5-15-2019

UNDERSTANDING THE INFLUENCE OF TECHNOSTRESS ON WORKERS' JOB SATISFACTION IN GIG-ECONOMY: AN EXPLORATORY INVESTIGATION

Azka Umair
National University of Ireland Galway, a.umair1@nuigalway.ie

Kieran Conboy
NUI Galway, kieran.conboy@nuigalway.ie

Eoin Whelan
National University of Ireland, Galway, eoin.whelan@nuigalway.ie

UNDERSTANDING THE INFLUENCE OF TECHNOSTRESS ON WORKERS' JOB SATISFACTION IN GIG-ECONOMY: AN EXPLORATORY INVESTIGATION

Research in Progress

Azka Umair, National University of Ireland, Galway, Ireland, a.umair1@nuigalway.ie

Kieran Conboy, National University of Ireland Galway, Ireland, kieran.conboy@nuigalway.ie

Eoin Whelan, National University of Ireland Galway, Ireland, eoin.whelan@nuigalway.ie

Abstract

Gig-economy is a recent concept that has been attracting growing attention. Online labour markets (OLMs) are a prominent part of gig-economy and require completion of tasks digitally through platforms such as MTurk and Upwork. The World Bank estimated the total market size of OLMs to be $4.8 billion in 2016 which is expected to increase up to $25 billion in 2020. Despite the rapid growth of OLMs, the implications of workers' wellbeing in such markets are not well understood and highly debated. A report commissioned by EU-OSHA has identified psycho-social risks associated with the work in OLMs. The highly competitive and fast-paced nature of OLMs necessitates workers to multitask and perform intense technology-enabled work which may lead to technostress. This paper investigates workers' job satisfaction in OLMs using technostress and job characteristic theories with the aim of providing an in-depth understanding of the experiences and perceptions of workers. Our research model has both theoretical and practical implications which will help to diagnose potential problems and improve the wellbeing of workers by formulating strategies for OLMs and workers. The paper presents the results of a pilot study in a popular OLM using structural equation modelling.

Keywords: Gig-economy, Online Labour Markets, Technostress, Job Satisfaction, Job Characteristics Theory

1 Introduction

The recent *gig-economy* has been attracting growing attention in popular media and academic research (Abraham et al., 2018). It is defined as a collection of markets that match workers and employers via internet-based technological platforms or mobile applications to perform a jobs that are either digital or physical (Donovan, Bradley, and Shimabukuro, 2016; Heeks, 2017). Particularly, the digital gig-economy includes completion of tasks that are facilitated by online platforms, also referred to as *online labour markets* (OLMs), such as Amazon Mechanical Turk (MTurk) and Upwork (Garben, 2017; Horton, 2010). Online labour markets are the primary focus of this paper since they play a central role in understanding the possible implications of broader gig-economy. Specifically, this paper aims to address the following research question:

What influence does technology and job characteristics play on workers job satisfaction when mediated by technology-induced stressors in online labour markets?

Online labour markets are gaining more importance because of their rapidly increasing prevalence. In recent years, these markets have made exponential growth with an expected encroachment on traditional forms of work in future (Codagnone et al., 2016). More than 162 million people in Europe and the United States, which is almost 30% of the working-age population, are engaged in these markets (Manyika et al., 2016). The World Bank estimated the total market size of OLMs to be $4.8 billion in 2016 (Durward and Blohm, 2017). Mckinsey Global Institute, in 2015, estimated that OLMs can contribute up to $2.7 trillion to global GDP thus benefiting more than 540 million individuals by 2025.

Despite rapid growth of OLMs, the implications of workers' wellbeing in such platforms have attracted controversy (Kuhn and Maleki, 2017; Valenduc, 2017). Although OLMs create significant job opportunities, increase just-in-time workforce and provide temporal flexibility (Stefano, 2016; Wood et al., 2018). Social, health and financial risks can be associated with OLMs due their reliance on precarious forms of employment (Codagnone et al., 2016; Garben, 2017). At a broader level, OLMs are believed to erode labour protections, contribute to economic insecurity and unpredictability of working life (Kässi and Lehdonvirta, 2016). While, the problems encountered by workers in the platforms include tedious tasks, low payment, rejection of task, time pressure and no social interaction (Bergvall-Kåreborn and Howcroft, 2014). Therefore, it is essential to understand the implications of work in OLMs from both an individual worker and a societal perspective.

Information technology (IT) has played a significant role in the rapid growth of OLMs thus allowing individuals to find immediate work globally. But, excessive and prolonged use of technology is linked to stress, referred to as *technostress*, which directly influences worker *wellbeing* (Tarafdar, Tu, T. S. Ragu-Nathan, et al., 2011). Wellbeing is fundamental for workers and organisations, which if overlooked can have serious consequences (Danna and Griffin, 1999). In OLMs, technostress can manifest due to tight work schedules, constant connectivity, multi-tasking, lower income, inconsistent productivity and blurred work-life distinction. A recent, survey shows, 54% of workers must work at very high speeds, 22% feel distressed because of their work, and 60% meet tight deadlines in OLMs (Graham et al., 2017). Literature also points to the evidence that IT professionals are at a higher risk of experiencing stress; therefore, it will be useful to examine the consequences of IT use on workers in OLMs (Ahuja et al., 2006).

