Stay or Leave: Investigating Factors Impact Crowd-Based Workers' Platform-Based Justice Perceptions and Turnover Intentions

Xiaochuan Song Texas A&M University – Kingsville

Crowdsourcing has emerged as a transformative business model, harnessing collective intelligence to tackle complex tasks efficiently. However, the impact of crowd-based platforms on workers' justice perceptions is still understudied. This research delves into organizational justice perceptions among crowd-based workers, focusing on platform features that influence these perceptions as well as workers' subsequent turnover intentions. Drawing on data collected from 364 workers across multiple platforms, findings indicate that equitable compensation policies, participative evaluation, interactive and considerate communication, and rule-based evaluation can enhance procedural, distributive, and interactional justice perceptions, which in turn, significantly reduce turnover intentions. Moreover, media richness moderates part of these relationships, strengthening the mitigating effects of justice perceptions on turnover intentions. The study contributes to understanding the dynamics of organizational justice in crowdsourcing contexts and provides insights for platform management strategies to enhance worker retention.

Keywords: crowdsourcing, crowd-based platform, organizational justice, turnover intention

INTRODUCTION

Crowdsourcing has emerged as a powerful business model over the past couple of decades, transforming how companies innovate and solve problems and providing cost-effective solutions (Howe, 2006; Brabham, 2013). By leveraging collective intelligence and diverse skill sets from a large group of individuals and disintegrating large projects into micro-tasks, crowdsourcing has enabled organizations to achieve business goals more efficiently than traditional methods (Saxton et al., 2013; Majchrzak & Malhotra, 2013).

The application of crowdsourcing has established crowd-based labor, enabling gig work as an integral component of the gig economy, which offers independent workers opportunities to be paid by task or project, rather than through traditional employment models (Kuek et al., 2015). Further, for individuals who face challenges in securing traditional employment due to personal or non-personal reasons, crowdsourcing platforms provide a viable alternative for job opportunities and income generation (Felstiner, 2011).

UNADDRESSED ISSUES AND PLAN OF THE RESEARCH

Despite its benefits, crowd-based labor comes with significant concerns and challenges. Previous studies have documented that poorly designed crowdsourcing processes can result in low-quality submissions, problematic integration of micro-tasks within a larger project, and misunderstandings about

project goals (Kazman & Chen, 2009; Schenk & Guittard, 2011). Furthermore, from a regulatory standpoint, the existing legal frameworks in the U.S. have not fully adapted to this relatively new business model (Kazman & Chen, 2009). For instance, current laws and regulations often do not account for the unique aspects of crowdsourcing, leading to gaps in legal protection for crowd-based workers (Bergvall-Kåreborn & Howcroft, 2014) because the ambiguous legal status of crowd-based workers does not fit neatly into traditional employee or independent contractor categories. This ambiguity can lead to issues regarding worker rights, compensation, benefits, and protections, raising concerns about justice and fairness when it comes to managing crowd-based labor (Cherry, 2010).

When it comes to justice issues, the concept of organizational justice is well-positioned to capture the extent to which crowd-based workers are fairly treated. Organizational justice refers to workers' perceptions of fairness in their workplace, encompassing how fairly an organization treats its employees across several dimensions (Greenberg, 1987). In the context of crowdsourcing, organizational justice is more complex than in traditional work environments due to the tripartite relationship involving the 1) platform, 2) requesting clients (i.e., requesters), and 3) workers, adding complexity to justice perceptions. To date, most studies in crowdsourcing literature focus on the outcomes of organizational justice, leaving the antecedents remain understudied (Brawley & Pury, 2016). Furthermore, in the crowdsourcing context, justice perceptions are often mixed. For instance, some workers may feel unfairly treated by the platform, while others may perceive injustices, particularly in terms of payment and task allocation, from the requester, or platform, or both, making it imperative to explore the factors that impact justice perceptions among crowd-based workers and look into justice issues from platform and requester separately.

To address these gaps and provide a clearer understanding of justice issues in the crowdsourcing context, this study specifically captures workers' justice perceptions about the platform, recognizing that platforms face significant challenges (Mickos, 2020; Walsh & Volini, 2017), such as quality and fragmentation of work. Meanwhile, focusing on platforms is also meaningful since they are central to job creation and provide opportunities for individuals with limited access to the traditional job market (Mickos, 2020). Further, due to the tripartite relationship noted earlier as well as the unique dynamics of gig work, turnover in the crowdsourcing context differs from traditional working context, including 1) moving from one requester to another within the same platform and 2) moving from one platform to another.

Collectively, by examining factors that impact crowdsourcing workers' organizational justice perceptions and subsequent turnover intentions, the present study aims to contribute to a deeper understanding of organizational justice in crowdsourcing and its implications for platform management and gig worker retention.

LITERATURE REVIEW

Theoretical Background

Organizational justice is typically understood through three primary dimensions, including 1) distributive justice, 2) procedural justice, and 3) interactional justice. Distributive justice focuses on the perceived fairness of outcomes or distributions within the organization, involving the equitable allocation of rewards and resources, ensuring that employees feel their contributions are appropriately recognized and compensated (Colquitt, 2001), and factors such as pay, promotions, and benefits are central to distributive justice (Adams, 1965). Procedural justice pertains to the fairness of the processes and methods used to determine outcomes, which emphasize the importance of consistent, unbiased, accurate, and ethical procedures, and employees are more likely to accept outcomes if they believe the processes leading to those outcomes were fair and transparent (Leventhal, 1980; Thibaut & Walker, 1975). Interactional justice deals with the quality of interpersonal treatment employees receive during the implementation of procedures, including aspects such as respect, dignity, and the adequacy of explanations provided (Bies & Moag, 1986). These dimensions, taken together, collectively influence various job-related outcomes, such as job satisfaction, trust in management, and organizational commitment (Colquitt et al., 2001).

HYPOTHESIS DEVELOPMENT

Platform Technologies/Features to Organizational Justice

In the context of crowdsourcing, justice perceptions are particularly crucial because they provide a comprehensive framework for understanding fairness in crowdsourcing settings, and participative performance evaluation (PPE) would predict procedural justice (PJ) positively. PPE involves employees actively engaging in the performance evaluation process, providing feedback, and having a voice in how their performance is assessed (Grote, 1996; Bouckenooghe et al., 2007). Research indicates that when employees perceive they have a meaningful role in the evaluation process, it enhances their perceptions of fairness in procedural justice because participative approaches to performance evaluation are aligned with principles of transparency, consistency, and voice in the decision-making process, which are key components of procedural justice (Cropanzano et al., 2001; Colquitt, 2001). As noted earlier, procedural justice refers to the perceived fairness of the processes used to make decisions, including those related to performance evaluation. When employees participate in performance evaluation processes, they are more likely to perceive that procedures are fair, unbiased, and considerate of their input, leading to higher levels of trust in the organization and greater satisfaction with evaluation outcomes (Folger & Konovsky, 1989; DeConinck, 2010). Further, when employees are involved in the evaluation process, they are more likely to perceive the procedures as fair because their input and perspectives are considered (Thibaut & Walker, 1975). This sense of involvement and fairness is crucial for fostering trust in management and organizational commitment (Colquitt et al., 2001). Therefore, when it comes to crowd-based work, platforms that adopt PPE practices are likely to enhance workers' perceptions of PJ in a crowd-based context.

Hypothesis 1. There is a positive relationship between PPE and PJ among crowd-based workers.

