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Examining technostress and its impact on worker well-being in the digital gig economy

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Abstract

Purpose – Online labour markets (OLMs) have recently become a widespread phenomenon of digital work. While the implications of OLMs on worker well-being are hotly debated, little empirical research examines the impact of such work on individuals. The highly competitive and fast-paced nature of OLMs compels workers to multitask and to perform intense technology-enabled work, which can potentially enhance technostress. This paper examines the antecedents and well-being consequences of technostress arising from work in OLMs.

Design/methodology/approach – The authors draw from person–environment fit theory and job characteristics theory and test a research model of the antecedents and consequences of worker technostress in OLMs. Data were gathered from 366 workers in a popular OLM through a large-scale online survey. Structural equation modelling was used to evaluate the research model.

Findings – The findings extend existing research by validating the relationships between specific OLM characteristics and strain. Contrary to previous literature, the results indicate a link between technology complexity and work overload in OLMs. Furthermore, in OLMs, feedback is positively associated with work overload and job insecurity, while strain directly influences workers' negative affective well-being and discontinuous intention.

Originality/value – This study contributes to technostress literature by developing and testing a research model relevant to a new form of work conducted through OLMs. The authors expand the current research on technostress by integrating job characteristics as new antecedents to technostress and demonstrating its impact on different types of subjective well-being and discontinuous intention. In addition, while examining the impact of technostressors on outcomes, the authors consider their impact at the individual level (disaggregated approach) to capture the subtlety involved in understanding technostressors' unique relationships with outcomes.

Keywords Gig economy, Online labour markets, Technostress, Technostressors, Cognitive well-being, Affective well-being, Discontinuous intention

Paper type Research paper

1. Introduction

As platform technology has advanced, new business models and forms of work have emerged. One such type of work is the *gig economy* (Berg *et al.*, 2018), which is defined as a collection of markets that match workers and employers via internet-based technological platforms to perform specific tasks (Donovan *et al.*, 2016). The gig economy has attracted growing attention in both mainstream and academic publications and is usually discussed in terms of two key

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Ethics: The research has been approved by the ethical research committee of the University of Galway (Ref-19 Dec 30).

types, namely the physical gig economy and the digital gig economy (Heeks, 2017). The physical gig economy involves work that is transacted via platforms but that requires location-bound physical activity such as food delivery and ride provision (Heeks *et al.*, 2021). The digital gig economy includes completion of location-independent digital tasks that are facilitated by online platforms, also referred to as *online labour markets* (OLMs), for example, Amazon Mechanical Turk (MTurk) [1] and Upwork (Heeks, 2017; Horton, 2010). These markets offer a wide variety of tasks, varying from simple to complex in nature, and include data verification, data processing, audio transcription, survey taking, software development and web design, among others (Hunt and Scheetz, 2019). The primary focus of this paper is OLMs, which represent the digitisation of both work process and work organisation (Huws, 2017). In recent years, the number and scale of OLMs have increased significantly, and their contribution to the broader gig economy continues to grow (Tay and Large, 2022).

More than 162 million people in Europe and the United States, or almost 30% of the working-age population, are engaged in these digital markets (Manyika *et al.*, 2016; Möhlmann *et al.*, 2020). The McKinsey Global Institute (2015) estimated that OLMs could contribute up to US$2.7 trillion to global GDP, benefitting more than 540 million individuals by 2025. A recent prediction shows that these platforms are growing at an annual rate of 25% and will mediate every one in three labour transactions within the next decade (Heeks *et al.*, 2021; Wood *et al.*, 2019a). These figures are likely to increase after the COVID-19 pandemic, as many people are turning towards OLMs for work flexibility and additional income (Fairwork, 2020).

OLMs offer many opportunities, such as additional income, a just-in-time workforce and temporal flexibility (Wood *et al.*, 2019b). Yet, they have created significant social, economic and individual challenges (Bajwa *et al.*, 2018a). In particular, the implications of OLMs for worker well-being are much debated (Ashford *et al.*, 2018; Freni-Sterrantino and Salerno, 2021; Kuhn and Maleki, 2017; Valenduc, 2017). At a broader level, it is argued that OLMs erode labour protections, undermine the standard employment relationship and advocate casualisation of work, due to their precarious nature (Kässi and Lehdonvirta, 2018; De Stefano, 2016). At the individual level, problems like tedious tasks, constant rejection, low payment, time pressure and limited social interaction are well-documented (Bajwa *et al.*, 2018b; Bergvall-Kåreborn and Howcroft, 2014; Heeks, 2017; Wood *et al.*, 2019b). A survey by the International Labour Office on OLMs reports that almost nine out of ten workers get rejections, and with the median hourly wage being only US$2 (Berg *et al.*, 2018). Similarly, another survey on OLMs reports that 54% of workers work at very high speeds, 22% feel distressed because of their work and 60% struggle to meet tight deadlines (Wood *et al.*, 2019b). While initial research has examined the underlying motivations to join OLMs (Durward *et al.*, 2020; Keith *et al.*, 2019) and job quality and control (Möhlmann *et al.*, 2020; Wood *et al.*, 2019b), empirical insights related to worker health and well-being, and the impact of gig work in the information technology (IT) field, are limited to date (Bajwa *et al.*, 2018b; Freni-Sterrantino and Salerno, 2021; Kaine and Josserand, 2019). This is particularly true where OLMs are concerned.

OLMs are inherently different from traditional employment due to structural differences in the way work is performed (Möhlmann *et al.*, 2020). The centrality of digital elements allows for greater flexibility and freedom for workers (Brawley, 2017; Ens *et al.*, 2018). However, technology can be a double-edged sword, as excessive and prolonged use of technology adds to stress (Krishnan, 2017). The experience of individual stress caused by using information technology is referred to as *technostress* (Tarafdar *et al.*, 2007). Technostress research typically focusses on the misfit between individuals and their environment by distinguishing between technostressors (events encountered by individuals (and also known as technology-induced stressors)), strain (immediate adverse reaction to technostressors) and outcomes (the decrease in psychological and behavioural functioning of the individual) (Ayyagari *et al.*, 2011; Tandon *et al.*, 2021). Apart from the digital propensity of work, distress can be intensified in OLMs due to the way they are designed and operated (Bajwa *et al.*, 2018b). Without hierarchical relationships and self-management enabled by algorithms, workers' behaviour and performance are hampered (Duggan *et al.*, 2022). For instance, some OLMs limit the worker's ability to find tasks, restrict workers with lower ratings and restrict workers' ability to negotiate prices (Kellogg *et al.*, 2020; Wood *et al.*, 2019b). The prevalence and impact of these sources of strain make workers more vulnerable (Ashford *et al.*, 2018), and they feel penalised for factors beyond their control (Bajwa *et al.*, 2018b). Therefore, determining the effects of technostress on workers in OLMs is a novel and significant area of enquiry.

In this paper, we draw from the theoretical perspectives of technostress, person–environment fit and job characteristics to inform the development of a research model which advances our understanding of the effects of digital technology on gig workers. Our research aligns with the United Nations Sustainable Development Goals (SDGs), which emphasise ensuring healthy lives and promoting well-being as a fundamental requirement for decent work (United Nations, 2015). If more people are working on OLMs, it is critical to understand how adverse outcomes of worker well-being materialise so that targeted interventions can be designed, tested and implemented. Specifically, this paper aims to address the following research question:

> Do the technology and job characteristics of online labour markets influence strain, and is this relationship mediated by technology-induced stressors?

Our research contributes to information systems (IS) literature on technostress and technology-based work environments. Technostress is a multi-phase process, and focussing on subsets of the process is typical due to the complexity of assessing all the elements simultaneously (Cram *et al.*, 2022). Prior research has contributed in various ways by identifying antecedents (Ayyagari *et al.*, 2011) and consequences (Ragu-Nathan *et al.*, 2008; Srivastava *et al.*, 2015; Wang *et al.*, 2008), classifying technostressors (Tarafdar *et al.*, 2007) or focussing solely on appraisal and coping (Pirkkalainen *et al.*, 2019). Traditionally, technostress is studied in a wide range of professionals, for example, IT professionals, sales workers, healthcare workers and academics. Research in this context reports technology characteristics as the primary antecedent of technostress, leading to lower productivity, organisational commitment and satisfaction (Ayyagari *et al.*, 2011; Califf *et al.*, 2020; Ragu-Nathan *et al.*, 2008; Tarafdar *et al.*, 2015; Whelan *et al.*, 2022). OLMs are a unique work arrangement, and we have a limited understanding of how technostress materialises on such platforms.