Existing literature on OLMs has mainly focused on market-centric issues such as pricing mechanisms and bidding strategies (Horton, 2010; Snir and Hitt, 2003). The limited number of studies focusing on worker-centric issues have highlighted the need to understand the experiences and wellbeing of workers in OLMs (Deng and Joshi, 2016; Kuhn and Maleki, 2017). Additionally, OLMs being a novel form of work are inherently different from traditional forms of work and telework (Aguinis and Lawal, 2013; Ma, Hou, and Khansa, 2016). Apart from the differences in the overall work process and having multiple employers simultaneously, the essential characteristics that make OLMs unique are the presence of digital control and algorithmic management (Deng and Joshi, 2016; Wood et al., 2018). Thus, the concepts and theories of traditional work need to be reconsidered and adapted for this new form of work (Brawley and Pury, 2016). We aim to address this gap by highlighting a key issue relevant to the nature of technology-based work and wellbeing, with respect to job satisfaction, of workers in OLMs. A pilot study was conducted on one of the popular OLMs to validate the proposed model through an online survey, and the results are presented in this paper. We plan to extend the study with large-scale data collection in future. To the best of our knowledge, this paper is the first to develop and empirically study a technostress model in the context of OLMs. The outcomes of our research will help in understanding the work environment of OLMs and develop informed strategies that can be beneficial for both workers and platforms.

2 Related Work

In this section, we provide an overview of research work related to technostress and job satisfaction in its relevance to OLMs.

2.1 Technostress

The term *technostress*, first introduced by Craig Brod (1984), refers to stress experienced due to the use of information technology (Tarafdar, Tu, B. S. Ragu-Nathan, et al., 2007). The topic attracted interest from IS researchers for two reasons. First, because of the negative consequences of IT use on workers behaviours and attitudes at the workplace (Weil and Rosen, 1997). Second, the emergence of new digital working environments, which along with its benefits impose a threat to workers health (Nauwerck and Forssell, 2018). Prior literature shows evidence that IT professionals and remote workers are at a higher risk of experiencing technostress that has adverse consequences including decreased job satisfaction, productivity, increased workload and work–home conflict (Ahuja et al., 2006; T. S. Ragu-Nathan et al., 2008). Previous studies have shown that teleworkers, who have greater flexibility and control in managing their work, indicate social isolation and technostress (Suh and Lee, 2017; Weinert et al., 2014).

By integrating stress and IS literature, Ayyagari, Grover, and Purvis (2011) proposed a technostress model based on the idea that technology characteristics contribute to specific stressors which ultimately create an impact on individuals and their job outcomes . Technology characteristics refer to features of the technology that can be either be usability features (complexity, reliability), intrusive features (presenteeism, anonymity) or dynamic feature (pace of change). These characteristics act as an antecedent and play an essential role in inducing stress by creating a misfit between the worker's abilities and demands. This misfit is characterised as stressors, for instance, work overload, role ambiguity, job insecurity (Tarafdar, Pullins, and T. S. Ragu-Nathan, 2015). Finally, the response to stress can be strain, burnout, or dissatisfaction. To our best of our knowledge, no empirical research exists addressing the technostress model to predict workers job satisfaction in OLMs.

2.2 Technostress in Online Labor Markets

OLMs are technology-enabled markets where technology and work are inseparable as workers need constant connectivity for work (Brawley, 2017). The highly competitive and fast-paced nature of OLMs necessitates workers to multitask and work at high speed to meet tight deadlines (Graham et al., 2017). Although OLMs provide greater temporal flexibility to workers, they simultaneously enforce workers to work much harder and longer by constantly staying online when the availability of work is limited (Lehdonvirta, 2018). This pressure to spend long hours in front of the screen leads to risks such as visual fatigue, technostress and work-life conflict, as highlighted in a report commissioned by European Agency for Safety and Health at Work (EU-OSHA) (Garben, 2017; Valenduc, 2017). Moreover, workers are from different geographical locations where the availability of technological resources and devices may vary. Prior literature shows that most OLM workers are from developing countries while employers are from developed countries (Chan and Wang, 2017). Also, there may be differences between the knowledge needed to perform various tasks using IT and the level of such knowledge among workers (T. S. Ragu-Nathan et al., 2008). IT tools will remain an integral part of OLMs; therefore, it is essential to investigate technostress and its consequences on the job satisfaction of workers.

2.3 Job Satisfaction

Locke (1969) defined *job satisfaction* as a pleasurable feeling arising from one's job. In the context of OLMs, it is "workers' contentment derived from participating in micro-task crowdsourcing" (Deng and Joshi, 2016). It is one of the most widely studied constructs and is central to organisational research interest due to its impact on outcomes such as turnover, performance and commitment (Locke, 1969; Rutner, Hardgrave, and McKnight, 2008). In prior literature, job satisfaction is mostly studied in the context of intrinsic or extrinsic factors and personality traits (Glisson and Durick, 1988; Lawler and Porter, 1967). In OLMs, there are limited studies related to the perception of workers regarding their work (Ross et al., 2010). Researchers have shown interest in understanding the job satisfaction of OLM workers;

however, there is a lack of research which focuses on job satisfaction in terms of technostress (Brawley and Pury, 2016; Deng and Joshi, 2016). In terms of technostress, job satisfaction is clearly an important outcome to measure since it is the desired result of implementation and use of IT and essential to both business success and worker wellbeing (Brawley, 2017; T. S. Ragu-Nathan et al., 2008).