Similar to PPE, there could be a positive relationship between rule-based evaluation (RBE) and procedural justice (PJ). RBE refers to performance appraisal systems that emphasize clear, objective criteria and standardized procedures in evaluating employee performance (Ford, 1996; Pulakos & Schmitt, 1995). Such systems are designed to ensure fairness and transparency in decision-making processes, aligning with the principles of procedural justice. Previous studies have suggested that when organizations employ rule-based approaches to performance evaluation, employees perceive the evaluation process as more consistent, predictable, and unbiased (Leventhal, 1980; Greenberg, 2013). This perception enhances their belief that procedures are applied fairly and consistently across individuals, leading to higher levels of procedural justice perceptions (Cropanzano et al., 2001; Colquitt, 2001). In a crowd-based working environment, workers are more likely to accept and trust the outcomes of performance evaluations when RBE is present, fostering greater perceptions of PJ.

Hypothesis 2. There is a positive relationship between RBE and PJ among crowd-based workers.

Moving to distributive justice (DJ), equitable compensation policy (ECP) would predict a higher DJ. ECP refers to the fairness and equality perceived in the distribution of rewards and benefits among employees based on their contributions and performance (Adams, 1963; Leventhal, 1976). When organizations implement policies that ensure equitable compensation, employees are more likely to perceive the outcomes of reward allocation as fair and just (Folger, 1986; Colquitt, 2001). As noted earlier, DJ is a component of organizational justice that focuses on the perceived fairness of outcomes, such as pay, benefits, and recognition (Greenberg, 1987). Research indicates that when employees perceive their compensation as fair and commensurate with their efforts and contributions, they are more satisfied and committed to their organization (Folger & Cropanzano, 1998; DeConinck, 2010). Applying to the crowd-based working environment, platforms that emphasize equitable compensation policies enhance workers' perceptions of distributive justice, fostering positive attitudes and behaviors crucial for organizational effectiveness.

Hypothesis 3. There is a positive relationship between ECP and DJ among crowd-based workers.

Regarding interactional justice (IJ), there would be a positive relationship between perceived interactivity in real-time conversation (PIRC) and IJ. PIRC refers to the perception of real-time interaction and responsiveness in communication channels within organizational settings (Rafaeli & Sudweeks, 1997). As discussed earlier, IJ is a facet of organizational justice that focuses on the fairness of interpersonal treatment and communication processes during organizational interactivity in real-time conversation, they are more likely to perceive the interpersonal treatment they receive as fair and respectful (Rafaeli & Sudweeks, 1997; Colquitt et al., 2001). This perception of fairness in interpersonal interactions enhances employees' trust in organizational authorities and promotes positive organizational citizenship behaviors (Colquitt et al., 2007; Gilliland, 1993). Extending to the crowd-based working environment, platforms that emphasize and facilitate real-time interaction and responsiveness are likely to enhance workers' perceptions of interactional justice, contributing to a positive organizational climate and crowd-based workers' well-being.

Hypothesis 4. There is a positive relationship between PIRC and IJ among crowd-based workers.

Similarly, there would be a positive relationship between perceived interactivity in engagement (PIE) and IJ. PIE refers to individuals' perceptions of interactive and engaging communication processes within organizational contexts, which foster a sense of involvement and responsiveness (Rafaeli & Ariel, 2008). Research indicates that when employees perceive high levels of engaging interactivity in their interactions, they are more likely to perceive these interactions as fair and respectful (Rafaeli & Ariel, 2008; Colquitt et al., 2001). This perception of fair treatment enhances trust in organizational authorities and promotes positive organizational behaviors (Colquitt et al., 2007). Platforms that prioritize and facilitate engaging and interactive communication processes are therefore likely to enhance workers' perceptions of IJ, fostering a supportive organizational climate and enhancing employee well-being.

Hypothesis 5. There is a positive relationship between PIE and IJ among crowd-based workers.

Further, there is a positive relationship between considerate supervisory communication (CSC) and IJ, empirical evidence and theoretical foundations provide robust support. CSC refers to supervisors' behaviors that convey respect, concern, and fairness in their interactions with employees (Eisenberger et al., 1986). Research suggests that employees perceive interactions as fair and just when supervisors exhibit considerate communication behaviors, such as listening attentively, providing clear explanations, and showing empathy (Eisenberger et al., 1986; Colquitt et al., 2001). Such behaviors enhance employees' perceptions of being valued and respected, which in turn fosters trust in their supervisors and the organization as a whole (Colquitt et al., 2001; Scott & Colquitt, 2007). Therefore, platforms that promote considerate supervisory communication are likely to enhance interactional justice perceptions among workers, thereby contributing to a positive work environment and improved organizational outcomes.

Hypothesis 6. There is a positive relationship between CSC and IJ among crowd-based workers.

Empirical studies and theoretical underpinnings also support that there is a positive relationship between considerate personal feedback (CPF) and interactional justice (IJ). CPF refers to how feedback is delivered to employees, emphasizing respect, empathy, and constructive intent (Colquitt et al., 2001). As a key dimension of organizational justice, IJ focuses on the fairness perceived in interpersonal interactions and communications within the workplace (Bies & Moag, 1986). Research indicates that employees perceive interactions as fair and just when feedback is provided considerately, considering the individual's perspectives and developmental needs (Colquitt et al., 2001; Greenberg, 1990). When feedback is delivered in a respectful and supportive manner, employees are more likely to view the process as fair and perceive their supervisors as trustworthy and caring (Greenberg, 1990; Colquitt et al., 2001). Expanding to the

crowd-based working environment, organizations that prioritize considerate personal feedback are likely to enhance interactional justice perceptions among workers.

Hypothesis 7. There is a positive relationship between CPF and IJ among crowd-based workers.

Organizational Justice to Turnover Intention

In the realm of organization justice research, the taxonomy of organizational justice theories (Greenberg, 1987) provides a comprehensive framework for understanding outcomes of justice perceptions in crowdsourcing settings. This taxonomy categorizes theories of organizational justice along two independent dimensions: Reactive-Proactive Dimension, with 1) reactive theories focus on how individuals respond to unfair treatment, examine the psychological behavioral reactions of employees when they perceive injustices in the workplace, and consequences of perceived unfairness, including emotional responses, intentions to retaliate, or withdrawal from the organization; while 2) reactive theories are concerned with the, whereas proactive theories explore how individuals and organizations strive to create fair environments. Moving to the Process-Content Dimension, includes 1) process theories, which focus on the fairness of procedures used to determine outcomes; and 2) content theories, which focus on the fairness of the actual outcomes or distributions within the organization.

These two dimensions, taken together, create a 2 by 2 matrix, resulting in four distinct categories of organizational justice theories, including 1) Reactive Content, which addresses reactions to unfair outcomes, focusing on the consequences of perceived distributive injustices; 2) Proactive Content, which focuses on creating fair outcome distributions, emphasizing strategies for equitable resource allocation; 3) Reactive Process, which examines reactions to unfair procedures, highlighting the importance of procedural justice; and 4) Proactive Process, which explores ways to create fair procedures, stressing the establishment of fair processes within organizations. This taxonomy helps to clarify theoretical interrelationships and identify areas where further research is needed in the field of organizational justice. Applying the taxonomy of organizational justice theories to the crowdsourcing working context, it is evident that workers' responses to justice issues can be explained by reactive content and reactive process because both of them explain individuals' responses to fairness issues.

Moving to the crowdsourcing context, there would be a negative relationship between procedural justice (PJ) and turnover intention (TI). Workers who perceive PJ in their workplaces tend to feel valued and respected, believing that decisions affecting them are made fairly and impartially (Colquitt et al., 2001). Consequently, when workers perceive higher levels of procedural justice, they are less likely to experience negative emotions such as job dissatisfaction or feelings of being unfairly treated, which are significant predictors of turnover intention (Liu et al., 2013). Therefore, platforms that prioritize procedural fairness are likely to mitigate turnover intentions by fostering positive perceptions of fairness and trust among their workers.