In addition to the characteristics of technology, to advance our understanding of the technostress process in OLMs, we focus on OLM job characteristics, namely job autonomy (decision-making authority in relation to work) and feedback (*negative* feedback is the evaluation of work performed as poor or insufficient). Job autonomy and feedback are key attributes of gig work as autonomy means that workers are responsible for managing their work logistics and establishing routines without anyone holding them accountable, while feedback fosters trust and guarantees reward (Ashford *et al.*, 2018; Kokkodis and Ipeirotis, 2015). We also provide a more fine-grained assessment of the impact of technostress on worker well-being by examining different well-being dimensions (i.e. cognitive well-being and affective well-being), as well as discontinuous intention. Previous technostress research which has investigated well-being outcomes has generally focussed on broad well-being constructs (Ragu-Nathan *et al.*, 2008; Srivastava *et al.*, 2015). In addition, most previous studies assessing technostress have analysed the overall effect of technostressors (i.e. amalgamated as a second-order construct), indicating an overall negative impact on outcomes (Pflügner *et al.*, 2021; Ragu-Nathan *et al.*, 2008; Tarafdar *et al.*, 2007). However, few studies have examined the impact of individual technostressors on outcomes (i.e. using a first-order construct), for example, invasion, uncertainty, role-ambiguity (Brooks and Califf, 2017; Califf *et al.*, 2020; Maier *et al.*, 2015). These studies have suggested that the impact of technostressors may differ depending on the outcome being measured. For example, insecurity has a positive impact on strain, a negative impact on productivity and no significant impact on organisational commitment (Ayyagari *et al.*, 2011; Tu *et al.*, 2005; Sarabadani *et al.*, 2018). Therefore, further research is needed to gain a more nuanced understanding of the individual roles of technostressors and to contribute to the ongoing debate in this field (Nastjuk *et al.*, 2023). In this context, our study adds to existing literature by providing insights into how concepts related to technostress differ from emerging work environments such as OLMs, as opposed to the traditional workplace. We collected data from an OLM through a large-scale online survey to validate our proposed research model.

2. Theoretical framework

Stress is often discussed as a mismatch between a person's resources and what they experience in their environment, which thereby threatens their well-being (Cooper and Cartwright, 1997). The term technostress was first introduced by Craig Brod (1984), and it refers to the stress experienced due to the use of IT (Tarafdar *et al.*, 2007). Since then, the concept has been extended by researchers to a wide range of conditions that exacerbate technostress, including but not limited to multitasking, constant connectivity and information overload (Benlian, 2020; Ragu-Nathan *et al.*, 2008; Srivastava *et al.*, 2015). In IS literature, as Figure 1 illustrates, the phenomenon of technostress is considered a holistic process that consists of four stages: *environmental antecedents*, *technostressors*, *strain* and *outcomes* (Ayyagari *et al.*, 2011; Califf *et al.*, 2020). Each stage in this process is interconnected and represents the pathway of a stressful encounter by an individual (Califf *et al.*, 2020). Environmental antecedents are predictive of technostressors through appraisal of the situation, which in turn contributes to an immediate short-term reaction known as strain. At the end, depending on how a person copes with the situation, strain can lead to further detrimental outcomes (Lazarus and Folkman, 1987). Before further detailing this process, we first describe the *person–environment* (P-E) fit theory, which provides a conceptual basis for our understanding of technostress within the context of OLMs.

2.1 Person–environment fit theory

The P-E fit theory advocates that the emergence of stress is due to a change or mismatch in the equilibrium relationship between an individual and their environment (Edwards and Cooper, 1990; Yang *et al.*, 2008). This theory has been widely used to examine stress in organisational studies (Wang *et al.*, 2020; Yang *et al.*, 2008), psychology (Edwards *et al.*, 2006; Kristof-Brown *et al.*, 2005) and information systems (Ayyagari *et al.*, 2011; Brooks and Califf, 2017). The prominence of P-E fit theory is primarily due to its conceptual advantages over alternatives in explaining why stress emerges (Edwards, 1996). Most importantly, it takes into consideration an individual and the individual differences in perceptual and cognitive processes underpinning the relationship between stress stimuli and response (Edwards and Cooper, 1990; Tarafdar *et al.*,

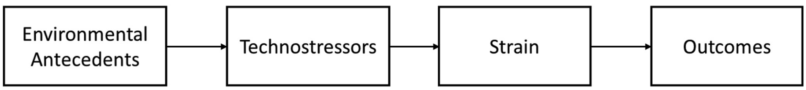

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Figure 1. Overview of the technostress process (Ayyagari *et al.*, 2011; Califf *et al.*, 2020; Fuglseth and Sørebø, 2014)

2019a). Within IS research, a person's compatibility with the technology environment has also been studied (Ayyagari *et al.*, 2011; Brooks and Califf, 2017; Yang *et al.*, 2008).

In OLMs, the requesting organisation or person is often unknown to workers, and the platform serves as an intermediary between task requesters and workers (Schulze *et al.*, 2012). Therefore, this study focuses on a worker's compatibility with their job and technology environment. The *person–job* (P-J) fit emphasises that stress arises due to a misfit between an individual's characteristics and their specific job-related tasks. This misfit, which is based on subjective evaluations, that is, how the individual perceives the job situation, can arise in two ways (Edwards, 1996). First, demand-ability is the match between the demands of the job and the worker's ability to meet those demands. Second, needs–supplies fit is the match between the worker's needs or interests and the job resources. The *person–technology* (P-T) fit underlines that the gap between an individual's abilities and the characteristics of their IT environment is also a significant cause of stress in a work setting (Ayyagari *et al.*, 2011). The technology environment in OLMs has unique characteristics, in terms of IT complexity and connectivity, that can generate stress. This evaluation of P-J and P-T misfit by the individual induces stress, increasing the impact of stressors and strain (Ayyagari *et al.*, 2011; Brooks and Califf, 2017).

2.2 Environmental antecedents

Environmental antecedents, also referred to as environmental conditions, are potential sources of stressful situations in the workplace (Califf *et al.*, 2020; Tarafdar *et al.*, 2019a). IS literature on technostress has largely considered technology characteristics as the environmental antecedent. For example, technology's pace of change is positively associated with role ambiguity, and technology reliability is negatively related to work overload (Ayyagari *et al.*, 2011). The technology environment in which gig workers operate brings its own peculiarities that can induce technostress (Cram *et al.*, 2022).

Based on prior research on OLMs, Umair *et al.* (2019) conducted a pilot test to identify the most important technology and job characteristics of these platforms. Using informal interviews and a survey that asked respondents to rank OLMs' attributes in terms of importance, the topmost emerging characteristics and stressors were included in the model. Accordingly, this study will focus on two technology characteristics of OLMs. *IT complexity* is defined as the degree to which the use of technology for work requires effort, and *IT presenteeism* is defined as the degree to which technology enables workers to be easily reachable (Ayyagari *et al.*, 2011). In OLMs, the complexity of IT knowledge needed to perform tasks varies, ranging from software engineering to online translation (Heeks, 2017; Kässi and Lehdonvirta, 2018; Wood *et al.*, 2019b). Consequently, OLM workers can experience a high work overload in a short time frame due to the IT complexity (Shu *et al.*, 2011; Wang *et al.*, 2008). Similarly, the need to search for and perform high-paying tasks increases IT presenteeism, and the geographical time zone difference between requesters and workers enhances this pressure (Brawley, 2017; Lehdonvirta, 2018). Thus, job insecurity increases due to intense competition for a single task, which prevents workers from working all the hours they desire (Keith *et al.*, 2020).

Besides technology characteristics, recent research has also considered environmental antecedents beyond technology, such as job characteristics (Brooks and Califf, 2017; Suh and Lee, 2017) and organisational climate (Fischer and Riedl, 2022). Suh and Lee (2017) showed that, for teleworkers, job autonomy and task interdependence are positively associated with technostressors. Brooks and Califf (2017) showed that job characteristics have a moderating effect between social media-induced technostress and job performance. Yet, the question of how job and technology characteristics jointly affect technostress remains unclear, especially in the context of OLMs.

Job characteristics theory provides an appropriate lens to examine the job environment of OLM workers because it focusses on understanding how job characteristics determine workers' attitudes and behaviours (Hackman and Oldham, 1976). This theory identifies five key attributes of a job, that is, skill variety, task identity, task significance, autonomy and feedback. Skill variety refers to the heterogeneity of skills needed to perform work activities, while task identity captures whether the work is completed as a holistic identifiable piece. Task significance is defined as work having a meaningful impact on others' lives. In this study, we focus on job autonomy and feedback as key environmental antecedents to technostress in OLMs. *Job autonomy* is the degree of freedom and discretion allowed to an employee over their job (Hackman and Oldham, 1976), and negative *feedback* is the evaluation of work performed as poor or insufficient (Steelman *et al.*, 2004). Job autonomy and feedback are central issues for OLMs since workers can perceive themselves to be controlled by algorithms (Kokkodis and Ipeirotis, 2015; Möhlmann *et al.*, 2020). In comparison, task significance, task identity and skill variety have been found to have limited relevance in the context of OLMs (Brawley and Pury, 2016; Liu *et al.*, 2023). More importantly, empirical evidence suggests that the well-being of IT professionals is positively associated with job characteristics such as feedback and job autonomy (Chen, 2008).