2.4 Job Characteristics Theory

Job characteristics theory provides a theoretical basis for understanding how job characteristics determine worker's attitudes and behaviours (Hackman and Oldham, 1976). It describes five significant attributes of a job, namely: skill variety, task identity, task significance, autonomy and feedback. Prior literature shows the application of job characteristic theory in the context of traditional organisations to study occupational health, job satisfaction and knowledge and skills (Hackman and Oldham, 1976; Lawler and Hall, 1970). Empirical evidence suggests that the job satisfaction of IT professionals is more positively related to job characteristics (Chen, 2008). Also, there is evidence that job autonomy is a source of technostress (Suh and Lee, 2017). To understand, the phenomena of stress, it is essential to consider work characteristics while undertaking a more in-depth analysis of the nature of work (Cotton and Hart, 2003). In the context of OLMs, this theory has been applied to understand motivation related factors such as intrinsic and extrinsic factors (Durward and Blohm, 2017; Kaufmann, Schulze, and Veit, 2011).

3 Research Model and Hypothesis

In recent years, considerable research on technostress has been published after the emergence of new digital working environments which along with their benefits impose a threat to workers' wellbeing (Nauwerck and Forssell, 2018; Tarafdar, Pullins, and T. S. Ragu-Nathan, 2015). IT professionals and teleworkers are believed to be at a higher risk of experiencing stress due to their dependence on IT devices (Ahuja et al., 2006; Suh and Lee, 2017). Inspired by such work, we propose a conceptual model to analyse the job satisfaction of workers by combining technostress and job characteristic theories in OLMs. Prior research has mainly focused on the cause and effect of techno-stressors with only limited studies on the antecedents of techno-stressors (Yan et al., 2013). Therefore, to understand the nature and dimensionality of technostress in OLMs, our framework has undertaken two important and relevant characteristics as antecedents, i.e. technology characteristics and job characteristics. Our model investigates how technology and job characteristics can trigger techno-stressors and influence workers perception of job satisfaction in OLMs. Specifically, our model includes two characteristics of technology (i.e. IT complexity and IT presenteeism) and job (i.e. autonomy and feedback) that act as precursors to techno-stressors.

Our choice of IT characteristics is based on the importance of complexity and presenteeism in OLMs. The complexity of each task varies in OLMs that may require a different level of IT knowledge to perform it, e.g. software designing needs more IT involvement while translation jobs (T. S. Ragu-Nathan et al., 2008; Teodoro et al., 2014). Presenteeism is applicable because workers mostly need to stay connected to get updates about upcoming tasks and time zone difference enhances this pressure to be active most of the time (Heeks, 2017). Similarly, job characteristics are selected based on the evidence that suggests their stronger relationship with the job satisfaction of IT professionals (Chen, 2008). For instance, feedback is known to be a key feature of OLMs and autonomy is shown to be a source of technostress (Kokkodis and Ipeirotis, 2015; Suh and Lee, 2017). Our proposed model includes two technology-induced stressors (i.e. workload and job insecurity) that serve as mediating variables between independent variables and job satisfaction. In the current study, the scope of techno-stressors is constraint only to appropriate and dominant stressors in OLM work environment. We chose to examine workers' perception of job satisfaction as it is the most fundamental aspect of any job which enhances work productivity and overall wellbeing in work settings (Brawley, 2017; Deci, Olafsen, and Ryan, 2017). Figure 1 illustrates our research model in detail.

