.752_
CP3	.110	.040	.112	.168	.294	-.100	_.804_

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

level, is plotted. For the interaction effect interpretation, while the intersection among the lines is not the focus in the three-way interaction diagram, the slopes of the lines under different situations are the main focus. The graph shows that ER's effect on CP is at its greatest (deepest slope) when DJ is high and SE is low. Hence, hypothesis H7a is supported.

Based on the interaction effect between IR and SE, as shown in Model 2b in Table 6, SE significantly weakens the negative relationship in between IR and CP ($\beta = 0.092$***). Hence, H4b is deemed to be supported. From the result of Model 2a ($\beta = -0.029$), H5b is not supported because the interaction effect between IR and DJ on CP is not significant.

We have noted that the results of the interaction effect of Model 3 are not coherent with those of the previous models (2a, 2c and 2d). In Model 2d in Table 6, DJ×SE is insignificant. However,

Figure 2. Three-way Interaction Effects Among ER, DJ and SE on CP in Crowdsourcing
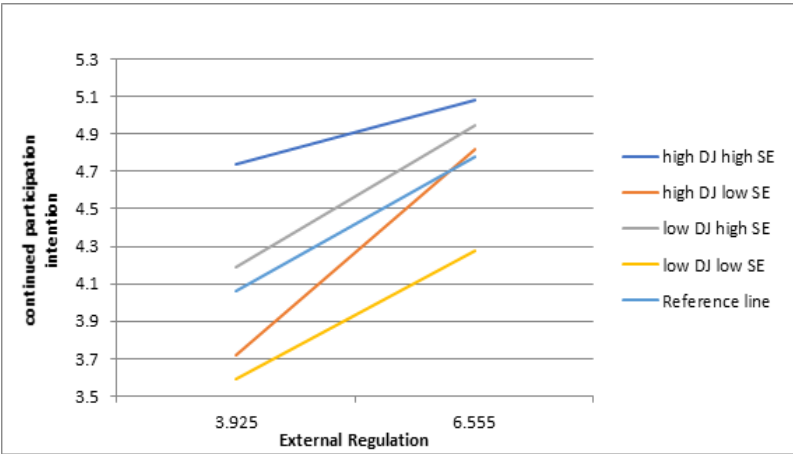
DJ×SE becomes significant with the presence of the three-way interactions IR×DJ×SE. Consequently, H7b is not supported.

Moderation Effect

Based on the interaction effect between IM and SE, as shown in Model 2b in Table 7, SE significantly strengthens the positive relationship between IM and CP ($\beta = 0.072$**). Hence, H4c is supported. Based upon the results of Model 2a ($\beta = -0.075$***), H5c is also supported because the interaction effect between IM and DJ on CP is negative and significant.

Three-Way Interaction Effect

Because the results of Model 3 in Table 7 is consistent with those of all previous models (2a, 2b, 2c and 2d) and the p-value of the three-way interaction among IM, SE and DJ is less than 0.001, the three-way interaction is validated, which confirms our hypothesis and supports H7c.

As shown in Figure 3, the relationships between IM and CP in four combinations. High and low SE and DJ levels were plotted, and the high and low points on the graph represent ±1 SD (Aiken et al., 1991). Similarly, a reference line without the interaction effect, that is, with both SE and DJ at the mean level, is plotted. The graph shows that, among the five lines, IM's effect on CP will be at its greatest (steepest slope) with high SE and low DJ. Hence, H7c is supported.

Control Variables

Among the control variables shown in Model 1 among Tables 5, 6 and 7, all these tables show that annual income ($\beta = -0.085$**) and task complexity ($\beta = -0.202$***) have significant effects on continued participation intention (CP). This result suggests that people with less annual income are more likely to participate in crowdsourcing in the future. Moreover, the result shows that, if the crowdsourcing task is more complicated, people are less likely to participate in crowdsourcing in the future.