2.3 Technostressors

Technostressors are technology-induced stimuli or demands appraised by individuals as threatening (Ayyagari *et al.*, 2011). In IS literature, there are five commonly identified technostressors: complexity, invasion, insecurity, uncertainty and overload (Ragu-Nathan *et al.*, 2008; Tarafdar *et al.*, 2007). Other forms of technostressors, such as boredom and involvement, are also highlighted in recent research (Fischer *et al.*, 2021). The phenomenon of technostress is tied to the nature of work, and context-specific studies focus on stressors that are most relevant to the work environment (Anh *et al.*, 2022; Cram *et al.*, 2022; Fischer and Riedl, 2022; Galluch *et al.*, 2015; Suh and Lee, 2017). Therefore, we chose to focus on two technostressors that are expected to have a unique relationship with technology and the job characteristics of OLMs (Umair *et al.*, 2019). First, we include *work overload*, which is defined as an individual's perception that assigned work exceeds their capability (Ayyagari *et al.*, 2011). It is particularly relevant to OLMs due to work transience resulting in a higher burden at the worker's end, which is also termed "front-stage work." To maintain a good reputation and become their own "brand," workers must constantly strive to meet the expectations of each requester, thus coming under significant pressure to present themselves in the best possible way (Ashford *et al.*, 2018, p. 27). The overwhelming demands of informal networking and finding quality work lead to work intensification (Ellmer and Reichel, 2018). Second, we include *job insecurity*, which is defined as an individual's perception of the threat of job loss (Ayyagari *et al.*, 2011). It is considered a key stressor under the competitive pressures of OLMs (Ashford *et al.*, 2018; Wood *et al.*, 2019b). Job insecurity in the gig economy may be experienced differently than in a traditional work environment, as workers cannot truly be fired. However, workers may be prevented from finding work because of lack of individual resources, such as the inability to meet requester expectations and the resulting lower ratings on the platform. The algorithmic control inherent to OLMs inevitably affects workers' job insecurity (Keith *et al.*, 2020), which can be a source of frustration and stress. The technostress process explains that increasing demands or technostressors that significantly tax individual resources lead to strain (Califf *et al.*, 2020; Fuglseth and Sørebø, 2014; Tarafdar *et al.*, 2019a).

2.4 Strain and outcomes

Strain is the immediate adverse reaction or state experienced due to various stressors (Lazarus and Folkman, 1987; Tarafdar *et al.*, 2019a). Depending on the intensity and duration of the stressors, strain can lead to other outcomes as well. Such outcomes are consequences that cause changes in psychological, physiological and behavioural functioning of an individual (Dhir *et al.*, 2019; Tandon *et al.*, 2021). For instance, technostress research reports that strain causes psychological outcomes such as exhaustion, lower commitment and burnout (Ayyagari *et al.*, 2011; Srivastava *et al.*, 2015; Tarafdar *et al.*, 2019b); potential physiological outcomes such as increased stress hormones (Galluch *et al.*, 2015; Riedl, 2012); and behavioural outcomes such as turnover and lower productivity (Ragu-Nathan *et al.*, 2008; Tarafdar *et al.*, 2007). Our research focusses on psychological and behavioural outcomes rather than physiological outcomes, as the latter are drawn from a different conceptual perspective, namely neurobiology.

In terms of psychological outcomes, we focus on subjective well-being. Subjective well-being is deeply intertwined with workers' income, employment and working conditions (Berger *et al.*, 2019). In the context of OLMs, subjective well-being is an important phenomenon for study because of the precarious environment, with lack of guidelines on how platforms support worker well-being (Arnoldi *et al.*, 2021). Berger *et al.* (2019) reported lower levels of subjective well-being and higher levels of anxiety for workers on these platforms. OLMs pose unique challenges, and it is critical to evaluate how this new form of work functions and how it impacts worker well-being (Keith *et al.*, 2020). Subjective well-being has two dimensions: cognitive well-being and affective well-being (Diener *et al.*, 1985). *Cognitive well-being* describes global judgements of one's life or an individual's evaluation of life satisfaction in general (Diener *et al.*, 1985). *Affective well-being* refers to the intensity with which an individual experiences two types of affect: *positive affective well-being* (experience of pleasant emotions and moods) and *negative affective well-being* (experience of unpleasant emotions and moods). Affective well-being can be assessed for any domain, for example, work, family, health and leisure (Diener, 2000). Since we focus on work in OLMs, we will refer to it as job-related affective well-being. Previous literature on technostress has investigated factors that contribute to individual well-being, for example, exhaustion and job satisfaction (Ragu-Nathan *et al.*, 2008; Tarafdar *et al.*, 2019b); however, it is not known whether and how technostress contributes to dimensions of subjective well-being.

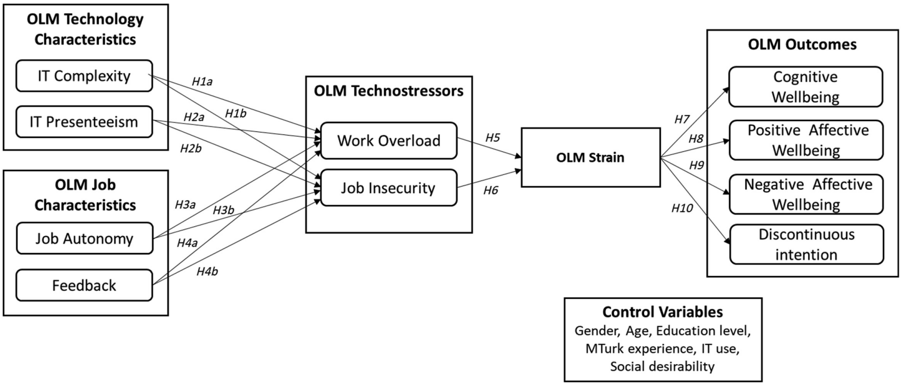
In terms of behavioural outcomes of technostress, we consider discontinuous intention, which is defined as an individual's decision to quit using a system (Turel, 2014). Prior research has studied discontinuous intention in the context of system adoption and social media, where negative feelings can lead to avoidance of a situation's recurrence or a switch to alternatives (Maier *et al.*, 2015; Zhang *et al.*, 2016). Workers have the flexibility to organise work in OLMs, but that comes at the cost of lower earnings. Therefore, an important question is whether an increase in technostress leads to discontinuous intention. Answering this question will help us understand workers' decisions to leave a platform or to continue to work on it even when they do not want to. Moreover, assessing discontinuous intention will help platforms to implement adequate strategies to deal with potential turnover of workers. In our research, we model the mediating effect of strain on the relationship between technostressors and the outcomes described above.

3. The research model

Based on the concepts and theoretical perspectives described earlier, we use the two instantiations of P-E fit (i.e. P-T fit and P-J fit) to frame the hypotheses associated with this study. Figure 2 illustrates our research model in detail.

3.1 Technology characteristics and technostressors

New features and updates occur continuously in IT systems, which can be challenging for workers since it requires them to spend more time learning, with this in turn leading to frustration (Tarafdar *et al.*, 2007). Such IT complexity also has importance in OLMs because



Source(s): Author's own creation/work

Figure 2.
Proposed research model

employees receive no formal training before joining a platform, and tasks vary in their complexity (Lascău *et al.*, 2019). Given the competitive nature of OLMs, workers are constantly under pressure to meet tight deadlines (Wood *et al.*, 2019b). IT complexity means that apart from the regular search for available tasks, workers frequently need to develop new skills. For example, installing a web-based HIT scraper, creating extensions for user scripts and organising tasks do not come under the actual task requirements but are still necessary skills. On average, workers spend an extra 20 min on each task. This extra effort includes searching for new tasks and fulfilling qualifications, which creates frequent interruptions during work (Berg *et al.*, 2018). To deal with high complexity, workers need to expend more effort in gathering knowledge, resulting in an enhanced P-T misfit (Ayyagari *et al.*, 2011). Therefore, we hypothesise the following:

H1a. In OLMs, IT complexity is positively associated with work overload.

OLM workers are usually located in different geographical regions, where technology resources may be limited (Heeks, 2017). Technical issues, constant interruptions, workflow changes and IT equipment also impact productivity and technostress (Lascău *et al.*, 2019; Srivastava *et al.*, 2015). For example, a worker may have to search for new tasks while working on another task in parallel, which means they must manage multiple streams of information concurrently (Brooks and Califf, 2017). In OLMs, this frustration is reflected in worker job insecurity, due to limited task availability and loss of work (Lehdonvirta, 2018; Wood *et al.*, 2019b). The additional time and effort needed to complete tasks create stress as workers are left with unpaid or rejected work when another worker submits the same task first. Such technology-induced factors disrupt valued job-related aspects such as continuity and stability, resulting in P-T misfit associated with technostress. Thus,

H1b. In OLMs, IT complexity is positively associated with job insecurity.