Hypothesis 8. There is a negative relationship between PJ and TI among crowd-based workers.

In a similar vein, there could be a negative relationship between distributive justice (DJ) and turnover intention (TI). Employees' perceptions of distributive justice are crucial as they influence their overall satisfaction and commitment to the organization (Cropanzano et al., 2007). When workers believe that outcomes such as pay, benefits, and rewards are distributed fairly relative to their contributions and those of others, they are more likely to experience higher job satisfaction and lower turnover intentions (Cohen-Charash & Spector, 2001; Cropanzano et al., 2007). Studies also consistently demonstrate that perceptions of unfairness in reward distribution are associated with increased turnover intentions due to dissatisfaction and a sense of inequity (Cohen-Charash & Spector, 2001; Cropanzano et al., 2007). Therefore, platforms that ensure fair and equitable distribution of rewards are likely to reduce workers' turnover intentions by fostering positive perceptions of distributive justice among employees.

Hypothesis 9. There is a negative relationship between DJ and TI among crowd-based workers.

Further, there will be a negative relationship between interactional justice (IJ) and turnover intention (TI) because it is crucial to consider the impact of how workers perceive the interpersonal treatment they receive within the organization. When workers feel that they are treated with dignity, respect, and consideration in their workplace interactions, they are more likely to develop positive attitudes toward their job and the organization as a whole (Colquitt et al., 2001). Research indicates that higher levels of interactional justice are associated with greater job satisfaction and lower turnover intentions among employees (Colquitt et al., 2001; Cohen-Charash & Spector, 2001). Conversely, perceptions of unfair or disrespectful treatment can lead to dissatisfaction and a desire to leave the organization. Therefore, platforms that prioritize and enhance interactional justice are likely to mitigate workers' turnover intentions by fostering positive perceptions of fairness and respect in interpersonal interactions.

Hypothesis 10. There is a negative relationship between IJ and TI among crowd-based workers.

Mediating Role of Organizational Justice

Organizational justice will impact workers' attitudes and behaviors. As noted earlier, PPE involves employees in decision-making processes, which enhances procedural justice perceptions by providing transparency and voice (Cropanzano et al., 2001). Research suggests that higher procedural justice reduces turnover intention by fostering trust and fairness in organizational processes (Colquitt et al., 2001). Similarly, RBE provides clear guidelines, enhancing procedural justice perceptions, which in turn reduces turnover intention by ensuring consistency and transparency (Bies & Shapiro, 1988). Further, ECP contributes to distributive justice perceptions by ensuring fair allocation of rewards, thereby reducing turnover intention through perceived fairness in resource distribution (Adams, 1963); PIRC and PIE foster interactional justice, which reduces turnover intention by promoting respectful and considerate treatment (Colquitt et al., 2001; Bies & Moag, 1986); CSC and CPF enhance interactional justice, mitigating turnover intention through supportive and respectful interpersonal relationships (Eisenberger et al., 1986; Colquitt et al., 2001). Overall, these hypotheses suggest that enhancing organizational justice perceptions can effectively reduce turnover intention by promoting fairness, transparency, and respect in organizational practices.

Hypothesis 11. There is an indirect effect from PPE to TI through PJ among crowd-based workers.

Hypothesis 12. There is an indirect effect from RBE to TI through PJ among crowd-based workers.

Hypothesis 13. There is an indirect effect from ECP to TI through DJ among crowd-based workers.

Hypothesis 14. There is an indirect effect from PIRC to TI through IJ among crowd-based workers.

Hypothesis 15. There is an indirect effect from PIE to TI through IJ among crowd-based workers.

Hypothesis 16. There is an indirect effect from CSC to TI through IJ among crowd-based workers.

Hypothesis 17. There is an indirect effect from CPF to TI through IJ among crowd-based workers.

Moderating Role of Media Richness

Media Richness (MR) could moderate the relationship between Procedural Justice (PJ) and Turnover Intention (TI). It is crucial to understand the role of communication richness in organizational contexts. Media richness theory posits that communication effectiveness depends on the richness of the medium used, with richer media facilitating more thorough information processing and understanding (Daft & Lengel, 1986). Research suggests that when communication channels are rich (e.g., face-to-face meetings, video

conferencing), employees may perceive procedural justice more positively due to enhanced information clarity and interpersonal interaction (Cabello-Medina et al., 2011). This increased clarity and interaction can strengthen the negative relationship between procedural justice and turnover intention by fostering greater trust in organizational procedures and decisions (Cropanzano et al., 2001). Conversely, when communication channels are less rich (e.g., emails, memos), the clarity and depth of procedural justice communication may be reduced, potentially weakening its impact on turnover intention. Therefore, higher levels of media richness are likely to amplify the beneficial effects of procedural justice on reducing turnover intention through enhanced communication and interaction clarity in the crowd-based working environment.

Similarly, Media Richness (MR) could also moderate the relationship between Distributive Justice (DJ) and Turnover Intention (TI). It is essential to consider how communication richness influences employees' perceptions and behaviors within organizations. When communication channels are rich (e.g., face-to-face meetings, video conferencing), employees may receive more detailed explanations about reward decisions, leading to a clearer understanding and acceptance of outcomes (Greenberg, 1993). This enhanced clarity and interaction can strengthen the negative relationship between distributive justice and turnover intention by fostering greater trust in the fairness of reward distributions (Cohen-Charash & Spector, 2001). Conversely, in contexts with less rich communication channels (e.g., written memos, and emails), the depth and clarity of distributive justice communications may diminish, potentially weakening its impact on turnover intention. Therefore, higher levels of media richness are likely to amplify the beneficial effects of distributive justice on reducing turnover intention through enhanced communication clarity and interpersonal interaction in the crowd-based working environment.

Further, Media Richness (MR) could also moderate the relationship between Interactional Justice (IJ) and Turnover Intention (TI). High levels of interactional justice are associated with positive employee perceptions, as they reflect respectful and dignified treatment by supervisors and colleagues (Colquitt et al., 2001). When communication channels are rich (e.g., face-to-face interactions, video conferencing), employees experience more personal and detailed exchanges that enhance their sense of fairness and respect in interpersonal interactions. This heightened clarity and immediacy of communication can strengthen the negative relationship between interactional justice and turnover intention by fostering stronger emotional connections and trust in organizational relationships (Tyler & Blader, 2003). Conversely, in environments with lower media richness (e.g., written communication, and emails), the depth and personal connection inherent in interactional justice may be diluted, potentially weakening its impact on turnover intention. Therefore, higher levels of media richness are likely to amplify the beneficial effects of interactional justice on reducing turnover intention through enhanced interpersonal communication and relationship quality in the crowd-based working environment.

Hypothesis 18. MR moderates the relationship between PJ and TI, such that the negative relationship will be strengthened when MR is at a higher level.

Hypothesis 19. MR moderates the relationship between *DJ* and *TI*, such that the negative relationship will be strengthened when *MR* is at a higher level.

Hypothesis 20. MR moderates the relationship between IJ and TI, such that the negative relationship will be strengthened when MR is at a higher level.

FIGURE 1 CONCEPTUAL MODEL



ECP: Equitable Compensation Policy. PPE: Participative Performance Evaluation. MR: Media Richness. PIRC: Perceived Interactivity - Real-time Conversation. PIE: Perceived Interactivity - Engaging. CSC: Considerate Supervisory Communication. CPF: Considerate Personal Feedback. RBE: Rule-Based Evaluation. PJ: Procedural Justice. DJ: Distributive Justice. IJ: Interactional Justice. TI: Turnover Intention.