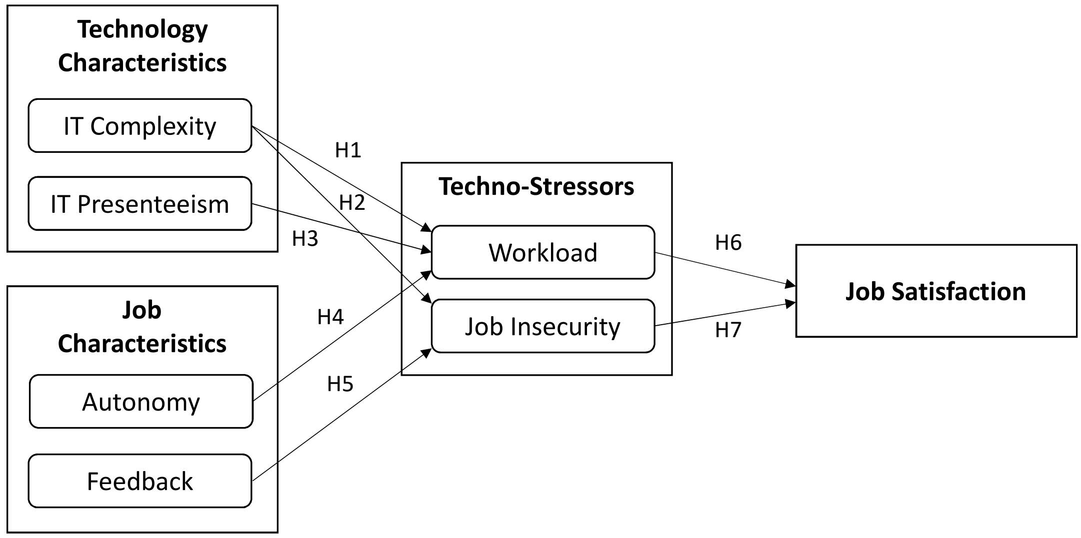

Figure 1. Proposed Research Model

3.1 Technology Characteristics and Techno-Stressors

IT complexity is the degree to which the use of IT for work requires effort (T. S. Ragu-Nathan et al., 2008). New IT features and updates occur continuously, which can be challenging for workers since they require time to learn thus causing frustration (Tarafdar, Tu, B. S. Ragu-Nathan, et al., 2007). IT complexity holds importance in OLMs because employees receive no formal training before joining the platform and tasks are varying in complexity (Lascau et al., 2019). Given the competitive nature of OLMs, there is a pressure to meet tight deadlines (Ellmer and Reichel, 2018). It means that apart from the regular search for available tasks workers also frequently need to develop the skills required to use IT. For example, HIT scrapper installation, experimenting with new features, organising tasks which do not come under the actual task requirement but are necessary. Also, the workers are from different geographical regions where technological resources may be limited, e.g. internet speed, uploading times which can be a source of workload meaning spending longer time to finish a task (Heeks, 2017). This additional time and effort placed in completing the tasks create stress by increasing the workload and sometimes the workers are left with unpaid or rejected work (Kaplan et al., 2018; Tarafdar, Tu, B. S. Ragu-Nathan, et al., 2007). This frustration may influence job insecurity of workers, by limiting the task availability for them. Thus,

H1: In OLMs, workers' perception of IT complexity is positively associated with their perceived workload.

H2: In OLMs, workers' perception of IT complexity is positively associated with their perceived job insecurity.

IT presenteeism is the degree to which technology enables users to be reachable (Ayyagari, Grover, and Purvis, 2011). New digital and collaborative tools have increased the electronic connectivity which at the same has enhanced the flow of information process leading to "information overload" (Suh and Lee, 2017). When individuals receive more information than the required, it may cause fatigue in them (Fonner and Roloff, 2010). Evidence suggests that enabling employees to be accessible anytime and anywhere through devices leads to stress over time by increasing availability, responsiveness and higher employer expectations (Mazmanian, 2013). Although workers have a choice to remain disconnected, it may not be possible every time. For example, a worker may need to spend longer time staying connected when the work availability is limited (Lehdonvirta, 2018). In this respect, the increased permeability of work boundaries can affect workers that can cause work intensification and higher stress (Ellmer and Reichel, 2018). That is, IT presenteeism may aggravate the perception of work overload in OLMs. Thus, *H3: In OLMs, workers' perception of IT presenteeism is positively associated with their perceived workload.*

3.2 Job Characteristics and Techno-Stressors

Job autonomy is the degree or level of freedom and discretion allowed to an employee over his or her job (Hackman and Oldham, 1976). Job autonomy is essential because it reduces workload and workers can manage the time between different activities (Ahuja et al., 2006). In OLMs, workers perceive a certain amount of autonomy regarding their work scheduling as they can not only decide when and where to perform work but also how they work (Durward and Blohm, 2017). On the other hand, workers have little control over the task requirements, quality, feedback and deadlines which have pre-specified instructions (Ma, Hou, and Khansa, 2016). Despite experiencing some level of autonomy, competitive environment creates an undesirable pressure to complete as many tasks as possible in a short span which leads to work intensification with little control (Wood et al., 2018). At times, the tasks become difficult to complete due to unclear instructions or qualification embedded (Kaplan et al., 2018). Workers engaged in creative tasks face challenging higher pressure and irregular working hours (night and weekend) (Ellmer and Reichel, 2018). The job demand-control model, by Karasek (1979), explains the interaction between demands such as workload and job autonomy, where workload is thought to induce stress and job autonomy reduces that effect. Based on this analysis, our hypothesis is

H4: In OLMs, workers' perception of job autonomy is negatively related with perceived workload.

Feedback is the extent to which the platform and employers provide the workers with clear information about their performance (Morris and Venkatesh, 2010). Feedback, both favourable and unfavourable, creates an impact on work-related outcomes such as performance and satisfaction (Steelman, Levy, and Snell, 2004). Feedback plays a more critical role in OLMs because it allows hiring of efficient workers based on previous ratings and guarantees future selection by building trust (Kokkodis and Ipeirotis, 2015). Primarily to maintain a reputation in OLM, workers face constant pressure to keep higher ratings (Ellmer and Reichel, 2018). However, feedback is sometimes a source of worry because workers feel punished for factors beyond their control in OLMs (Bajwa et al., 2018). If workers get negative feedback, their job is insecure because the probability of their future selection on a task reduces. In Mturk most employers use filters to ensure that workers with acceptance rates and below a specified percentage are not able to view their task, which limits tasks availability (Lovett et al., 2018). Also, the workers with consistent lower ratings or rejected work may need to exert more effort, thus increasing their job insecurity (Wessling, Huber, and Netzer, 2017). Therefore, we have following hypothesis

H5: In OLMs, unfavourable feedback is positively related with perceived job insecurity.