5. DISCUSSION

This study examines the relationship among motivation, organisational justice, and self-efficacy in influencing participants' continued participation intention to work on compensation-based MCS platforms. According to the findings, respondents were most motivated by external regulation,

Table 5. Model set 1 - Regression analyses

	Model 0	*Model 1*	*Model 2a*	*Model 2b*	*Model 2c*	*Model 2d*	*Model 3*
Control Variable							
Task Complexity	-0.237***	-0.202***	-0.202***	-0.206***	-0.2***	-0.2***	-0.197***
Gender	0.057	0.007	0.007	0.007	0.008	0.008	0.008
Nationality	0.09*	0.009	0.009	0.015	0.009	0.015	0.018
Age	-0.021	0.019	0.019	0.011	0.02	0.012	0.005
Education	0.001	-0.003	-0.003	-0.01	-0.003	-0.011	-0.01
Field	-0.025	-0.011	-0.011	-0.011	-0.011	-0.011	-0.017
Job Experience	0.133**	0.063	0.063	0.068	0.063	0.069	0.071
Management Position	-0.017	-0.001	-0.001	-0.005	-0.001	-0.005	-0.008
Crowdsourcing Experience	0.101**	0	0	0.002	-0.001	-0.001	0
Annual Income	-0.091*	-0.085**	-0.085**	-0.089**	-0.084**	-0.088**	-0.084**
Base Effect							
Intrinsic Motivation		0.286***	0.286***	0.294***	0.285***	0.291***	0.278***
Interjected Regulation		-0.218***	-0.218***	-0.222***	-0.216***	-0.217***	-0.177***
External Regulation		0.287***	0.287***	0.29***	0.287***	0.289***	0.274***
Self-Efficacy		0.341***	0.341***	0.331***	0.346***	0.346***	0.378***
Distributive Justice		0.181***	0.18***	0.183***	0.176***	0.169***	0.168***
Moderation Effect							
ER x DJ			-0.002			-0.003	0.023
ER x SE				-0.087**		-0.097***	-0.085**
DJ x SE					0.013	0.04	0.015
ER x DJ x SE							-0.103***
Model Information							
R²	0.1	0.497	0.497	0.505	0.498	0.507	0.53
ΔR² from previous model		0.397	0	0.008	0.001	0.01	0.023
*p < 0.05, **p < 0.01, ***p < 0.001							
Note: ΔR² of Models 2a, 2b, 2c, and 2d are compared with the R² of Model 1 while DR² of Model 3 compared with the R² of Model 2d							

Model set 2 – introjected regulation (IR) × self-efficacy (SE) × distributive justice (DJ)

Table 6. Model Set 2 – Regression Analyses

	Model 0	Model 1	Model 2a	Model 2b	Model 2c	Model 2d	Model 3
Control Variable							
Task Complexity	-0.237***	-0.202***	-0.201***	-0.195***	-0.2***	-0.195***	-0.187***
Gender	0.057	0.007	0.006	0.011	0.008	0.009	0.01
Nationality	0.09*	0.009	0.011	0.011	0.009	0.014	0.016
Age	-0.021	0.019	0.018	0.015	0.02	0.009	0.002
Education	0.001	-0.003	-0.003	-0.008	-0.003	-0.008	-0.007
Field	-0.025	-0.011	-0.013	-0.013	-0.011	-0.017	-0.017
Job Experience	0.133**	0.063	0.065	0.061	0.063	0.065	0.065
Management Position	-0.017	-0.001	-0.002	-0.005	-0.001	-0.007	-0.013
Crowdsourcing Experience	0.101**	0	0	0	-0.001	0.004	0.007
Annual Income	-0.091*	-0.085**	-0.085**	-0.08**	-0.084**	-0.079*	-0.078**
Base Effect							
Intrinsic Motivation		0.286***	0.283***	0.284***	0.285***	0.281***	0.275***
Interjected Regulation		-0.218***	-0.214***	-0.248***	-0.216***	-0.256***	-0.233***
External Regulation		0.287***	0.289***	0.284***	0.287***	0.286***	0.275***
Self-Efficacy		0.341***	0.347***	0.348***	0.346***	0.342***	0.371***
Distributive Justice		0.181***	0.173***	0.186***	0.176***	0.187***	0.186***
Moderation Effect							
IR x DJ			-0.029			-0.055*	-0.027
IR x SE				0.092***		0.127***	0.125***
DJ x SE					0.013	-0.044	-0.069**
IR x DJ x SE							-0.1***
Model Information							
R^2	0.1	0.497	0.496	0.512	0.498	0.518	0.542
ΔR^2 from previous model		0.397	-0.001	0.015	0.001	0.021	0.024