IT presenteeism is associated with additional work demands arising from increased responsiveness (Ayyagari *et al.*, 2011). New digital and collaborative tools have increased connectivity, which at the same time has enhanced the flow of information, leading to information overload. When individuals receive more information than required, it causes fatigue (Suh and Lee, 2017). Evidence suggests that enabling employees to be accessible anytime and anywhere through IT devices leads to stress over time, by increasing availability, responsiveness and employer expectations (Mazmanian, 2013). In OLMs, workers can simultaneously have as many employers as they see fit in a day or an hour, meaning they face varying employer demands. Moreover, workers rely on informal sources of information such as forums to learn new tricks or get notified of high-paying tasks. This increase in demands can lead to stress arising from P-T misfit. Hence, IT presenteeism may aggravate the perception of work overload in OLMs.

H2a. In OLMs, IT presenteeism is positively associated with work overload.

Due to the competitive nature of OLMs and the need to be always online to get the "best" high-paying tasks, presenteeism can also lead to job insecurity. Although workers have a choice to remain disconnected, this may not always be possible. For instance, a worker may need to stay connected longer when the amount of available work is limited, thus increasing job insecurity (Lehdonvirta, 2018; Wood *et al.*, 2019b). The increased permeability of work boundaries can affect workers, which can cause work intensification and higher stress (Ellmer and Reichel, 2018). Workers may experience a blurring of the line between work and personal life, which has been associated with increased technostress (Ayyagari *et al.*, 2011). As individuals are limited in their abilities (resources), the increased pressure can create a P-T misfit. Thus,

H2b. In OLMs, IT presenteeism is positively associated with job insecurity.

3.2 Job characteristics and technostressors

Autonomy is essential in a job because it reduces work overload, and workers can effectively manage their time between different activities (Ahuja *et al.*, 2006). In OLMs, workers perceive a certain amount of autonomy regarding their work scheduling as they can decide when and where to perform work and how they work (Durward *et al.*, 2020). On the other hand, workers have little control over the task requirements, quality expectations, feedback and deadlines, which are pre-specified as instructions (Ma *et al.*, 2016). Despite experiencing some autonomy, the competitive environment creates an undesirable pressure to quickly complete as many tasks as possible, leading to work intensification (Wood *et al.*, 2019b). Tasks also become challenging due to unclear instructions, irregular working hours or embedded qualification requirements (Kaplan *et al.*, 2018; Ellmer and Reichel, 2018). The job demands–control model explains the interaction between job demands and job autonomy, where work overload is thought to induce stress and job autonomy to reduce that effect (Karasek, 1979). Therefore, it follows that workers with a higher level of job autonomy are less likely to experience a P-J misfit. Hence,

H3a. In OLMs, job autonomy is negatively associated with work overload.

Job autonomy in IT professionals has been associated with reduced stress, given that workers are offered the flexibility to manage their schedules (Brooks and Califf, 2017). Although OLMs offer autonomy to workers, it comes at the cost of uncertainty and insecurity (Bajwa *et al.*, 2018b). The decisions governed by invisible algorithms heavily impact workers' ability to perform tasks (Duggan *et al.*, 2022). The benefits of autonomy accrue to only the few workers who are favoured by algorithms. In contrast, for income-dependent workers, this leads to anxiety, overwork and hope for secure work (Petriglieri *et al.*, 2019; Wood *et al.*, 2019b). The job-related benefits, such as freedom to schedule one's own work and career opportunities, minimise job threat (Ashford *et al.*, 2018). Job autonomy allows workers to manage time better; hence, individuals experience less P-J misfit. Based on this analysis, our hypothesis is as follows:

H3b. In OLMs, job autonomy is negatively associated with job insecurity.

Feedback, both favourable and unfavourable, creates an impact on work-related outcomes such as performance and satisfaction (Steelman *et al.*, 2004). OLM workers typically expect requesters to provide feedback about why their work is rejected or accepted (Liu *et al.*, 2023). Feedback plays a more critical role in OLMs because it allows the hiring of efficient workers based on their previous ratings and guarantees future selection by creating mutual trust (Kokkodis and Ipeirotis, 2015). OLM workers face constant pressure to maintain a good reputation and higher ratings (Ellmer and Reichel, 2018). Workers with consistently lower ratings or a larger number of rejections may need to exert more effort to overcome the bad ratings. Therefore, workers who receive negative feedback are more likely to experience work overload resulting in a P-J misfit. Thus, we have the following hypothesis:

H4a. In OLMs, feedback is positively associated with work overload.

In OLMs, direct feedback is considered essential because receiving approval for work is a prerequisite for payment. Feedback can take various forms, including notification of acceptance, rating of quality of work and individual feedback from the requester (Durward *et al.*, 2020). However, feedback is sometimes a source of worry because workers feel punished for factors beyond their control in OLMs (Bajwa *et al.*, 2018b). Specifically, unfair rejection is a major risk that workers experience (McInnis *et al.*, 2016). Furthermore, when workers get negative or insufficient feedback, this raises the threat of job insecurity because the probability of their future selection for a task is reduced, making continuity of work on the platform less viable (Wood *et al.*, 2019b). In MTurk, most employers use filters to screen workers to ensure that workers with low acceptance rates and below a specified percentage cannot view their tasks, thus limiting task availability (Lovett *et al.*, 2018). Therefore, workers who receive negative feedback are more likely to experience stress and a P-J misfit. Hence, we have the following hypothesis:

H4b. In OLMs, feedback is positively associated with job insecurity.

3.3 Technostressors, strain and outcomes

In this study, our primary emphasis is on two technostressors: work overload and job insecurity. Due to algorithmic control and user-interaction mechanisms in OLMs, the work can be highly intense despite workers being given the flexibility and choice to manage tasks. Workers experience high levels of competition, as maximising the number of tasks requires completion as quickly as possible, increasing work overload (Wood *et al.*, 2019b). The stressors, such as work overload, are associated with strain as they compel one to work faster and to process excessive information, resulting in exhaustion (Karasek, 1979; Tarafdar *et al.*, 2007). Thus:

H5. In OLMs, work overload is positively associated with strain.

Research demonstrates that job insecurity is strongly linked to work-related well-being (Freni-Sterrantino and Salerno, 2021; Karasek, 1979) as it impacts emotional experiences such as worry and results in an immediate unconscious reaction, that is, strain (Maier *et al.*, 2015). In OLMs, constantly finding new tasks under pressure makes workers feel easily replaceable, creating greater job insecurity. Job insecurity is associated with strain because a job is a source of stability and self-efficacy (Ashford *et al.*, 2018; De Witte, 1999). Therefore, we hypothesise the following:

H6. In OLMs, job insecurity is positively associated with strain.

Once individuals experience strain, they may assess the stressful situation and respond either psychologically by feeling exhausted as a result of using IT, or by showing a behavioural outcome such as withdrawing from the threatening situation (Maier *et al.*, 2015). In this study, we consider cognitive well-being (i.e. overall life satisfaction), positive affective well-being and negative affective well-being as psychological outcomes of strain; we also examine discontinuous intention as a behavioural outcome of strain.

Traditionally, the effects of strain outside the workplace are limited but still substantial on life satisfaction (De Witte, 1999; De Witte *et al.*, 2015). However, OLMs are known for the trade-off between flexibility and the challenges associated with a digital form of work. Existing studies on OLMs report high life satisfaction, even at low income, primarily because of various push and pull motivations to join the platform (Berger *et al.*, 2019; Keith *et al.*, 2019). Strain can create an immediate effect on emotions during and right after the stressful encounter (Lazarus and Folkman, 1987). Prior studies have linked job stressors to a wide range of positive and negative affective states at work, such as enthusiasm, happiness, fear and anxiety (Anderson *et al.*, 2015; Paul *et al.*, 2000). While all workers experience emotions at work, the unique environment of OLMs makes workers more prone to intense and oscillating experiences within a short time. For instance, negative emotions may arise due to financial instability, identity issues, work transience and unpredictability (Ashford *et al.*, 2018; Petriglieri *et al.*, 2019). However, the work environment in OLMs also emphasises the positive emotions accompanied by these challenges. For example, a worker who is consistently earning a low wage may feel frustrated but is likely to continue working for the same requester because it gives a feeling of accomplishment.

Prior research has established that strain can lead to behavioural outcomes such as turnover and lower productivity (Ragu-Nathan *et al.*, 2008; Tarafdar *et al.*, 2007). In the context of social media, constant negative feelings lead to avoiding a situation's recurrence, which results in discontinuous intention (Maier *et al.*, 2015). Similarly, in OLMs, constant strain may result in workers ceasing to work for a particular requester or platform. Since most workers depend on OLMs for income, a better understanding of both psychological and behavioural outcomes is necessary. Based on the technostress process described in Figure 1, we propose the following hypotheses:

H7. In OLMs, strain is negatively associated with cognitive well-being.