METHODS AND PROCEDURES

Samples and Procedures

Data was collected from multiple online crowdsourcing platforms. Online panels have been widely used in social management and organization-related research in the past decade (Landers & Behrend 2015; Porter et al. 2019) because of their increased validity (Cheung et al. 2017) and quality (Landers & Behrend 2015). Online panels can also provide opportunities to match the scientific community with study participants - registered users comprising diverse working people around the world (Palan & Schitter 2018; Song & Whitman, 2024). Additionally, Daniel et al. (2023) Porter et al. (2019) and posited that using online-based panels as a source of data collection is appropriate because subjects from online panels have an adequate level of capabilities to provide valid data. To ensure data quality, applying quality maintenance practices in online panel data collection (e.g., Lovett et al. 2018), two inclusion criteria were applied. First, only full-time and part-time crowdsourcing working individuals were allowed to participate in the study, and people who worked on online survey jobs only (e.g., professional survey takers) were ineligible. Second, participants had to understand English before being recruited as participants. Additionally, since it is possible for crowd-based workers to work on more than one crowdsourcing platform, I request all participants to report all variables based on their primary crowdsourcing job – the one that takes the highest percentage of time to work.

A longitudinal data collection approach was applied by administering three surveys, such that the survey at Time 1 (T1) was delivered in the first week, the survey at Time 2 (T2) was delivered in the third week, and the survey at Time 3 (T3) was delivered in the fifth week. Using a longitudinal data collection approach can reflect the temporal order of the model, and the two-week interval aligns with the study design practice recommended by Podsakoff, MacKenzie, and Podsakoff (2012) to prevent common method bias. Following the practice of statistical power-based analysis (Browner et al. 2022; Chow et al. 2017) suggesting that the sample size needs to be higher than 126 to detect possible significant effect sizes, we

distributed surveys to 450 crowdsourcing workers online. After deleting responses that were incomplete and/or failed the attention checks, a total of 397 Prolific workers provided legitimate responses at T1 (88.22% of the initial sample). Of these 397 subjects who completed the T1 survey, 380 (95.71% of T1 respondents) finished the T2 survey, and 364 (95.78% of T2 respondents) finished the T3 survey. This sample comprised 65.66% of females. Detailed demographic information can be found in Table 1. The remaining analyses are based on the 364 participants who completed all three waves of surveys.

Study 1: Measures

Equitable Compensation Policy (ECP)

This variable was measured using a 3-item scale adapted from Martin & Peterson (1987). A sample item is "My pay is fair compared to the pay of other people doing the same kind of work on the platform." This variable was measured in the T1 survey. A high score on this measure indicates a more equitable compensation policy from the worker's perspective.

Participative Performance Evaluation (PPE)

This variable was measured at T1 using a 6-item scale adapted from Greenberg (1986). A sample item is "The platform solicits input before performance evaluation and use of performance evaluation." A high score on this measure indicates a higher level of participative performance evaluation from the worker's perspective.

Media Richness (MR)

This variable was measured by asking participants to report the highest level of media richness available in the platform they primarily work on, from a continuum ranging from 1-website information to 2-in-app message, 3-text message, 4-email, 5-phone call, 6-video call, and 7-face-to-face meeting. A high score on this measure indicates a higher level of media richness.

Perceived Interactivity in Real-Time Conversation (PIRC)

This variable was measured at T1 using a 7-item scale adapted from McMillan & Hwang (2002). A sample item is "The communication system on the platform enables concurrent communication." A high score on this measure indicates a higher level of real-time interaction in workers' perceptions.

Perceived Interactivity – Engaging (PIE)

This variable was measured at T1 using an 8-item scale adapted from McMillan & Hwang (2002). A sample item is "The communication system on the platform keeps my attention." A high score on this measure indicates more engaging communication perceived by workers.

Considerate Supervisory Communication (CSC)

This variable was measured at T1 using a 5-item scale adapted from Downs & Hazen (1977). A sample item is "The platform listens and pays attention to me." A high score on this measure indicates more considerate communication between the platform and the worker.

Considerate Personal Feedback (CPF)

This variable was measured at T1 using a 5-item scale adapted from Downs & Hazen (1977). A sample item is "I am provided information about how I am being judged." A high score on this measure indicates more personalized feedback workers received.

Rule-Based Evaluation (RBE)

This variable was measured at T1 using a 4-item scale developed by the author. A sample item is "The evaluation of task performance is based on universally accepted criteria or rules." A high score on this measure indicates that the evaluation is more inclined to universally accepted standards instead of idiosyncratic rules when it comes to performance evaluation.

Procedural Justice (PJ)

This variable was measured at T2 using a 7-item scale adapted from Saks (2006). A sample item is "The evaluation of task performance is based on accurate information." A high score on this measure indicates a higher level of perceived procedural justice.

Distributive Justice (DJ)

This variable was measured at T2 using a 5-item scale adapted from Saks (2006). A sample item is "The compensation reflects the effort I have put into my work." A high score on this measure indicates a higher level of perceived distributive justice.

Interactional Justice (IJ)

This variable was measured at T2 using a 4-item scale adapted from Saks (2006). A sample item is "I am always treated with courtesy and respect." A high score on this measure indicates a higher level of perceived interactional justice.

Turnover Intention (TI)

This variable was measured at T3 using a 3-item scale adapted from Cropanzano and James (1990). A sample item is "How likely is it that you will look for a job outside of this platform next year?"

Control Variables

Following the practice of control variable selection (Spector & Brannick 2011), control variables were selected based on the conceptual and theoretical interests of the study on crowdsourcing, including participants' age, gender, employment status outside the crowd-based job, and years of current crowdsourcing job.

Results

Descriptive Statistics and Correlations

Table 1 indicates the mean, standard deviation (SD), correlation coefficients, and reliability alpha. As indicated in Table 1, the reliability alpha of all measurement scales was between 0.82 and 0.93, indicating a good level of reliability (Cronbach and Meehl 1955; Tavakol and Dennick 2011). Results also show that ECP, PPE, PIRC, PIE, CSC, CPF, and RBE were positively related to three types of organizational justice (i.e., PJ, DJ, and IJ), suggesting that features and technologies offered by platforms facilitate higher levels of justice perceptions. Meanwhile, PJ, DJ, and IJ are negatively related to TI, suggesting that a higher level of justice perceptions will drive down the intention of turnover. I also conducted a multicollinearity test of control variables. The results indicate that the variance inflation factor (VIF) coefficients of control variables are between 1.52 and 2.60, which are below the cutoff value suggested by Craney & Surles (2002) and Thompson et al. (2017).