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Note: ΔR^2 of Models 2a, 2b, 2c, and 2d are compared with the R^2 of Model 1 while ΔR^2 of Model 3 compared with the R^2 of Model 2d

Model set 3 – intrinsic motivation (IM) × self-efficacy (SE) × distributive justice (DJ)

followed by intrinsic motivation and introjected regulation, when deciding whether to participate in an MCS platform. The respondents also considered themselves to have high self-efficacy and the reward distribution to be fair enough to participate in MCS when the tasks are easy. Furthermore, a high distributive justice environment is confirmed as essential for convincing most participants to

Figure 3. Three-way Interaction Effects Among IM, DJ and SE on CP in Crowdsourcing
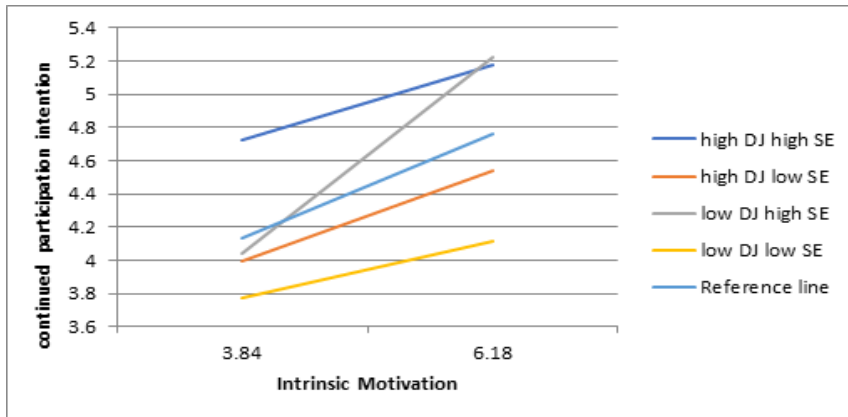
return to an MCS platform. These phenomena make sense because participants intend to earn money and fulfil their innate needs if they believe that the payout is fair.

However, when incorporating self-efficiency as a moderator, the findings differ. Crowd workers' high self-efficacy undermines external regulation's positive effect on continued participation intention (H4a). When the crowd workers are of high self-efficacy, their return-on-investment mindset makes them believe that only minimal effort is needed for completing tasks. Hence, continued participation intention in an MCS platform is hindered.

In contrast, a positive moderation effect between introjected regulation (IR) and continued participation intention (CP) is observed (H4b), which suggests that, when crowd workers are of high self-efficacy, their intention to continue to participate is stronger because their fear of losing weakens and they believe they can complete tasks and sustain their reputations.

Similarly, a positive moderation effect is also observed between intrinsic motivation (IM) and continued participation intention (H4c): when crowd workers perceive high levels of self-efficacy, the influence of IM (e.g., self-affirmation) on continued participation is stronger because they believe that they are capable of and enjoy completing tasks.

Nevertheless, when putting distributive justice as a moderator, its impact on the positive interaction effect between external regulation and CP (H5a) is rejected. This could be due to the nature of compensation-based MCS, in which the return of payout is usually low. The majority of the participants considered MCS participation to be work that exists only on a part-time basis and the rewards to be incomparable to regular income. Similarly, distributive justice also does not influence the negative relationship between introjected regulated participants and their continued participation intention (H5b). We estimate that, due to the large number of MCS participants who compete on individual tasks, requesters cannot easily identify high-quality performers.

Furthermore, distributive justice's interaction effect upon self-efficacy and continued participation intention was found to be insignificant (H6). Our explanation is that most participants are considered to be MCS part-timers; their focus is primarily devoted to their full-time jobs regardless of their self-efficacy level. As such, distributive justice does not cause any impact on their participation intention.