3.3 Techno-Stressors and Job Satisfaction

Stressors are defined as events or conditions encountered by individuals in the work environment that cause stress (Cooper and Cartwright, 1997). Ayyagari, Grover, and Purvis (2011) explains a work situation can be stressful for several reasons, but specific stressors have a profound effect in the presence of technology such as work overload, role ambiguity, work/home conflict, invasion of privacy and job insecurity, hence called techno-stressors. For the current study, we limit the scope of stressors to the most relevant in OLMs-work overload, i.e. "perception that assigned work exceeds an individual's capability or skill level" and job insecurity, i.e. "an individual's perception of the threat of job loss" (Ayyagari, Grover, and Purvis, 2011). We hypothesise that both techno-stressors influence job satisfaction of workers in OLMs. Our assumption is consistent with the existing literature, which explains that workers' negative feelings due to techno-stressors lead to reduced job satisfaction (T. S. Ragu-Nathan et al., 2008). The stressors such as higher workload demands are associated with decreased job satisfaction as it compels one to work faster and process excessive amount of information (Karasek, 1979; Tarafdar, Tu, T. S. Ragu-Nathan, et al., 2011). Job insecurity is associated with decreased job satisfaction because it's a source of stability, social contact and self-efficacy (Reisel et al., 2010). Thus,

H6: In OLMs, perceived workload is negatively associated with job Satisfaction.

H7: In OLMs, perceived job insecurity is negatively associated with job satisfaction.

4 Research Methodology

4.1 Measures

We adopted the measurement items from existing well-established literature (Ma, Hou, and Khansa, 2016). IT complexity, IT presenteeism, workload and job insecurity were measured by the items given by Ayyagari, Grover, and Purvis (2011). Job autonomy and feedback were measured by items given by Ahuja et al. (2006) and Steelman, Levy, and Snell (2004), respectively. Specifically, we have used items of unfavourable feedback by slightly modifying the wording to fit our research model. All the above items were measured using a 5-point Likert scale, where 5 is "strongly disagree", and 1 is "strongly agree". Job satisfaction was measured using the scale given by Bhattacherjee (2001) and employed in recent technostress research (Suh and Lee, 2017). The scale captures satisfaction levels along 5-point scales anchored between three semantic differential adjective pairs, e.g. "very dissatisfied/very satisfied," because satisfaction level is best measured along bipolar evaluative dimensions (Ajzen and Fishbein, 1977).

4.2 Data Collection

The data is collected from Amazon Mechanical Turk (MTurk), one of the most popular OLMs, by posting an online survey following the guidelines for conducting behavioural research (Mason and Suri, 2012). The compensation rate was determined by considering the time estimated to complete the task and the minimum US wage rate (i.e. $7.25 per hour). The data was collected from the workers who were currently active and holds a Master qualification, i.e. have completed at least 1000 tasks with 99% approval rate. This qualification was used to make sure that workers are familiar with the platform and have prior experience with tasks and platform. To address the issue of spam individuals, we used appropriate attention check strategies i.e. workers who did not responded to test questions were excluded from analysis. In this paper, we present preliminary results of data of collected from 30 workers. Nevertheless, we plan to collect data from at least 300 workers as future work.

4.3 Results and Data Analysis

First, we conducted descriptive analysis of data to extract demographics information about MTurk workers. Next, we employed *structural equation modelling* (SEM) using *partial least squares* (PLS) method to analyse our research model with the help of SmartPLS.As a second-generation SEM technique, PLS has been widely used for modelling causal networks of effects simultaneously and it is of much value in behavioural research (Lowry and Gaskin, 2014). Additionally, compared with other SEM techniques, PLS does not require a large sample which is the case in our study (Chin, 1998). Also, PLS is considered appropriate for our study because our is an exploratory research investigating the impact of technostress on job satisfaction in OLMs. The SEM analysis is conducted following a two-stage analytical procedure (Hair Jr et al., 2014). The first stage assessed the measurement model for reliability and validity. The second stage examined the structural model to test the research hypotheses.

First, path modelling procedure was carried out by calculating PLS algorithm with a maximum of 300 iterations (Ringle, Da Silva, and Bido, 2014). This helped in evaluating the measurement model (Chin, 1998; Hair Jr et al., 2014). We used *composite reliability* (CR) to measure the reliability (CR > 0.7). The results indicate that the CR for all the variables is greater than 0.7. Furthermore, Cronbach's alpha was used to check the internal consistency reliability ($\alpha > 0.7$). The results indicate that alpha is above threshold value for all variables except autonomy which showed a relatively low consistency reliability ($\alpha = 0.539$). To verify the convergent validity, we used *average variance extracted* (AVE) which in our case was greater than 0.5 for all variables. For most of the items, outer loadings were higher than 0.7. Items with outer loadings less than 0.7 were eliminated. For the discriminant validity, square root of AVE of each latent variable should be greater than the correlations among the latent variable (Fornell and Larcker, 1981). In our case, each latent variable showed satisfactory discriminant validity. The inner *variance inflation factors* (VIFs) were lower than 3.3 indicating common method bias should not be a serious concern (Kock, 2015). Control variables were gender, age and education level.

Next, we performed bootstrapping and compared t-statistics and p-values of the variables. The initial results indicate that only IT complexity shows a significant relationship with workload since t-value was greater than 1.96 ($p < 0.005$). In case of job characteristics, only feedback showed a significant relationship with job insecurity as t-value was 5.361 ($p < 0.05$). Among stressors, only job insecurity showed a significant relationship with job satisfaction at t-value 2.952 ($p < 0.005$).