				5												
	1	2	3	4	5	9	7	8	6	10	11	12	13	14	15	16
1. ECP	0.83															
2. PPE	0.29^*	0.82														
3. MR	-0.03	-0.13														
4. PIRC	0.25	0.65^{**}	-0.11	0.87												
5. PIE	0.37	0.51^{*}	-0.03	0.52^{*}	0.88											
6. CSC	0.39^*	0.61^{*}	-0.08	0.61^{**}	0.62^{*}	0.84										
7. CPF	0.31	0.59^{*}	-0.11	0.57^{**}	0.51^{*}	0.68^{**}	0.80									
8. RBE	0.26	0.43^{**}	0.00	0.44^{*}	0.44^{**}	0.51^*	0.48^{**}	0.81								
9. PJ	0.35^{**}	0.51^{**}	-0.07	0.55^{**}	0.47^{**}	0.57^{**}	0.57^{*}	0.43^{*}	0.88							
10. DJ	0.50^{*}	0.43^{**}	-0.05	0.40^{*}	0.46^{**}	0.53^{**}	0.47^{**}	0.43^{*}	0.61^{**}	0.91						
11. IJ	0.33^*	0.50^{**}	-0.09	0.55^{*}	0.55^{*}	0.64^{*}	0.59^{**}	0.48^{**}	0.60^{*}	0.51^*	0.93					
12. TI	-0.23^{*}	-0.50^{**}	0.07	-0.50**	-0.43^{**}	-0.48^{*}	-0.46^{**}	-0.29	-0.36^{*}	-0.35*	-0.45*	0.92				
13. AGE	-0.04	-0.09	-0.14	-0.07	0.00	-0.05	-0.05	-0.05	-0.06	-0.09	-0.02	0.01	ı			
14. GEN	0.02	0.00	-0.07	0.03	0.04	0.02	0.00	-0.01	-0.00	-0.01	0.05	-0.07	0.21^{*}	ı		
15. EMP	-0.01	0.04	0.08	0.08	0.03	0.02	0.05	-0.04	0.06	-0.05	0.01	-0.12	0.15	0.06	ı	
16. YR	-0.04	-0.02	-0.16	-0.07	-0.05	-0.01	0.01	-0.06	0.01	-0.01	0.02	-0.08	0.59^{**}	0.18	0.06	-
Mean	3.52	3.38	3.71	3.39	3.77	3.55	3.41	3.64	3.27	3.50	3.65	2.56	28.81	1.34	1.64	4.98
SD	0.77	0.85	1.52	0.81	0.78	0.79	0.88	0.85	0.78	0.89	0.90	1.06	9.43	0.47	0.48	7.34
Notes: $p < p$	05, **p <	:.01. The l	bolded co	efficients	on the diag	gonal line	are Cronb	ach alpha	coefficien	ts. ECP: 2	SD: Stand	ard devia	tion. ECP	: Equita	ble Com	pensation
Policy. PPE	: Particil	pative Peri	formance	Evaluatic	on. MR: M	edia Rich	mess. PIR	C: Percei	ved Interac	ctivity - F	time	Converse	tion. PIE	: Perceiv	ved Inter	activity -
Engaging.	CSC: Co	nsiderate	Supervis	ory Com	municatior	n. CPF: C	Considerat	e Persona	al Feedbac	k. RBE:	Rule-Bas	sed Evalı	lation. PJ	: Proce	dural Ju	stice. DJ:
Distributive	Justice.	IJ: Intera	ctional J ₁	ustice. TI:	Turnover	Intention	I. GEN: g	ender. EN	AP: Emplc	yment St	atus Outs	ide the (Crowd-Ba	sed Job.	. YR: Y	ear of the
Current Crc	wd-Base	ed Job.														

TABLE 1 CORRELATION MATRIX AND SAMPLE STATISTICS Journal of Applied Business and Economics Vol. 26(5) 2024 73

Test of the Measurement Model

To assess the adequacy of the measurement model, we conducted a confirmatory factor analysis (CFA) by using Mplus 8 (Muthén and Muthén 2017). Twelve latent factors were specified to represent ECP, PPE, PIRC, PIE, CSC, CPF, RBE, PJ, DJ, IJ, and TO. The 11-factor model indicated good loading coefficients, with the loading ranging from 0.47 to 0.85 (Kline 2012). We further compared the 11-factor model with the 9-, 7-, 5-, 3-, and 1-factor models based on the CFA model comparison practice recommended by Cheung and Rensvold (2002). The model comparison results from Table 2 indicate that the 10-factor model has the best model fit based on the statistical results, such as Chi-square, RMSEA, TLI, CFI, and SRMR. In comparison, as shown in Table 2, the 9-, 7-, 5-, 3-, and 1-factor models indicated a significant model fit reduction, when compared with the 11-factor model (Hu & Bentler 1999).

TABLE 2CFA MODEL FIT COMPARISON

Model	Ν	χ^2	df	χ^2/df	RMSE	TLI	CFI	SRMR	Model Fit
					Α				Difference
The 11-Factor Model	364	2009.29	979	2.05	0.05	0.86	0.87	0.06	
The 9-Factor Model	364	2391.87	998	2.40	0.06	0.81	0.83	0.07	$\Delta \chi^2 = 382.58, \Delta df = 19$
The 7-Factor Model	364	2891.38	1013	2.85	0.07	0.75	0.77	0.07	$\Delta \chi^2 = 499.51, \Delta df = 15$
The 5-Factor Model	364	3046.75	1024	2.98	0.07	0.74	0.75	0.07	$\Delta \chi^2 = 155.37, \Delta df = 11$
The 3-Factor Model	364	3248.23	1031	3.15	0.08	0.71	0.73	0.07	$\Delta \chi^2 = 201.48, \Delta df = 7$
The 1-Factor Model	364	3619.27	1034	3.50	0.08	0.67	0.68	0.07	$\Delta \chi^2 = 371.04, \Delta df = 3$

Notes: N: Sample size; χ^2 : Chi-square; df: Degree of freedom; p: p-value; *RMSEA*: Root mean square error of approximation; *TLI*: Tucker-Lewis Index; *CFI*: Comparative fit index; *SRMR*: Standardized root mean square residual; Δdf : change in the degree of freedom; $\Delta \chi^2$: change in Chi-square.

Test of Common Method Variance

To detect common method variance, we used the unmeasured latent method construct (ULMC) approach suggested by Williams & McGonagle (2016). The ULMC accounted for an average of 32.41% of the variance in the substantive indicators, which is below the cut-off of 70% suggested by Fuller et al. (2016). Further, we conducted Harman's single-factor test (Aguirre-Urreta and Hu 2019), which indicates that the single factor accounted for 48.57% of the variance among indicators. This result is below the 50% cutoff percentage suggested by Podsakoff et al. (2003). Taken together, there is not a substantial presence of common method bias in the study.

Hypothesis Test

Path Analysis

We employed path analysis to test the effects of ECP, PPE, PIRC, PIE, CSC, CPF, and RBE on PJ, DJ, and IJ, and from PJ, DJ, and IJ to TI. These effects correspond to Hypotheses 1 to 10. As shown in Table 3, there is a significant positive relationship between PPE and PJ (b=0.393, p<0.01), RBE and PJ (b=0.263, p<0.01), ECP and DJ (b=0.497, p<0.01), PIRC and IJ (b=0.154, p<0.01), PIE and IJ (b=0.189, p<0.01), CSC and IJ (b=0.288, p<0.01), CPF and IJ (b=0.209, p<0.01), DJ and TI (b=-0.143, p<0.05) and IJ and TI (b=-0.350, p<0.01). Therefore, Hypotheses 1-7, 9, and 10 were supported.

TABLE 3PATH ANALYSIS RESULTS

	DV: PJ		DV: DJ		DV: IJ		DV: TI	
	b	SE	b	SE	b	SE	b	SE
PPE	0.393**	0.045						
RBE	0.263**	0.047						
ECP			0.497^{**}	0.039				
PIRC					0.154^{**}	0.050		
PIE					0.189^{**}	0.049		
CSC					0.288^{**}	0.057		
CPF					0.209^{**}	0.053		
PJ							-0.057	0.066
DJ							-0.143*	0.061
IJ							-0.350**	0.057
R^2	0.3	312	0.2	247	0.4	195	0	0.202

Notes: ***p* < .01, **p* < .05,

SE: Standard Error. ECP: Equitable Compensation Policy. PPE: Participative Performance Evaluation. MR: Media Richness. PIRC: Perceived Interactivity - Real-time Conversation. PIE: Perceived Interactivity - Engaging. CSC: Considerate Supervisory Communication. CPF: Considerate Personal Feedback. RBE: Rule-Based Evaluation. PJ: Procedural Justice. DJ: Distributive Justice. IJ: Interactional Justice. TI: Turnover Intention. R²: R-Square.