Most interesting, when asserting both self-efficacy and distributive justice upon the positive relationship between ER and CP, we found that high distributive justice would greatly help external regulation-motivated and low–self-efficacy crowd workers to sustain their participation in an MCS platform. In contrast, low distributive justice would greatly help intrinsically motivated and high–self-efficacy crowd workers to sustain their participation. This result reflected the tendency for excessive or over-justified (Lepper, Greene & Nisbett, 1973) distributive justice to create a significant

Table 7. Model Set 3 – Regression Analyses

	Model 0	Model 1	Model 2a	Model 2b	Model 2c	Model 2d	Model 3
Control Variable							
Task Complexity	-0.237***	-0.202***	-0.199***	-0.195***	-0.2***	-0.188***	-0.183***
Gender	0.057	0.007	0.005	0.011	0.008	0.008	0.01
Nationality	0.09*	0.009	0.011	0.009	0.009	0.011	0.007
Age	-0.021	0.019	0.014	0.023	0.02	0.016	0.01
Education	0.001	-0.003	-0.002	-0.004	-0.003	-0.003	-0.002
Field	-0.025	-0.011	-0.011	-0.01	-0.011	-0.008	-0.01
Job Experience	0.133**	0.063	0.07	0.062	0.063	0.071	0.074*
Management Position	-0.017	-0.001	-0.004	0.001	-0.001	-0.002	-0.006
Crowdsourcing Experience	0.101**	0	0.005	-0.001	-0.001	0.006	0.003
Annual Income	-0.091*	-0.085**	-0.087**	-0.081**	-0.084**	-0.081**	-0.081**
Base Effect							
Intrinsic Motivation		0.286***	0.266***	0.272***	0.285***	0.232***	0.27***
Interjected Regulation		-0.218***	-0.204***	-0.22***	-0.216***	-0.202***	-0.197***
External Regulation		0.287***	0.29***	0.284***	0.287***	0.284***	0.266***
Self-Efficacy		0.341***	0.361***	0.355***	0.346***	0.382***	0.406***
Distributive Justice		0.181***	0.16***	0.179***	0.176***	0.155***	0.158***
Moderation Effect							
IM x DJ			-0.075**			-0.113***	-0.066*
IM x SE				0.072**		0.122***	0.094***
DJ x SE					0.013	-0.026	-0.038
IM x DJ x SE							-0.115***
Model Information							
R^2	0.1	0.497	0.495	0.501	0.498	0.506	0.545
ΔR^2 from previous model		0.397	-0.002	0.004	0.001	0.009	0.039

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Note: ΔR^2 of Models 2a, 2b, 2c, and 2d are compared with the R^2 of Model 1 while ΔR^2 of Model 3 compared with the R^2 of Model 2d

undermining effect on high–self-efficacy crowd workers with intrinsic motivation on their continued participation intention but a catalytic effects on those crowd workers of low self-efficacy when they are externally motivated.

5.1 Theoretical Implications

This study advances theoretical development in motivation, distributive justice and self-efficacy in the literature on crowdsourcing. First, while SDT has gradually been adopted by researchers in the

MCS environment (Xu & Li, 2015), the impact of how different forms of motivation that influence the continued participation intention of workers with different levels of self-efficacy has been controversial (Bandura, 2012; Hewett & Conway, 2015; Vancouver et al., 2008). Moreover, how motivations, distributive justice and self-efficacy interact have not covered in the literature. The followings are our responses to this important research question.

Our findings show that introjected regulation is negatively related to continued participation intention, meaning that crowd workers' decision to join and continue participation in MCS is precise; they will not waste time pursuing something if they fear harming their reputations is too large to bear. These results are consistent with the previous view, namely, that people participate in MCS communities mainly for the expected benefits (Von Hippel & Von Krogh, 2006). Furthermore, the undermining effect of extrinsic rewards (triggered by emphasising distributive justice) is insufficient for decreasing crowd workers' intrinsic motivation in continued participation intention in an MCS platform when their self-efficacy is at a low level. Still, the undermining effect of extrinsic reward is salient when crowd workers are of high self-efficacy.

Second, a fair compensation-based MCS community is an important mechanism for crowd workers' continued participation intention in both motivation stages (ER and IM). Distributive justice (DJ) could substantially help low self-efficacy crowd workers to sustain their participation intention when they are externally motivated. Still, too much DJ would undermine intrinsically motivated, high self-efficacy crowd workers' continued participation intention. These findings support Vancouver et al.'s (2008) conclusion that self-efficacy was found to relate negatively to the magnitude of resources allocated for accepted goals but positively to directing resources towards an unattained goal. It is logical that, when crowd workers are motivated by ER and have chosen to participate in compensation-based MCS, they are vastly working for economic rewards. Conversely, when crowd workers are motivated by IM and IR, they pursue rewards beyond tangible measurements. This latter group of crowd workers will consistently and continuously expend effort until its needs are satisfied and its obligations are fulfilled, and hence, the probability-centric logic positive model is suitably applied.