H8. In OLMs, strain is negatively associated with positive affective well-being.

H9. In OLMs, strain is positively associated with negative affective well-being.

H10. In OLMs, strain is positively associated with discontinuous intention.

4. Research methodology

4.1 Data collection

4.1.1 Participant recruitment. The data were collected through a survey via MTurk by following the guidelines for conducting behavioural research (Kaplan *et al.*, 2018; Mason and Suri, 2012). A sample consisting of 366 workers was recruited to perform this survey, which was posted as a human intelligence task (HIT) on MTurk with a clear description. Workers were able to click on a web link which redirected them to the online survey hosted through the Qualtrics platform. The data were collected from both Master [2] and regular workers. We staggered the release of HITs to recruit workers with varying numbers of HITs previously completed. Starting with qualifying workers who have completed 10,000 HITs, we gradually reduced the criteria and made the HIT available to workers who have completed at least 5000, 1000, 500 and 100 HITs. The HIT approval rate was initially set at 98% and then slowly reduced to 96% to create more diversity in data and to increase the chance of participation. Generally, setting HIT approval rate at 95% can produce high-quality data (Hunt and Scheetz, 2019).

4.1.2 Duration. The data were collected for 15 days, including weekends, between the months of May and June in 2020. The survey was administered in six batches at various times each day (starting time in Pacific Daylight Time, PDT: 2, 6, 10 am, 2, 6 and 10 pm).

We posted batches of HITs each day by moving the above timings ahead by one hour to collect the data throughout the entire 24-h period on MTurk. We employed this approach because researchers have indicated a difference in the online sample across the time of the day. In addition, workers' participation in online studies can impact task performance as people have different experiences and personality profiles (Arechar *et al.*, 2017).

4.1.3 Remuneration. Before running the experiment, a test-run was conducted. Two experienced workers reviewed the survey critically. The feedback recommended no significant changes besides a minor design issue which was corrected. As well as the HIT payment, a bonus of US$5 was paid to them. The compensation rate for the HIT was determined by considering the time estimated to complete the HIT and the US minimum wage (i.e. US$7.25 per hour). We estimated the payment for the HIT at US$10 per hour, which is higher than the US minimum wage. Consequently, the payment was set to US$2.50 for the 15 min the HIT takes.

4.1.4 Data quality. MTurk is a popular tool for data collection. Nevertheless, researchers have raised some concerns over its data quality (Lovett *et al.*, 2018). Therefore, we took appropriate measures to minimise the risk of low-quality data. First, to assess workers who may be using form-filling software or bots to complete surveys quickly, we used the reCAPTCHA test at the start of the survey to identify whether the activity on the screen was produced by a human or a computer program such as a bot. Second, we used instructed-response items to address the issue of spam individuals. Two attention-check items with an obvious correct response were included, embedded at different points in the survey. In addition, a single data quality item was included, as suggested by Brawley (2017). See Table A1 in the *Appendix*.

4.2 Measures

We adopted the measurement items from well-established existing literature to enhance validity. However, where needed, we slightly modified the wording of the items to fit our research context. For example, employers and tasks were referred to as requesters and HITs, respectively, and workers were instructed to base their answers on their "job" or "work" on their "use of MTurk" as suggested by earlier research in MTurk (Brawley and Pury, 2016; Brawley, 2017). IT complexity, IT presenteeism, work overload, job insecurity and strain were measured by the items given by Ayyagari *et al.* (2011). IT complexity measures were reverse coded (i.e. higher scores on these items imply lower complexity), as used by Ayyagari *et al.* (2011). Job autonomy was measured using items given by Ahuja *et al.* (2006). Feedback was measured using items given by Steelman *et al.* (2004). The dependent variable cognitive well-being was measured using items given by Diener *et al.* (1985). Job-related affective well-being was measured through the scale used by Anderson *et al.* (2015), including positive affective well-being (PAWB) and negative affective well-being (NAWB). Discontinuous intention was measured using the items given by Turel (2014). The measures for all constructs, the source and the response scale are shown in detail in the *Appendix* (see Table A1).

We included several control variables within the model that have been shown to potentially influence the hypothesised relationships. Therefore, we controlled individuals' gender, age, education level, MTurk experience and IT use. Furthermore, we also controlled social desirability bias, that is, the tendency of individuals to give socially desirable responses, which is usually a concern in self-report surveys (Kwak *et al.*, 2021), measured as true and false on the scale given by Reynolds (1982).

4.3 Data filtering and sample size

We started by looking at evidence for the use of bots as, lately, there have been concerns about a "bot panic", that is, automated programs mimicking human behaviour on MTurk

(Dreyfuss, 2018). All respondents who were asked to confirm that they were human using the reCAPTCHA passed the test. A total of 474 responses were received in Qualtrics. After eliminating the incomplete responses (41), respondents who failed the attention check (34), unsuccessful data quality tests (6) and multiple submission attempts (27), only 366 responses were suitable for data analysis. We used Qualtrics built-in IP address feature to minimise the risk of multiple submissions and eliminate any misleading information about location. To determine the adequate sample size requirement, we used the G* power tool (Faul *et al.*, 2009). The proposed sample size had an effect size of 0.15, an alpha of 0.05 and a power of 0.95; the minimum sample size needed was 89 for four independent variables. Thus, our sample size of 366 is sufficient to report findings with confidence.

4.4 Demographic profile

We conducted a descriptive analysis to extract the demographic profile of MTurk respondents. Our sample included 63.39% men and 36.61% women. The top two countries from which MTurk workers completed our survey were the United States (72.13%) and India (23.49%) followed by Brazil, Italy, Ireland, Pakistan, Thailand, Singapore, North Macedonia, Canada and Germany. The dominance of the United States and India among the worker population is well-documented in the literature (Berg *et al.*, 2018). Table 1 shows the demographic profile of participants.

5. Results and data analysis

In this section, we represent the results of common method bias and non-response bias followed by primary analysis.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	232	63.39%
	Female	134	36.61%
Age	18–24 years	17	4.64%
	25–30 years	90	24.59%
	31–40 years	146	39.89%
	41–50 years	75	20.49%
	51–60 years	31	8.47%
	Greater than 60	7	1.91%
Education level	Some high school	1	0.27%
	High school	35	9.56%
	Some college	45	12.30%
	Associate degree	35	9.56%
	Bachelor's degree	200	54.64%
	Master's degree	43	11.75%
	Advanced graduate work or PhD	7	1.91%
MTurk experience	Less than 1 year	38	10.38%
	1–2 years	49	13.39%
	3–4 years	99	27.05%
	5 or more years	180	49.18%
MTurk status	Regular status	141	38.52%
	Master status	225	61.47%

Note(s): Total Respondents n = 366
Source(s): Author's own creation/work

Table 1.
Demographic profile of respondents

5.1 Common method bias and non-response bias

We tested all the measured variables for *common method bias* (CMB) since the data were self-reported and collected from a single source. The extent of common method bias was assessed using two approaches. First, Harman's one-factor test, which was performed by including all items in principal components factor analysis (Podsakoff *et al.*, 2003). Evidence for common method bias exists when one factor accounts for most of the covariance (i.e. explained variance >50%). The specified "one factor" explained 17% variance, and hence the data do not indicate evidence of common method bias. Second, we tested for CMB based on variance inflation factors (VIF), as suggested by Kock (2015). The highest VIF value was for work overload and strain, that is, 1.741. The occurrence of a VIF greater than 3.30 for any latent variable indicates CMB may contaminate the model. Our model indicates values lower than 3.30; thus, the model is considered free of CMB.

As the data were collected through survey, the presence of non-response bias can be an issue regardless of the response rate achieved. To test for non-response bias, we performed wave analysis and compared the late responders to the early responders (Atif *et al.*, 2012; Lewis *et al.*, 2013). We assessed the response variation by comparing the means of the first and the last 50 responders using the sample *t*-test method. We found no significant differences in the set of comparisons; thus, we deemed non-response bias not to be a significant issue (see Table A2 in the *Appendix*).

5.2 Structural equation modelling

Next, we used structural equation modelling (SEM) using partial least squares (PLS) to test our proposed research model with the help of SmartPLS software v.3.3.3. As a second-generation SEM technique, PLS has been used for modelling causal networks of effects simultaneously, and it is of much value in behavioural research (Lowry and Gaskin, 2014). The SEM analysis is conducted following a two-stage analytical procedure (Hair *et al.*, 2014). The first stage assessed the measurement model for reliability and validity. The second stage evaluated the structural model to test the research hypotheses.