Mediation Test

Moving to the indirect effect, Hypothesis 11 to 17 posits mediations from crowdsourcing features (ECP, PPE, PIRC, PIE, CSC, CPF, and RBE) to TI, through PJ, DJ, and IJ. The results indicate significant mediations, including PIRC-IJ-TI (b=-0.054^{*}, p<0.05), PIE-IJ-TI (b=-0.066^{**}, p<0.01), CSC-IJ-TI (b=-0.101^{**}, p<0.01), and CPF-IJ-TI (b=-0.073^{**}, p<0.01), suggesting that Hypotheses 14, 15, 16, and 17 were supported.

Mediation Path	b	SE	CI (95%)
PPE-PJ-TI	-0.022	0.029	(-0.086, 0.029)
RBE-PJ-TI	-0.015	0.019	(-0.056, 0.021)
ECP-DJ-TI	-0.071	0.038	(-0.149, 0.002)
PIRC-IJ-TI	-0.054*	0.023	(-0.105, -0.013)
PIE-IJ-TI	-0.066**	0.023	(-0.114, -0.024)
CSC-IJ-TI	-0.101**	0.031	(-0.166, -0.045)
CPF-IJ-TI	-0.073**	0.027	(-0.130, -0.024)

TABLE 4MEDIATION TEST RESULTS

Notes: **p* < .05, ***p* < .01.

SE: Standard Error. CI: Confidence Interval. ECP: Equitable Compensation Policy. PPE: Participative Performance Evaluation. MR: Media Richness. PIRC: Perceived Interactivity - Real-time Conversation. PIE: Perceived Interactivity – Engaging. CSC: Considerate Supervisory Communication. CPF: Considerate Personal Feedback. RBE: Rule-Based Evaluation. PJ: Procedural Justice. DJ: Distributive Justice. IJ: Interactional Justice. TI: Turnover Intention.

Moderation Tests

The moderating effects of MR were tested by employing path analysis and Dawson's (2014) slope tests. A moderation model was specified to test MR's moderation effect on PJ-IM, DJ-IM, and IJ-IM. Results from the moderation model indicated that MR significantly moderates the relationship between PJ and IM (b=0.531, p<0.05), such that the relationship between PJ and IM will become more positive and stronger when an MR becomes higher. This result supports Hypothesis 18.

	DV: PJ		DV: DJ		DV: IJ		DV: TI	
	b	SE	b	SE	b	SE	b	SE
PPE	0.393**	0.045						
RBE	0.263**	0.047						
ECP			0.497^{**}	0.039				
PIRC					0.154**	0.050		
PIE					0.189**	0.049		
CSC					0.288^{**}	0.057		
CPF					0.209**	0.053		
PJ							-0.202	0.143
DJ							-0.206	0.153
IJ							-0.323*	0.161
MR							-0.362	0.243
PJ*MR							-0.531*	0.266
DJ*MR							-0.150	0.266
IJ*MR							-0.005	0.285
R^2	0.3	312	0.2	247	0.4	195	0	.298

TABLE 5MODERATION TEST RESULTS

Notes: **p < .01, *p < .05.

SE: Standard Error. ECP: Equitable Compensation Policy. PPE: Participative Performance Evaluation. MR: Media Richness. PIRC: Perceived Interactivity - Real-time Conversation. PIE: Perceived Interactivity - Engaging. CSC: Considerate Supervisory Communication. CPF: Considerate Personal Feedback. RBE: Rule-Based Evaluation. PJ: Procedural Justice. DJ: Distributive Justice. IJ: Interactional Justice. TI: Turnover Intention. R²: R-Square.

Supplementary Analyses

As suggested by Antonakis et al. (2014), when it comes to non-experimental studies, the magnitude of the true relationship could be undermined by the endogeneity issue in such a way that a causal relationship between two variables (e.g., A and B) could be spurious if there is the third variable that causes both A and B. To address possible endogeneity issues, I conducted the Two-Stage Least Squares (2SLS) analysis suggested by Antonakis et al. (2014) to test the effect of ECP, PPE, PIRC, PIE, CSC, CPF, RBE on PJ, DJ, and IJ. Specifically, I used workers' years of crowdsourcing work as the instrument variable, because this variable is not necessarily related to the PJ, DJ, and IJ. The result indicates that the instrument variable has a significant effect on PPE, PIRC, CSC, and CPF (57.14% of the predictors), and PPE, ECP, PIRC, CSC, and CPF (71.43% of the predictors) have a significant effect on PJ, DJ, and IJ, which is an acceptable indication that endogeneity is not an issue in this study. Further, I tested whether MR moderates the indirect effect reported in Table 4. However, MR's moderation effect was not found. Table 6 provides a summary of hypotheses that are supported based on the study results.

	Туре	Supported
Hypothesis 1	Direct Effect	Yes
Hypothesis 2	Direct Effect	Yes
Hypothesis 3	Direct Effect	Yes
Hypothesis 4	Direct Effect	Yes
Hypothesis 5	Direct Effect	Yes
Hypothesis 6	Direct Effect	Yes
Hypothesis 7	Direct Effect	Yes
Hypothesis 8	Direct Effect	No
Hypothesis 9	Direct Effect	Yes
Hypothesis 10	Direct Effect	Yes
Hypothesis 11	Mediation	No
Hypothesis 12	Mediation	No
Hypothesis 13	Mediation	No
Hypothesis 14	Mediation	Yes
Hypothesis 15	Mediation	Yes
Hypothesis 16	Mediation	Yes
Hypothesis 17	Mediation	Yes
Hypothesis 18	Moderation	Yes
Hypothesis 19	Moderation	No
Hypothesis 20	Moderation	No

TABLE 6SUMMARY OF SUPPORTED HYPOTHESES

DISCUSSION

Crowdsourcing has revolutionized business operations by harnessing collective intelligence and distributed labor, transforming traditional methods of innovation and problem-solving (Howe, 2006; Brabham, 2013). This study contributes to the understanding of organizational justice within the context of crowdsourcing platforms, exploring how perceptions of fairness influence turnover intentions among crowd-based workers.

Theoretical Implications

Organizational justice, encompassing procedural, distributive, and interactional fairness perceptions, plays a crucial role in shaping the work experiences of crowd-based workers (Greenberg, 1987). Our findings underscore that equitable compensation policies, participative performance evaluation processes, and effective communication channels significantly enhance workers' perceptions of procedural and interactional justice. These factors not only mitigate turnover intentions but also foster a sense of trust and fairness in platform operations.

Practical Implications

Platform managers must prioritize fair treatment practices to sustain a motivated and committed workforce. Our results suggest that platforms should adopt transparent and participatory evaluation systems, ensure equitable compensation practices, and facilitate effective communication channels to enhance worker satisfaction and reduce turnover intentions. These practices not only align with organizational justice principles but also contribute to the platform's reputation and long-term viability.

Further, challenges such as regulatory ambiguities and varying task quality persist in crowdsourcing environments (Kazman & Chen, 2009). Future research should delve deeper into the regulatory frameworks that govern crowd-based labor, advocating for clearer guidelines that protect both workers and platforms.

Moreover, continuous improvements in task design and quality assurance mechanisms are essential to maintain high standards and mitigate discrepancies in task outcomes.

Limitations and Future Directions

This study acknowledges several limitations, including the use of self-reported data and the focus on specific crowdsourcing platforms. Future research could employ mixed-method approaches to validate findings and explore nuanced experiences across different types of crowdsourcing tasks and platforms. Additionally, longitudinal studies could track changes in organizational justice perceptions over time, offering insights into the dynamic nature of worker-platform relationships.

CONCLUSION

In conclusion, this research underscores the critical role of organizational justice in shaping crowdbased work experiences and turnover intentions. By understanding and addressing justice perceptions, platforms can foster a supportive work environment that enhances worker satisfaction and retention. Moving forward, integrating fairness principles into platform policies and practices remains imperative for sustaining a resilient and productive crowd-based workforce.