5.2 Practical Implications

This study offers several practical insights into compensation-based MCS practitioners such as crowd workers in Amazon's mechanical Turk, oDesk and Rent-a-coder. First, the critical success factor of MCS is the continuous participation of the crowd workers. Because these platforms have low entry barriers, crowd workers can join and leave at any time. To sustain high-quality crowd workers, requesters must address both crowd workers' extrinsic and intrinsic motivations in good balance. Tasks should be set at the appropriate complexity level; otherwise, intrinsically motivated crowd workers would not participate because their competence needs would remain unfulfilled. Crowd workers who are motivated by external regulation only choose to participate in tasks according to their return-on-investment calculation. They may lessen their effort if they find that the incentive is no longer attractive, and this reduction directly affects the quality of their task submissions. MCS platform operators may consider enhancing the reward system based on their previous participation records and qualifications. The magnitude of rewards could be increased from previous rewards to attract experienced crowd workers to participate in future MCS tasks.

Finally, too much emphasis on distributive justice will hinder instead of enhancing continued participation intention of intrinsically motivated crowd workers with high self-efficacy. Requesters should pay more attention to ways to praise crowd workers' value and contributions instead of merely emphasising the fairness of reward distribution.

5.3 Limitations

There are several limitations present in this research study, the first of which pertains to generalizability. Data collection was restricted to one single crowdsourcing platform – Amazon MTurk – on which most of the respondents were from the U.S. and India. This geographic bias may limit the generalizability

of results to other platforms that feature participants from different cultures, such as the China-based MCS platform Taskcn, or that feature tasks of a different nature, such as Topcoder, information technology-based MCS platform. Future research may consider collecting data from other MCS platforms worldwide.

Second, the problem of common method bias may exist because the data were self-reported (Podsakoff, MacKenzie & Podsakoff, 2012) and were collected over a single period (Straub, Limayem & Karahanna-Evaristo, 1995). Although the common method bias did not significantly influence the findings, future research should consider using multiple methods (e.g., focus groups, direct observation and log files) and longitudinal research designs to address the above issues. Hence, no causality relationship among the constructs is obtained because this research is considered cross-sectional in nature. Longitudinal data may allow researchers to examine further the causality of the hypothesised relationship in this study.

Third, the current study surveys a general perception of crowd workers. As Franzoni and Sauermann (2014) suggested, crowd workers would be favourable to a specific challenging task and intrinsically motivated to complete the task. Future studies could ask crowd workers to participate in a simple experiment to complete a specific task, as Goodman and Paolacci (2017) advised, followed by reliability measures in the crowdsourced populations. Our model variables were tailored to reflect attitudes towards the task in which the respondents had participated and assess their intention to complete future tasks of a similar kind on that crowdsourcing platform. Moreover, self-efficacy measurement should be specific to the particular task (Feng et al., 2018).

Fourth, it would be interesting to examine the trade-offs among different tasks, depending on the respondents' underlying motivations, self-efficacy, and perhaps even distributive justice. For example, a choice-based experiment would allow for assessing the varying importance of options for continued engagement in compensation-based context (e.g., how much compensation is needed for a high-complexity task in consideration of different levels of self-efficacy).

Last, according to the expectation–confirmation theory, participants' continued participation intention and ongoing use of information systems stem primarily from their satisfaction with prior use of those products or services (Anderson & Sullivan, 1993), and in turn, satisfaction is determined by consumers'/participants' pre-consumption expectations and post-consumption confirmation. Confirmation comprises subjective judgments resulting from comparing expectations and perceptions of performance received. Future research may include both constructs – participants' satisfaction and confirmation – into the model.