5 Expected Contributions

Our research is one of the initial studies to propose a model that examines worker's technostress and perceived job satisfaction in OLMs. While our research focuses on OLMs, the results can have further theoretical implications for other IT driven work environments. The research will help to diagnose more precisely potential problems within OLMs. The research will provide an in-depth and better understanding of the experiences and perceptions of workers in OLMs which are limited to date. The outcomes of research show in what ways upcoming changes and challenges in work can be coped and how IT systems could be used in sustainable and beneficial ways for workers. Based on our findings, OLMs can take appropriate steps to design their workplace policies and strategies to retain workers. That is, managerial approaches and practices should be adjusted in conjunction with this emerging form of work.

6 Limitations and Future Research

There are several limitations of this work. First, although our pilot study demonstrates some relationship between chosen variables, larger sample size is required to find insightful results and ensure external validity. Second, increasing the sample size may not necessarily guarantee that the current results will be similar in future. The samples may have been biased because the workers were limited to one platform. Another reason for variation of results in future might be the heterogeneity of OLMs because these markets might not possess similar characteristics as those of other digital working environments. MTurk is a micro-task market with tasks such as tagging a picture or labelling an object which usually require one to two minutes, meaning that the worker is not exposed longer to technology for a single task but must spend longer time to earn a decent income. Even within OLMs, results may vary depending on the platform such as Upwork which includes complex tasks such as software development and web designing.

In future, we intend to extend the model by considering other antecedents, IT characteristics and stressors in our model. Moreover, we would also like to expand our analysis by performing studies in other OLMs for validation. Another possible area of future exploration is to consider gender, computer confidence and other worker characteristics that may have a major influence on technostress.

References

Abraham, K. G., K. Sandusky, J. C. Haltiwanger, and J. R. Speletzer (2018). *Measuring the Gig Economy: Current Knowledge and Open Issues*. Tech. rep. National Bureau of Economic Research.

Aguinis, H. and S. O. Lawal (2013). "eLancing: A review and research agenda for bridging the science–practice gap." *Human Resource Management Review* 23 (1), 6–17.

Ahuja, M. K., K. M. Chudoba, C. J. Kacmar, D. H. Mcknight, and J. F. George (2006). "IT Road Warriors: Balancing Work-Family Conflict, Job Autonomy, and Work Overload to Mitigate Turnover Intentions." *MIS Quarterly* 30 (1), 1–18.

Ajzen, I. and M. Fishbein (1977). "Attitude-Behavior Relations: A Theoretical Analysis and Review of Empirical Research." *Psychological Bulletin* 84 (5), 888–918.

Ayyagari, R., V. Grover, and R. Purvis (2011). "Technostress: Technological antecedents and implications." *MIS Quarterly* 35 (4), 831–858.

Bajwa, U., L. Knorr, E. D. Ruggiero, D. Gastaldo, and A. Zendel (2018). *Towards an understanding of workers ' experiences in the global gig economy*.

Bergvall-Kåreborn, B. and D. Howcroft (2014). "Amazon Mechanical Turk and the commodification of labour." *New Technology, Work and Employment* 29 (3), 213–224.

Bhattacherjee, A. (2001). "Understanding Information Systems Continuance: An Expectation-Confirmation Model." *MIS quarterly* 25 (3), 351–370.

Brawley, A. M. (2017). "The Big, Gig Picture: We Can't Assume the Same Constructs Matter." *Industrial and Organizational Psychology* 10 (4), 687–696.

Brawley, A. M. and C. L. Pury (2016). "Work experiences on MTurk: Job satisfaction, turnover, and information sharing." *Computers in Human Behavior* 54, 531–546.

Chan, J. and J. Wang (2017). "Hiring preferences in Online Labor Markets: Evidence of a Female Hiring Bias." *Management Science* 64 (7), 2973–2994.

Chen, L.-H. (Jan. 2008). "Job satisfaction among information system (IS) personnel." *Computers in Human Behavior* 24 (1), 105–118.

Chin, W. W. (1998). "The partial least squares approach to structural equation modeling." In: *Methodology for business and management. Modern methods for business research*. Ed. by G. A. Marcoulides. Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers, pp. 295–336.

Codagnone, C., F. Biagi, F. Abadie, and F. Biagi (2016). *The Future of Work in the 'Sharing Economy'. Market Efficiency and Equitable Opportunities or Unfair Precarisation?* Tech. rep. Institute for Prospective Technological Studies, p. 100.

Cooper, C. L. and S. Cartwright (1997). "An Intervention strategy for workplace stress." *Journal of Psychosomatic Research* 43 (1), 7–16.

Cotton, P. and P. M. Hart (July 2003). "Occupational Wellbeing and Performance: A Review of Organisational Health Research." *Australian Psychologist* 38 (2), 118–127.

Danna, K. and R. W. Griffin (1999). "Health and well-being in the workplace: A review and synthesis of the literature." *Journal of Management* 25 (3), 357–384.

Deci, E. L., A. H. Olafsen, and R. M. Ryan (2017). "Self-Determination Theory in Work Organizations: The State of a Science." *Annual Review of Organizational Psychology and Organizational Behavior* 4 (1), 19–43.

Deng, X. (and K. D. Joshi (2016). "Why Individuals Participate in Micro-task Crowdsourcing Work Environment: Revealing Crowdworkers' Perceptions." *Journal of the Association for Information Systems* 17 (10), 648–673.

Donovan, S. A., D. H. Bradley, and J. O. Shimabukuro (2016). *What Does the Gig Economy Mean for Workers?* Tech. rep. Washington, DC: Congressional Research Service.