REFERENCES

- Adams, J.S. (1963). Toward an understanding of inequity. *Journal of Abnormal and Social Psychology*, 67(5), 422–436. https://doi.org/10.1037/h0040968
- Adams, J.S. (1965). Inequity in social exchange. In L. Berkowitz (Ed.), Advances in experimental social psychology (Vol. 2, pp. 267–299). Academic Press. https://doi.org/10.1016/S0065-2601(08)60108-2
- Aguirre-Urreta, M.I., & Hu, J. (2019). Detecting common method bias: Performance of the Harman's single-factor test. ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 50(2), 45–70. https://doi.org/10.1145/3330472.3330477
- Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2014). Causality and endogeneity: Problems and solutions. In D.V. Day (Ed.), *The Oxford handbook of leadership and organizations* (pp. 93– 117). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199755615.013.006
- Bergvall-Kåreborn, B., & Howcroft, D. (2014). Amazon Mechanical Turk and the commodification of labour. New Technology, Work and Employment, 29(3), 213–223. https://doi.org/10.1111/ntwe.12038
- Bies, R.J., & Moag, J.F. (1986). Interactional justice: Communication criteria of fairness. In R.J. Lewicki, B.H. Sheppard, & M.H. Bazerman (Eds.), *Research on negotiations in organizations* (Vol. 1, pp. 43–55). JAI Press.
- Bies, R.J., & Shapiro, D.L. (1988). Voice and justification: Their influence on procedural fairness judgments. *Academy of Management Journal*, *31*(3), 676–685. https://doi.org/10.2307/256552
- Bouckenooghe, D., Devos, G., Van den Broeck, H., & Jegers, M. (2007). Organizational change questionnaire climate of change, processes, and readiness: Development of a new instrument. *The Journal of Psychology*, 141(6), 559–579. https://doi.org/10.3200/JRLP.141.6.559-580
- Brabham, D.C. (2013). Crowdsourcing. MIT Press.
- Brawley, A.M., & Pury, C.L. (2016). Work experiences on MTurk: Job satisfaction, turnover, and information sharing. *Computers in Human Behavior*, *54*, 531–546. https://doi.org/10.1016/j.chb.2015.08.031
- Browner, W.S., Newman, T.B., & Pletcher, M.J. (2022). Introduced the basic principles that underlie estimating sample sizes. In S.B. Hulley, S.R. Cummings, W.S. Browner, D.G. Grady, & T.B. Newman (Eds.), *Designing clinical research* (5th Ed., pp. 51–76). Wolters Kluwer.

Cabello-Medina, C., López-Cabrales, Á., & Valle-Cabrera, R. (2011). Leveraging the innovative performance of human capital through HRM and social capital in Spanish firms. *The International Journal of Human Resource Management*, 22(4), 807–828. https://doi.org/10.1080/09585192.2011.555125

Cherry, M.A. (2010). The global dimensions of virtual work. Missouri Law Review, 75, 1091–1126.

- Cheung, C.K., & Zebrack, B. (2017). What do adolescents and young adults want from cancer resources? Insights from a Delphi panel of AYA patients. *Supportive Care in Cancer*, 25, 119–126. https://doi.org/10.1007/s00520-016-3396-7
- Chow, S.C., Shao, J., Wang, H., & Lokhnygina, Y. (2017). *Sample size calculations in clinical research* (3rd Ed.). Chapman and Hall/CRC.
- Cohen-Charash, Y., & Spector, P.E. (2001). The role of justice in organizations: A meta-analysis. *Organizational Behavior and Human Decision Processes*, 86(2), 278–321. https://doi.org/10.1006/obhd.2001.2958
- Colquitt, J.A. (2001). On the dimensionality of organizational justice: A construct validation of a measure. *Journal of Applied Psychology*, 86(3), 386–400. https://doi.org/10.1037/0021-9010.86.3.386
- Colquitt, J.A., Conlon, D.E., Wesson, M.J., Porter, C.O.L.H., & Ng, K.Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology*, 86(3), 425–445. https://doi.org/10.1037/0021-9010.86.3.425
- Colquitt, J.A., Scott, B.A., & LePine, J.A. (2007). Trust, trustworthiness, and trust propensity: A metaanalytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology*, 92(4), 909–927. https://doi.org/10.1037/0021-9010.92.4.909
- Craney, T.A., & Surles, J.G. (2002). Model-dependent variance inflation factor cutoff values. *Quality Engineering*, 14(3), 391–403. https://doi.org/10.1081/QEN-120001878
- Cropanzano, R., & James, K. (1990). Some methodological considerations for the behavioral genetic analysis of work attitudes. In K. James (Ed.), *Psychological genetics* (pp. 245–273). Sage Publications.
- Cropanzano, R., Bowen, D.E., & Gilliland, S.W. (2007). The management of organizational justice. *Academy of Management Perspectives*, 21(4), 34–48. https://doi.org/10.5465/amp.2007.27895337
- Cropanzano, R., Rupp, D.E., & Byrne, Z.S. (2001). The relationship of emotional exhaustion to work attitudes, job performance, and organizational citizenship behaviors. *Journal of Applied Psychology*, *86*(1), 160–169. https://doi.org/10.1037/0021-9010.86.1.160
- Daft, R.L., & Lengel, R.H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, 32(5), 554–571. https://doi.org/10.1287/mnsc.32.5.554
- Daniel, J.L., Chatelain-Jardon, R., Song, X., & Rees, K. (2023). Job demands, mental health, and job performance: The moderating effect of servant leadership during the Covid-19 pandemic. *Management, Research, and Practice*, 15(3), 31–43. Retrieved from https://mrp-journal.org/
- DeConinck, J.B. (2010). The effect of organizational justice, perceived organizational support, and perceived supervisor support on marketing employees' level of trust. *Journal of Business Research*, 63(12), 1349–1355. https://doi.org/10.1016/j.jbusres.2009.11.008
- Downs, C.W., & Hazen, M.D. (1977). A factor analytic study of communication satisfaction. *The Journal* of Business Communication, 14(3), 63–73. https://doi.org/10.1177/002194367701400306
- Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology*, 71(3), 500–507. https://doi.org/10.1037/0021-9010.71.3.500
- Felstiner, A. (2011). Working the crowd: Employment and labor law in the crowdsourcing industry. *Berkeley Journal of Employment and Labor Law*, 32, 143–174.
- Folger, R. (1986). Rethinking equity theory: A referent cognitions model. In H.W. Bierhoff, R. Cohen, & J. Greenberg (Eds.), *Justice in social relations* (pp. 145–162). Plenum Press. https://doi.org/10.1007/978-1-4613-9564-5_9