6. CONCLUSION

The micro-task crowdsourcing community has emerged as a popular innovation tool and attracted increasing attention from practitioners and academics over the past decade. Motivated by the importance of continued participation intention for compensation-based micro-task crowdsourcing communities, we adopted expectancy theory, self-determination theory, organisational justice theory and self-efficacy theory to develop and test a theoretical model that demonstrates how different motivational factors could affect continued participation intention. Distributive justice and self-efficacy are considered to moderate the relationship among different motivations and continued participation intention. The confirmed three-way interaction effects indicate that external regulation and intrinsic motivation on continued participation intention are contingent on distributive justice and the level of self-efficacy. The findings enrich the understanding of MCS communities and provide important guidelines for requesters to motivate crowd workers to continue to participate in crowdsourcing platforms. This research echoes the following quote by Albert Bandura (http://learningandtheadolescentmind.org/people_06.html): 'To succeed, people need a sense of self-efficacy, to struggle together with resilience to meet the inevitable obstacles and inequities of life'.

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Gabriel Shing-Koon Leung is the Managing Director of Hewlett Packard Enterprise, Hong Kong and Macau, responsible for overseeing the company's business strategy and operations in these markets. Dr. Leung was the General Manager of EMC Corporation, Hong Kong and Macau for 17 years; and prior to joining EMC, he was the General Manager of Sun Microsystems, Hong Kong and Macau. With extensive experience in the ICT industry, Dr. Leung is keen on driving the development of the local ICT industry as well as coaching and nurturing local IT talent. He was born in Hong Kong and was graduated at the University of Birmingham, UK. He holds a bachelor's degree in Electronic and Electrical Engineering. He obtained his Doctor of Business Administration degree from The Hong Kong Polytechnic University and was conferred as Fellow of the Hong Kong Computer Society. Dr. Gabriel Leung actively serves the industry and the community at large. He currently holds the following related appointments / positions: Chairman of ICT Management Club & Executive Member of IT Management Committee - The Hong Kong Management Association. Vice President of Executive Committee - The Greater Bay Area 5G Industry Alliance. Member of Innovation and Technology Fund, Research Project Assessment Panel - Government of the HKSAR. Member of HK Cyberport Entrepreneurship Centre Advisory Group. Member of Hong Kong Retail Management Association Digital Advisory Panel. Council Member & Vice President - Hong Kong Computer Society (2010 - 2021). Member of the ICT Services Advisory Committee - Hong Kong Trade Development Council (2017 - 2021). Member of the Departmental Advisory Committee, Computer Science Department, City University of Hong Kong (2009 to 2016).

Vincent Cho is an associate Professor in the Department of Management and Marketing, The Hong Kong Polytechnic University. He obtained his PhD from the Hong Kong University of Science and Technology. His teaching interests are MIS, e-commerce and IT strategies. His research interests lie with social media influence, technology adoption, and data mining. He has published in IEEE Transactions on Engineering Management, Journal of Computer-mediated communications, Information & Management, Journal of Engineering and Technology Management, Expert Systems with Applications, Information Technology & People, Technological Forecasting and Social Change, Computers & Education, Knowledge and Information Systems, IEEE Systems Journal, Computers in Human Behavior, Behavior and Information Technology, International Journal of Production Research, Journal of Computer Information Systems, Expert Systems, Knowledge-Based Systems, Journal of Global Marketing, International Journal of Technology and Management, Journal of Hospitality & Tourism Research, International Journal of Hospitality Management, Tourism Management, Annals of Tourism Research and Journal of Tourism & Hospitality. Recently, he has involved with various consultancy projects relating to social media influence, software vendor partnership, and demand forecasting.

C. H. Wu holds a Bachelor of Engineering in Industrial and Systems Engineering, and a PhD in Manufacturing and Industrial Engineering. He also holds a six sigma black belt certification from the Hong Kong Society of Quality and he contributes regularly to research papers in the areas of Internet of Things, Engineering Optimisation and Business Intelligence. His project works and research outcomes have been presented in 10+ international conferences and published in 60+ international refereed journals. To stay at the top of his field, Dr Wu is a member of IEEE and a senior member of the Hong Kong Society of Quality. Additionally, Dr Wu serves on the editorial boards of the International Journal of Engineering Business Management, and Enterprise Information Systems. As he looks to the future, Dr Wu intends to continue researching in the fields of Industrial Internet of Things (IIoT), Industry 4.0 and healthcare technology.