Durward, D. and I. Blohm (2017). "I am a crowd worker– How Individuals Identify With a New Form of Digital Work." In: *Twenty-Fifth European Conference on Information Systems (ECIS)*. Guimarães, Portugal, pp. 1–11.

Ellmer, M. and A. Reichel (2018). *Crowdwork from an HRM Perspective – integrating Organizational Performance and Employee Welfare*.

Fonner, K. L. and M. E. Roloff (2010). “Why teleworkers are more satisfied with their jobs than are office-based workers: When less contact is beneficial.” *Journal of Applied Communication Research* 38 (4), 336–361.

Fornell, C. and D. F. Larcker (1981). “Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics.” *Journal of Marketing Research* 18 (3), 382.

Garben, S. (2017). *Protecting workers in the online platform economy: An overview of regulatory and policy developments in the EU*. Tech. rep. European Agency for Saftey and Health at Work.

Glisson, C. and M. Durick (Mar. 1988). “Predictors of Job Satisfaction and Organizational Commitment in Human Service Organizations.” *Administrative Science Quarterly* 33 (1), 61.

Graham, M., V. Lehdonvirta, A. Wood, H. Barnard, I. Hjorth, and D. P. Simon (2017). *The Risks and Rewrads of Online Gig Work At the Global Margins*. Tech. rep. Oxford Internet Institute, University of Oxford.

Hackman, J. and G. R. Oldham (Aug. 1976). “Motivation through the design of work: test of a theory.” *Organizational Behavior and Human Performance* 16 (2), 250–279.

Hair Jr, J. F., W. C. Black, B. J. Babin, and R. E.Anderson (2014). *Multivariate Data Analysis*. Seventh Edition. Edinburgh: Pearson Education Limited.

Heeks, R. (2017). *Decent Work and the Digital Gig Economy: A Developing Country Perspective on Employment Impacts and Standards in Online Outsourcing, Crowdwork, etc*.

Horton, J. J. (2010). “Online labor Markets.” *International Workshop on Internet and Network Economics*, 515–522.

Kaplan, T., S. Saito, K. Hara, and J. P. Bigham (2018). “Striving to earn more: a survey of work strategies and tool use among crowd workers.” In: *Sixth AAAI Conference on Human Computation and Crowdsourcing*.

Karasek, R. A. (1979). “Job Demands , Job Decision Latitude , and Mental Strain : Implications for Job Redesign.” *Administrative Science Quarterly* 24 (2), 285–308.

Kässi, O. and V. Lehdonvirta (2016). *Building the Online Labour Index : A Tool for Policy and Research*. Oxford Internet Institute, University of Oxford.

Kaufmann, N., T. Schulze, and D. Veit (2011). “More than fun and money. Worker Motivation in Crowdsourcing – A Study on Mechanical Turk.” *Proceedings of the Seventeenth Americas Conference on Information Systems* 4 (2009), 1–11.

Kock, N. (2015). “Common method bias in PLS-SEM: A full collinearity assessment approach.” *International Journal of e-Collaboration (IJeC)* 11 (4), 1–10.

Kokkodis, M. and P. G. Ipeirotis (2015). “Reputation Transferability in Online Labor Markets.” *Management Science* 62 (6), 1687–1706.

Kuhn, K. M. and A. Maleki (2017). “Micro-Entrepreneurs, Dependent Contractors, And Instaserfs: Undersatnding Online Labor Platform Workforces.” *Academy of Management Perspectives* 31 (3), 183–200.

Lascau, L., S. J. J. Gould, A. L. Cox, E. Karmannaya, and D. P. Brumby (2019). “Monotasking or Multitasking : Designing for Crowdworkers ’ Preferences.” In: *CHIConference on Human Factors in Computing Systems Proceedings (CHI 2019), May 4–9, 2019*. Glasgow, Scotland UK.

Lawler, E. E. and D. T. Hall (1970). “Relationship of job characteristics to job involvement, satisfaction, and intrinsic motivation.” *Journal of Applied Psychology* 54 (4), 305–312.

Lawler, E. E. and L. W. Porter (May 1967). “Antecedent attitudes of effective managerial performance.” *Organizational Behavior and Human Performance* 2 (2), 122–142.

Lehdonvirta, V. (2018). “Flexibility in the gig economy: managing time on three online piecework platforms.” *New Technology, Work and Employment* 33 (1), 13–29.

Locke, E. A. (Nov. 1969). “What is job satisfaction?” *Organizational Behavior and Human Performance* 4 (4), 309–336.

Lovett, M., S. Bajaba, M. Lovett, and M. J. Simmering (2018). "Data Quality from Crowdsourced Surveys: A Mixed Method Inquiry into Perceptions of Amazon's Mechanical Turk Masters." *Applied Psychology* 67 (2), 339–366.

Lowry, P. B. and J. Gaskin (July 2014). "Partial Least Squares (PLS) Structural Equation Modeling (SEM) for Building and Testing Behavioral Causal Theory: When to Choose It and How to Use It." *IEEE Transactions on Professional Communication* 57 (2), 123–146.

Ma, X., J. Hou, and L. Khansa (2016). "Toward a Contextual Theory of Turnover Intention in Online Crowdworking." *Thirty Seventh International Conference on Information Systems, Dublin 2016*, 1–19.