5.3 Measurement model

First, the path modelling procedure was carried out by calculating the PLS algorithm with a maximum of 300 iterations (with the path weighting scheme as a weighting method) to evaluate the measurement model. As all constructs in the model were reflective, we followed the procedures recommended by Hair *et al.* (2019). To ensure the reliability and validity of the measurement model, we assessed indicator loadings, internal consistency reliability, convergent validity and discriminant validity (Hair *et al.*, 2019). The first step requires measuring indicator loadings. Loadings above 0.7 are recommended as a benchmark. For a few items, outer loadings were below the threshold and were eliminated. Therefore, two items from job autonomy and one from job insecurity were removed (see Table A1 in the *Appendix*). In addition, each of the measurement items had a significant loading ($p < 0.01$) on the respective latent construct, which was below the 0.05 threshold proposed by Gefen and Straub (2005). Table 2 shows all item loadings.

As the second step, we used composite reliability (CR) to measure reliability (CR > 0.7). The results indicate that the CR for all the variables is greater than 0.7, indicating good internal consistency. In addition, Cronbach's alpha α was used to check the internal consistency reliability ($\alpha > 0.7$). The results indicate α above the threshold value for all the variables except job autonomy, which showed marginally low consistency reliability ($\alpha = 0.676$). However, studies support $\alpha = 0.6$ as an acceptable threshold (Kim *et al.*, 2009; Taber, 2018).

Construct	Item	Loading	Mean	Median	Standard deviation
IT complexity	ITC1	0.891	6.006	6	0.869
	ITC2	0.914	5.937	6	0.964
	ITC3	0.879	5.898	6	0.952
IT presenteeism	ITP1	0.728	5.788	6	1.045
	ITP2	0.833	5.890	6	1.009
	ITP3	0.902	5.956	6	0.989
	ITP4	0.889	5.915	6	0.942
Job autonomy	AU3	0.852	5.573	6	1.376
	AU4	0.885	5.171	5	1.627
Feedback	UF1	0.825	3.733	4	1.857
	UF2	0.810	4.849	5	1.645
	UF3	0.808	4.860	5	1.581
	UF4	0.821	4.758	5	1.549
Work overload	WO1	0.889	3.019	3	1.680
	WO2	0.924	3.193	3	1.754
	WO3	0.939	3.047	3	1.743
Job insecurity	JI1	0.870	3.992	4	1.629
	JI2	0.923	3.190	3	1.653
Strain	STR1	0.937	3.141	3	1.499
	STR2	0.951	3.107	3	1.513
	STR3	0.939	3.281	3	1.590
	STR4	0.928	3.220	3	1.628
Cognitive well-being	CW1	0.942	4.546	5	1.777
	CW2	0.914	4.686	5	1.738
	CW3	0.930	4.857	5	1.828
	CW4	0.882	4.658	5	1.790
	CW5	0.817	3.868	4	2.027
Positive affective well-being	PA1	0.807	3.358	3	0.953
	PA2	0.786	3.438	3	1.046
	PA3	0.894	3.063	3	1.085
	PA4	0.899	3.234	3	1.080
	PA5	0.867	3.039	3	1.175
Negative affective well-being	NA1	0.853	2.562	3	0.984
	NA2	0.829	2.025	2	0.989
	NA3	0.814	2.240	2	1.106
	NA4	0.852	2.504	3	1.129
	NA5	0.673	2.523	3	1.076
Discontinuous intention	DI1	0.929	1.796	1	1.692
	DI2	0.942	1.658	1	1.514
	DI3	0.936	1.678	1	1.551

Source(s): Author’s own creation/work

Table 2.
Item loadings and descriptive statistics

The third step involved measuring the convergent validity of each construct measure. For this purpose, we used average variance extracted (AVE) to verify each construct, which in our case was greater than 0.5 for all variables. In sum, the model’s convergent validity could be established. Table 3 shows reliability and validity for each construct.

The fourth step was to assess the discriminant validity, which is the extent to which a construct is empirically distinct from other constructs in the model. Traditionally used criteria, as proposed by Fornell and Larcker (1981), is to measure the square root of AVE of each latent variable that should be higher than the correlations among the latent variable. In Table 4, Fornell–Larcker criterion off-diagonal values represent the correlation coefficients between potential constructs, and the diagonal values represent the square root of the AVE

Construct	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
IT complexity	0.876	0.923	0.800
IT presenteeism	0.877	0.905	0.707
Job autonomy	0.677*	0.860	0.755
Feedback	0.854	0.889	0.666
Work overload	0.905	0.941	0.841
Job insecurity	0.760	0.892	0.805
Strain	0.955	0.967	0.881
Cognitive well-being	0.940	0.954	0.806
Positive affective well-being	0.906	0.929	0.725
Negative affective well-being	0.864	0.903	0.651
Discontinuous intention	0.929	0.955	0.876

Note(s): *Slightly lower than the threshold of 0.7
Source(s): Author's own creation/work

Table 3. Construct reliability and validity

value of each construct. Cross-loading factors are also used to test a reflective measurement model's discriminant validity. Table A3, in the *Appendix*, reports the cross-loading factors among the measured items, indicating that each indicator loading is higher than its cross-loadings. In addition, heterotrait–monotrait ratio (HTMT) of the correlations was utilised to assess further discriminant validity (Henseler *et al.*, 2015). The highest absolute HTMT value for our measures was 0.75, which satisfies the threshold of maximum 0.85. In summary, results show the data passes reliability and validity evaluation (see Table 5). Moreover, we checked the variance inflation factor (VIF) to assess the concern of possible multicollinearity for the structural model. The results reveal each VIF <3, as recommended by Hair *et al.* (2019). Thus, multicollinearity was not an issue in this study.

5.4 Structural model

To test the structural model, we assessed the path coefficients, the *t*-values of the variables and their statistical significance (*p*-values) using the bootstrap re-sampling method with 5000 samples. The results indicate that from the technology characteristics, IT complexity was significantly positively associated with both technostressors, that is, work overload supporting *H1a* (t = 2.698; *p*-value <0.01) and job insecurity *H1b* (t = 2.849; *p*-value <0.01). In terms of job characteristics, only feedback was significantly positively associated with work overload, supporting *H4a* (t = 5.019; *p*-value <0.001) and job insecurity *H4b* (t = 3.311; *p*-value <0.01). IT presenteeism and job autonomy showed no significant relationship with either technostressor. Therefore, none of hypotheses *H2a*, *H2b*, *H3a* or *H3b* are supported. Both the work overload and job insecurity technostressors showed a significantly positive relationship with strain (t = 8.629; *p*-value <0.001 and t = 3.865; *p*-value <0.001 respectively), supporting *H5* and *H6*. Among the dependent variables, strain had a significantly positive relationship with negative affective well-being (t = 8.445; *p*-value <0.001) and discontinuous intention (t = 9.954; *p*-value <0.001). Therefore, hypotheses *H9* and *H10* are supported. However, strain had no significant relationship with cognitive well-being or positive affective well-being, so hypotheses *H7* and *H8* are rejected. A summary of results along with path-coefficients, *t*-values and *p*-values is provided in Table 6.

The commonly used measure to evaluate the structural model is the coefficient of determination R^2 value, which explains the model's predictive power (Hair *et al.*, 2019). In terms of the model's predictive power (R^2), we find that in our model, technology and job

Table 4.
Discriminant validity: Fornell–Larcker criterion

	IT complexity	IT presenteeism	Job autonomy	Feedback	Work overload	Job insecurity	Strain	Cognitive well-being	Positive affective well-being	Negative affective well-being	Discontinuous intention
IT complexity	*0.895*										
IT presenteeism	0.560	*0.841*									
Job autonomy	0.200	0.149	*0.869*								
Feedback	−0.005	0.013	0.046	*0.816*							
Work overload	−0.211	−0.196	−0.068	0.271	*0.917*						
Job insecurity	−0.163	−0.081	−0.036	0.203	0.619	*0.897*					
Strain	−0.285	−0.180	−0.018	0.213	0.698	0.571	*0.939*				
Cognitive well-being	0.107	−0.022	0.206	0.187	0.017	−0.039	−0.108	*0.898*			
Positive affective well-being	0.164	0.065	0.182	0.225	0.049	−0.026	−0.064	0.580	*0.852*		
Negative affective well-being	−0.195	−0.091	−0.149	0.091	0.456	0.362	0.549	−0.357	−0.410	*0.807*	
Discontinuous intention	−0.207	−0.241	−0.055	0.231	0.470	0.355	0.489	0.159	0.108	0.339	*0.936*

Note(s): Numbers in italic are the square root of the AVE value for each variable
Source(s): Author's own creation/work