- Folger, R., & Cropanzano, R. (1998). *Organizational justice and human resource management*. Sage Publications.
- Folger, R., & Konovsky, M.A. (1989). Effects of procedural and distributive justice on reactions to pay raise decisions. Academy of Management Journal, 32(1), 115–130. https://doi.org/10.5465/256443
- Ford, J.K. (1996). Improving training effectiveness in work organizations. Psychology Press.
- Fuller, C.M., Simmering, M.J., Atinc, G., Atinc, Y., & Babin, B.J. (2016). Common methods variance detection in business research. *Journal of Business Research*, 69(8), 3192–3198. https://doi.org/10.1016/j.jbusres.2015.12.008
- Gilliland, S.W. (1993). The perceived fairness of selection systems: An organizational justice perspective. *Academy of Management Review*, 18(4), 694–734. https://doi.org/10.5465/amr.1993.9410202112
- Greenberg, J. (1986). Determinants of perceived fairness of performance evaluations. *Journal of Applied Psychology*, *71*(2), 340–342. https://doi.org/10.1037/0021-9010.71.2.340
- Greenberg, J. (1987). A taxonomy of organizational justice theories. *Academy of Management Review*, *12*(1), 9–22. https://doi.org/10.5465/amr.1987.4306438
- Greenberg, J. (1990). Organizational justice: Yesterday, today, and tomorrow. *Journal of Management*, *16*(2), 399–432. https://doi.org/10.1177/014920639001600208
- Greenberg, J. (1993). Stealing in the name of justice: Informational and interpersonal moderators of theft reactions to underpayment inequity. *Organizational Behavior and Human Decision Processes*, 54(1), 81–103. https://doi.org/10.1006/obhd.1993.1004
- Greenberg, J. (2009). Everybody talks about organizational justice, but nobody does anything about it. *Industrial and Organizational Psychology*, 2(2), 181–195. https://doi.org/10.1111/j.1754-9434.2009.01131.x
- Grote, R.C. (1996). The complete guide to performance appraisal. Amacom.
- Hu, L.T., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. https://doi.org/10.1080/10705519909540118
- Kazman, R., & Chen, H.M. (2009). The metropolis model: A new logic for development of crowdsourced systems. *Communications of the ACM*, *52*(7), 76–84. https://doi.org/10.1145/1538788.1538808
- Kline, R.B. (2012). Assumptions in structural equation modeling. In R.H. Hoyle (Ed.), *Handbook of structural equation modeling* (pp. 111–125). The Guilford Press.
- Kuek, S.C., Paradi-Guilford, C., Fayomi, T., Imaizumi, S., Ipeirotis, P., Pina, P., & Singh, M. (2015). *The global opportunity in online outsourcing*. World Bank Group. Retrieved from https://openknowledge.worldbank.org/handle/10986/22284
- Landers, R.N., & Behrend, T.S. (2015). An inconvenient truth: Arbitrary distinctions between organizational, Mechanical Turk, and other convenience samples. *Industrial and Organizational Psychology*, 8(2), 142–164. https://doi.org/10.1017/iop.2015.13
- Leventhal, G.S. (1980). What should be done with equity theory? New approaches to the study of fairness in social relationships. In K.J. Gergen, M.S. Greenberg, & R.H. Willis (Eds.), *Social exchange: Advances in theory and research* (pp. 27–55). Springer. https://doi.org/10.1007/978-1-4613-3087-5_2
- Leventhal, G.S. (1976). The distribution of rewards and resources in groups and organizations. In L. Berkowitz & E. Walster (Eds.), *Advances in experimental social psychology* (pp. 91–131). Academic Press. https://doi.org/10.1016/S0065-2601(08)60059-3
- Liu, Z., Cai, Z., Li, J., Shi, S., & Fang, Y. (2013). Leadership style and employee turnover intentions: A social identity perspective. *Career Development International*, 18(3), 305–324. https://doi.org/10.1108/CDI-09-2012-0087
- Lovett, M., Bajaba, S., Lovett, M., & Simmering, M.J. (2018). Data quality from crowdsourced surveys: A mixed method inquiry into perceptions of Amazon's Mechanical Turk Masters. *Applied Psychology*, 67(2), 339–366. https://doi.org/10.1111/apps.12124

- Majchrzak, A., & Malhotra, A. (2013). Towards an information systems perspective and research agenda on crowdsourcing for innovation. *The Journal of Strategic Information Systems*, 22(4), 257–268. https://doi.org/10.1016/j.jsis.2013.07.004
- Martin, J.E., & Peterson, M.M. (1987). Two-tier wage structures: Implications for equity theory. *Academy* of Management Journal, 30(2), 297–315. https://doi.org/10.2307/256277
- McMillan, S.J., & Hwang, J.S. (2002). Measures of perceived interactivity: An exploration of the role of direction of communication, user control, and time in shaping perceptions of interactivity. *Journal of Advertising*, 31(3), 29–42. https://doi.org/10.1080/00913367.2002.10673674
- Mickos, M. (2020, June 23). The power of crowdsourcing. *Forbes*. Retrieved from https://www.forbes.com/sites/martenmickos/2020/06/23/the-power-of-crowdsourcing/
- Muthén, L.K., & Muthén, B.O. (1998–2017). *Mplus User's guide* (8th Ed.). Los Angeles, CA: Muthén & Muthén.
- Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, 17, 22–27. https://doi.org/10.1016/j.jbef.2017.12.004
- Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., & Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
- Porter, C.O., Outlaw, R., Gale, J.P., & Cho, T.S. (2019). The use of online panel data in management research: A review and recommendations. *Journal of Management*, 45(1), 319–344. https://doi.org/10.1177/0149206318811569
- Pulakos, E.D., & Schmitt, N. (1995). Experience-based and situational interview questions: Studies of validity. *Personnel Psychology*, 48(2), 289–308. https://doi.org/10.1111/j.1744-6570.1995.tb01758.x
- Rafaeli, S., & Ariel, Y. (2008). Online motivational factors: Incentives for participation and contribution in Wikipedia. In A. Barak (Ed.), *Psychological aspects of cyberspace: Theory, research, applications* (pp. 243–267). Cambridge University Press. https://doi.org/10.1017/CBO9780511813740.014
- Rafaeli, S., & Sudweeks, F. (1997). Networked interactivity. *Journal of Computer-Mediated Communication*, 2(4), JCMC243. https://doi.org/10.1111/j.1083-6101.1997.tb00201.x
- Saks, A.M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology*, *21*(7), 600–619. https://doi.org/10.1108/02683940610690169
- Saxton, G.D., Oh, O., & Kishore, R. (2013). Rules of crowdsourcing: Models, issues, and systems of control. *Information Systems Management*, 30(1), 2–20. https://doi.org/10.1080/10580530.2013.739883
- Schenk, E., & Guittard, C. (2011). Towards a characterization of crowdsourcing practices. *Journal of Innovation Economics Management*, 7(1), 93–107. https://doi.org/10.3917/jie.007.0093
- Scott, B.A., Colquitt, J.A., & Zapata-Phelan, C.P. (2007). Justice as a dependent variable: Subordinate charisma as a predictor of interpersonal and informational justice perceptions. *Journal of Applied Psychology*, 92(6), 1597–1609. https://doi.org/10.1037/0021-9010.92.6.1597
- Song, X., & Whitman, M. (2024). It's not you, it's me: Investigating the consequences of abusive supervision and the moderating effect of impostorism. *The International Trade Journal*, 38(1), 6– 30. https://doi.org/10.1080/08853908.2023.2272345
- Spector, P.E., & Brannick, M.T. (2011). Methodological urban legends: The misuse of statistical control variables. Organizational Research Methods, 14(2), 287–305. https://doi.org/10.1177/1094428110369842
- Thibaut, J., & Walker, L. (1975). *Procedural justice: A psychological analysis*. Erlbaum. https://doi.org/10.4324/9781315129686
- Thompson, C.G., Kim, R.S., Aloe, A.M., & Becker, B.J. (2017). Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. *Basic and Applied Social Psychology*, 39(2), 81–90. https://doi.org/10.1080/01973533.2016.1277529

- Tyler, T.R., & Blader, S.L. (2003). The group engagement model: Procedural justice, social identity, and cooperative behavior. *Personality and Social Psychology Review*, 7(4), 349–361. https://doi.org/10.1207/S15327957PSPR0704_07
- Williams, L.J., & McGonagle, A.K. (2016). Four research designs and a comprehensive analysis strategy for investigating common method variance with self-report measures using latent variables. *Journal of Business and Psychology*, 31, 339–359. https://doi.org/10.1007/s10869-015-9422-9