Manyika, J., S. Lund, R. Kelsey, J. Mischke, M. Deepa, and J. Bughin (2016). *Independent Work: Choice, Necessity , and the Gig Economy*. Tech. rep. McKinsey Global Institute.

Mason, W. and S. Suri (2012). "Conducting behavioral research on Amazon's Mechanical Turk." *Behavior Research Methods* 44 (1), 1–23.

Mazmanian, M. (2013). "Avoiding the trap of constant connectivity: When congruent frames allow for heterogeneous practices." *Academy of Management Journal* 56 (5), 1225–1250.

Morris, M. G. and V. Venkatesh (2010). "Job Characteristics and Job Satisfaction: Understanding the Role of Enterprise Resource Planning System Implementation." *Mis Quarterly* 34 (1), 143–161.

Nauwerck, G. and R. C. Forssell (2018). "The Digital Work Environment–a Challenge and an Opportunity for CSCW." In: *Proceedings of 16th European Conference on Computer-Supported Cooperative Work*, pp. 1–18.

Pilz, D. and H. Gewald (2013). "Does Money Matter? Motivational Factors for Participation in Paid-and Non-Profit-Crowdsourcing Communities." *Wirtschaftsinformatik* 37, 73–82.

Ragu-Nathan, T. S., M. Tarafdar, B. S. Ragu-Nathan, and Q. Tu (2008). "The consequences of technostress for end users in organizations: Conceptual development and validation." *Information Systems Research* 19 (4), 417–433.

Reisel, W. D., T. M. Probst, S.-l. Chia, C. M. Maloles, C. J. König, W. D. Reisel, T. M. Probst, S.-l. Chia, and C. M. Maloles (2010). "The Effects of Job Insecurity on Job Satisfaction , Organizational Citizenship Behavior , Deviant Behavior , and Negative Emotions of Employees." *International Studies of Management & Organization* 40 (1), 74–91.

Ringle, C. M., D. Da Silva, and D. D. S. Bido (2014). "Structural Equation Modeling with the Smartpls." *Revista Brasileira de Marketing* 13 (02), 56–73.

Ross, J., L. Irani, M. S. Silberman, A. Zaldivar, and B. Tomlinson (2010). "Who are the Turkers? Worker Demographics in Amazon Mechanical Turk." In: *Proceedings of the 28th of the international conference extended abstracts on Human factors in computing systems - CHI EA '10*. July 2016. New York, New York, USA: ACM Press, p. 2863.

Rutner, P. S., B. C. Hardgrave, and D. H. McKnight (2008). "Emotional dissonance and the information technology professional." *Mis Quarterly*, 635–652.

Snir, E. M. and L. M. Hitt (2003). "Costly bidding in online markets for IT services." *Management Science* 49 (11), 1504–1520.

Steelman, L. A., P. E. Levy, and A. F. Snell (2004). "The feedback environment scale: Construct definition, measurement, and validation." *Educational and psychological measurement* 64 (1), 165–184.

Stefano, V. D. (2016). "The Rise of the Just-in-Time Workforce: On-Demand Work, Crowdwork, and Labor Protection in the Gig-Economy." *Comparative Labor Law & Policy Journal* 37 (3), 471–504.

Suh, A. and J. Lee (2017). "Understanding teleworkers' technostress and its influence on job satisfaction." *Internet Research* 27 (1), 140–159.

Tarafdar, M., E. B. Pullins, and T. S. Ragu-Nathan (2015). "Technostress: Negative effect on performance and possible mitigations." *Information Systems Journal* 25 (2), 103–132.

Tarafdar, M., Q. Tu, B. S. Ragu-Nathan, and T. S. Ragu-Nathan (July 2007). "The Impact of Technostress on Role Stress and Productivity." *Journal of Management Information Systems* 24 (1), 301–328.

Tarafdar, M., Q. Tu, T. S. Ragu-Nathan, and B. S. Ragu-Nathan (Sept. 2011). "Crossing to the dark side." *Communications of the ACM* 54 (9), 113.

Teodoro, R., P. Ozturk, M. Naaman, W. Mason, and J. Lindqvist (2014). “The motivations and experiences of the on-demand mobile workforce.” In: *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing - CSCW ’14*.

Valenduc, G. (2017). “Toeing the line. Working conditions in digital environments.” *HesaMag* Vol. 2017/2, 12–16.

Weil, M. M. and L. D. Rosen (1997). *TechnoStress: coping with technology @work @home @play*. Wiley New York.

Weinert, C., C. Maier, S. Laumer, and T. Weitzel (2014). “Does Teleworking Negatively Influence IT Professionals? An Empirical Analysis of IT Personnel’s Telework-enabled Stress.” In: *Proceedings of the 52nd ACM conference on Computers and people research, SIGSIM-CPR ’14*, pp. 139–147.

Wessling, K. S., J. Huber, and O. Netzer (2017). “MTurk character misrepresentation: Assessment and solutions.” *Journal of Consumer Research* 44 (1), 211–230.

Wood, A. J., M. Graham, V. Lehdonvirta, and I. Hjorth (2018). “Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy.” *Work, Employment and Society*, 1–20.

Yan, Z., X. Guo, M. K. Lee, and D. R. Vogel (2013). “A conceptual model of technology features and technostress in telemedicine communication.” *Information Technology & People* 26 (3), 283–297.