	IT complexity	IT presenteeism	Job autonomy	Feedback	Work overload	Job insecurity	Strain	Cognitive well-being	Positive affective well-being	Negative affective well-being
IT presenteeism	0.637									
Job autonomy	0.260	0.208								
Feedback	0.063	0.136	0.085							
Work overload	0.234	0.185	0.086	0.251						
Job insecurity	0.189	0.088	0.116	0.220	0.738					
Strain	0.309	0.166	0.035	0.184	0.749	0.659				
Cognitive well-being	0.119	0.049	0.254	0.175	0.064	0.078	0.116			
Positive affective well-being	0.184	0.099	0.233	0.217	0.092	0.040	0.090	0.624		
Negative affective well-being	0.219	0.104	0.195	0.121	0.511	0.437	0.597	0.398	0.467	
Discontinuous Intention	0.226	0.229	0.075	0.201	0.509	0.413	0.518	0.169	0.119	0.376

Source(s): Author's own creation/work

Table 5.
Heterotrait–monotrait ratio (HTMT)

Hypothesis	Path	Coefficient	t-value	p-value	Decision
H1a	IT complexity → Work overload	−0.150	2.698	0.007**	Supported
H1b	IT complexity → Job insecurity	−0.173	2.849	0.004**	Supported
H2a	IT presenteeism → Work overload	−0.100	1.916	0.055	Not supported
H2b	IT presenteeism → Job insecurity	0.035	0.546	0.585	Not supported
H3a	Job autonomy → Work overload	−0.030	0.555	0.579	Not supported
H3b	Job autonomy → Job insecurity	−0.020	0.320	0.749	Not supported
H4a	Feedback → Work overload	0.240	5.019	0.000***	Supported
H4b	Feedback → Job insecurity	0.179	3.311	0.001**	Supported
H5	Work overload → Strain	0.531	8.629	0.000***	Supported
H6	Job insecurity → Strain	0.203	3.865	0.000***	Supported
H7	Strain → Cognitive well-being	−0.040	0.709	0.478	Not supported
H8	Strain → Positive affective well-being	−0.010	0.199	0.842	Not supported
H9	Strain → Negative affective well-being	0.448	8.445	0.000***	Supported
H10	Strain → Discontinuous intention	0.460	9.954	0.000***	Supported

Note(s): *p-value <0.5; **p-value <0.01; ***p-value <0.001
Source(s): Author's own creation/work

Table 6.
Results for hypotheses

characteristics explain 22% of the variance in work overload and 13% in job insecurity. Both technostressors explain a variance of 55% on strain. The explained variance on dependent variable negative affective well-being is 39% and on discontinuous intention is 29%.

Next, we calculated the effect sizes f^2 for each path model. As a rule of thumb, values of 0.02, 0.15 and 0.35 are interpreted as small, medium and large effects (Hair *et al.*, 2019). The f^2 values for *H1a*, *H1b*, *H4a* and *H4b* are 0.020, 0.022, 0.072 and 0.036, respectively, indicating a weak effect. The f^2 values of *H2a*, *H2b*, *H3a* and *H3b* showed no effect as values were below 0.02. For both technostressors, the effect sizes f^2 indicate large effect for *H5* (0.362) and weak effect for *H6* (0.056). The effect sizes f^2 indicate medium effect of strain on two outcomes as the values for *H9* and *H10* were 0.279 and 0.255, respectively. The effect size f^2 of strain indicates no effect on outcomes *H7* and *H8* as the values were below 0.02.

Calculating the cross-validated redundancy Q^2 is another means to assess model's out-of-sample predictive power or predictive relevance (Hair *et al.*, 2019). As a rule of thumb, Q^2 values larger than zero for a particular endogenous construct indicate the path model's predictive relevance for that construct (Hair *et al.*, 2019). In our model, all the values were above 0, supporting the predictive relevance of the constructs. The Q^2 values for both technostressors work overload and job insecurity were 0.098 and 0.045, respectively, and the Q^2 value for strain was 0.452. The Q^2 values for the outcomes negative affective well-being, discontinuous intention, cognitive well-being and positive affective well-being were 0.192, 0.205, 0.009 and 0.002, respectively.

Finally, of the control variables, social desirability was related to cognitive well-being, positive affective well-being and negative affective well-being. The demographic controls of gender and age were not significantly related to any construct.

5.5 Post hoc analysis

In the technostress process, technostressors create a mediating pattern between environmental antecedents and strain. Early research has established that the translation of technostressors into workplace outcomes is through mediation like appraisal and coping (Gaudioso *et al.*, 2017; Lazarus and Folkman, 1987; Pflügner *et al.*, 2021). For a deeper interpretation of these findings, we examined the mediating effect of technostressors (work overload and job insecurity) between antecedents (technology and job characteristics) and strain, in a post hoc analysis. To estimate the mediating effect, we followed the method suggested by Zhao *et al.* (2010). For the mediation analysis, if the corresponding indirect effect is significant, then mediation is present. However, direct effects must be examined to establish the type of mediation. The mediation effects can be "indirect-only" ("full mediation" in terms of Baron and Kenny (1986)), "competitive mediation" or "complementary mediation" ("partial mediation" in terms of Baron and Kenny (1986)). Competitive mediation occurs when both the indirect effect and direct effect are significant and point in opposite directions, while complementary mediation occurs when both indirect and direct effect are significant and point in the same direction (Hair *et al.*, 2014).

Our results, as shown in Table 7, indicate that technostressors provide partial complementary mediation between IT complexity and strain since indirect and direct effect are significant and point in the same direction. The direct effect of feedback on strain is not significant; therefore, we conclude that technostressors fully mediate the relationship between feedback and strain. The results show that strain also plays a mediating role between technostressors and outcomes. Specifically, strain provides a partial complementary mediation between work overload and outcomes (negative affective well-being and discontinuous intention). Since the direct effect of job insecurity on outcomes (negative affective well-being and discontinuous intention) is not significant, we conclude that strain fully mediates this relationship. In terms of IT presenteeism and job autonomy, there was no evidence of technostressors providing a mediation effect. Similarly, there was no evidence of strain providing a mediation effect between technostressors and cognitive well-being or positive affective well-being. Table 7 details the results of both direct and indirect mediating effects with *t*-values and path coefficients.

6. Discussion

This study examined technostress from the theoretical perspective of person–environment fit and job characteristics theory in the context of OLMs. Specifically, a research model was proposed to investigate how technology and job characteristics jointly influence technostressors, strain and their outcomes.

Indirect path	Indirect effect ($p_1 \cdot p_2$)	Indirect *t*-value	Direct effect (p_3)	Direct *t*-value	Mediation
IT complexity → Work overload → Strain	−0.0739	*2.5691**	−0.1353	*3.7707****	Partial mediation
IT complexity → Job insecurity → Strain	−0.0338	*2.1881**	−0.1353	*3.7707****	Partial mediation
Feedback → Work overload → Strain	0.1197	*3.9231****	0.0333	0.7332	Full mediation
Feedback → Job insecurity → Strain	0.0355	*2.6752***	0.0333	0.7332	Full mediation
Work overload → Strain → Negative affective well-being	0.1618	*3.5838****	0.1673	*2.1715**	Partial mediation
Work overload → Strain → Discontinuous intention	0.1568	*3.9292****	0.1790	*2.9282***	Partial mediation
Job insecurity → Strain → Negative affective well-being	0.0644	*3.0501***	0.0125	0.2292	Full mediation
Job insecurity → Strain → Discontinuous intention	0.0624	*3.1667***	0.0379	0.7080	Full mediation

Note(s): **p*-value <0.05; ***p*-value <0.01; ****p*-value <0.001
Source(s): Author's own creation/work

Table 7.
Mediating effects

First, we analysed the relationship between technology characteristics (IT complexity and IT presenteeism) and technostressors (work overload and job insecurity). The results indicate that only IT complexity is significantly associated with both technostressors. In contrast, previous literature on technostress shows that in both traditional work and telework settings, IT complexity and work overload tend not to be correlated (Ayyagari *et al.*, 2011; Suh and Lee, 2017). We link this difference to the competitive nature of OLM work, where increased effort is required to deal with work demands and the complexity of specific technologies. Workers in such platforms frequently need to develop new skills beyond their regular tasks, which in turn may enhance work overload. For example, in platforms like MTurk, workers often develop sophisticated user scripts to secure the best-paying tasks (Berg *et al.*, 2018). The P-E misfit increases when workers are required to spend time and effort meeting work demands imposed by IT, such as to do more in less time.

Our results reveal that IT complexity impacts job insecurity. Failure to learn and to manage time places workers at risk of losing well-paying tasks to their counterparts. Moreover, previous technostress studies have focussed on the general use of IT (Ayyagari *et al.*, 2011; Suh and Lee, 2017), while we specifically focus on platform work-related IT use. In contrast to previous literature, our findings indicate that IT presenteeism showed no significant relationship with technostressors. One possible explanation for this result stems from the higher temporal flexibility these platforms offer. OLM workers have a choice to reschedule tasks at their convenience, unlike in the traditional work environment. A second explanation is that our research indicates the largest group of participants as individuals in their late twenties (24.59%) and mid-thirties (39.89%) with a high level of formal education. These respondents generally exhibit greater familiarity and proficiency with digital technology compared to older participants. According to Vogels (2019), different generations exhibit varying levels of technology usage. Younger users such as millennials rely heavily on digital technology and have positive experiences with its use. Conversely, older users face distinct obstacles when it comes to adopting new technologies, ranging from a lack of confidence in using unfamiliar devices to physical difficulties in manipulating various digital tools. Therefore, IT presenteeism may not be an issue for the sample we studied.

The next aspect of our analysis was examination of the relationship between job characteristics (job autonomy and feedback) and technostressors. In our study, job autonomy was not significantly related to either technostressor. OLMs facilitate workers with a certain job autonomy, as they are free to set their own schedule and less likely to experience a P-J misfit. This result is in line with previous research findings where there is no association between work overload and job autonomy for teleworkers (Suh and Lee, 2017). One possible explanation for the non-significant relationship is the impact of the COVID-19 pandemic and its repercussions. The data for this study were gathered during the COVID-19 lockdown. The relationship between job autonomy and work overload is contingent on the work environment—the initial phase of the pandemic led to reduced demand and a decline in work opportunities, which gradually recovered over time (Stephany *et al.*, 2020). OLM workers do not possess a traditional worker–employer relationship, as they have a choice as to which tasks to accept. For this reason, workers' job autonomy is less likely to impact job insecurity.

Feedback showed a significant relationship with both work overload and job insecurity. We explain this finding in terms of the feedback mechanism in OLMs, where approval ratings create pressure on workers. For example, if a worker gets two rejections, their approval rating will automatically drop. To address this, workers might work harder and longer to minimise the rejection effect. This effort to catch up with more high-paying HITs can potentially enhance work overload. The feedback will impact job insecurity because low approval ratings can make workers feel easily replaceable. Requesters prefer workers who possess high scores or appear on top in search results due to platform algorithms. Insecurity around ratings can be stressful for workers because algorithms filter work away from workers with low ratings (Wood *et al.*, 2019b). This result is consistent with the OLM literature, which highlights that reputation mechanisms influence the probability of future task selection (Kokkodis and Ipeirotis, 2015).

Our results indicate that approximately 55% of the variance in strain is explained by the proposed technostressors. This validates the view that work overload and job insecurity are noteworthy technostressors in OLM. We investigated the impact of strain on outcomes such as cognitive well-being, positive affective well-being, negative affective well-being and discontinuous intention. Our findings indicate that strain has no significant relationship with cognitive well-being or positive affective well-being. This result indicates that the strain of OLM work is less likely to impact cognitive well-being of workers. In contrast, the relationship between strain and worker well-being is more pronounced in traditional forms of work (De Witte *et al.*, 2015). The impact of these platforms on cognitive well-being may be low as many workers join these platforms to earn additional income. For others, OLM work represents their primary source of income. Thus, OLM workers are not a homogeneous group. Workers in both categories are likely to experience different outcomes such as life satisfaction, job satisfaction and turnover based on their push and pull motivations and the seriousness with which they regard their work (Brawley, 2017; Keith *et al.*, 2019).

The technostress phenomenon is aligned with research into the dark side of technology, as negative outcomes are likely. However, recent research suggests that technostress can also cultivate positive experiences, such as arousal and challenging situations (Benlian, 2020). Our findings indicate the strain due to platform work is less likely to impact positive affective well-being. Despite experiencing strain, workers may demonstrate positive emotions. For example, a worker may experience strain because of a rejection but simultaneously be happy to contribute to an exciting project. This builds upon previous research that portrays gig work as a form of emotional labour, where strain may result in dire outcomes for some workers but be quite positive for others, for example, suppressing emotions versus developing resilience (Ashford *et al.*, 2018; Kaplan *et al.*, 2018). However, strain will directly influence negative affective well-being linked to increase in unpleasant emotions. Low-paying tasks and rejections, frequent on these platforms, are usually a source of frustration and may directly influence workers' negative emotions (Ashford *et al.*, 2018; Kaplan *et al.*, 2018). The presence of strain can also provoke behaviours such as discontinuous intention. The study results show that strain is significantly associated with discontinuous intention. In OLMs, discontinuous intention may not necessarily result in actual turnover, as there are fewer barriers to quitting than in the traditional setting. Workers can stop working for a specific requester or stop working on the HIT, or in some scenarios, leave the platform altogether (Brawley and Pury, 2016).

These findings suggest that technostress is an evolving concept (Fischer *et al.*, 2021) that needs to be updated as new platforms alter user engagement with their environment. Some of the traditional relationships do not hold in the gig environment, probably because of the unique style of this work environment.

6.1 Implications for theory

This study provides several key research contributions in the domain of OLMs, technostress and IS. First, our study is the first to propose a technostress model in the context of the digital gig economy. It advances an understanding of workers' experiences and well-being in OLMs, an underexplored area. Our model provides a foundation with empirical insights to examine the phenomenon of technostress for similar dynamic environments and alternate gig platforms. The current research enhances our comprehension of OLMs by going beyond viewing them as an enigmatic phenomenon. Instead, we build upon prior studies by carefully examining the various facets of OLMs and how they influence technostress. The results of the present study indicate that the P–E fit theory can provide a valuable understanding of the relevance of gig work experience for workers' well-being. Our findings identify IT complexity and feedback as unique characteristics of OLMs and also a source of technostress. Our findings also highlight how OLM work differs from traditional work settings. For example, IT complexity has been shown to have a significant impact on work overload and job insecurity in OLMs.

Second, in the context of technostress, previous IS studies have focussed on technology characteristics as an environmental antecedent (Ayyagari *et al.*, 2011). We expand the technostress literature by investigating the role of job characteristics as an environmental antecedent to determine how they contribute to the technostress process. Specifically, we find that negative task feedback prompts perceptions of work overload and job insecurity in OLMs. Previous research has studied the role of technostressors and their impact on work-related outcomes such as job satisfaction, exhaustion and burnout (Ragu-Nathan *et al.*, 2008; Srivastava *et al.*, 2015). However, our study makes a key contribution by expanding technostress outcomes from the subjective well-being perspective. Our findings identify negative affective well-being and discontinuous intention as OLM outcomes. Most importantly, prior research has conceptualised technostressors generally as a higher-order construct (aggregated approach), with few studies considering the impact of technostressors at the individual level (disaggregated approach) (Sarabadani *et al.*, 2018; Nastjuk *et al.*, 2023). Our research is in line with the recent call to adopt a disaggregated approach to capture the subtlety involved in understanding technostressors. Furthermore, examining technostressors as they relate to individuals enables the development of more nuanced theoretical linkages with important outcomes (Nastjuk *et al.*, 2023).

6.2 Implications for practice

Platform owners or managers and those sourcing crowd-work can use the proposed model to recognise the characteristics that are a source of technostress. Based on our findings, OLMs can take the necessary steps to design their workplace policies and strategies to promote meaningful work. First, in our conclusions, IT complexity was significantly associated with work overload. Platform workers are engaged in multiple tasks as well as non-task-related activities, for example, monitoring HITs, using scripts and so on. To reduce work overload for workers, requesters can implement several strategies. Requesters should specify task requirements in a way that helps workers to minimise work overload. One option is to create well-designed tasks with clear titles, descriptions, pay and requirements. A second option is to establish reasonable time estimates by setting the time frame for HITs longer than the anticipated completion time. A third option is for requesters to enhance accountability and responsibility by transparently disclosing their identity, thereby enabling workers to spend less time gathering relevant information and verifying the legitimacy of the requester.

As results indicate that IT complexity is related to job insecurity, platforms can develop pre-emptive strategies to mitigate technostress. For example, limiting the number of tasks performed per worker can reduce work overload and increase participation chances. Some platforms have started implementing restrictions that prevent workers from finishing tasks once they reach the platform's limit. For example, MTurk imposes a daily limit of 3800 jobs for workers. At the same time, Prolific employed a mechanism that capped workers' earnings at a specific threshold (Lascău *et al.*, 2022). Meanwhile, platform managers can play a role by ensuring that tasks posted on the platform adhere to realistic guidelines and fair compensation. Additionally, they can provide workers with different types of training to increase the knowledge required to complete work demands.

Second, given the significant and positive relationship between feedback and technostressors, requesters should provide constructive and supportive feedback. Instead of relying on accept or reject notifications, briefly commenting on task performance will improve subsequent task submission and performance. Research suggests that providing feedback during a task enables users to immediately apply the information to the task (Gould *et al.*, 2016; Maior *et al.*, 2018). Requesters should use positive language to encourage workers and clarify task-related questions. Platforms should also take steps to implement positive communication practices. For example, making corrective feedback mandatory after every task and allowing workers to appeal unfair rejections would be useful additions. Finally, platforms must develop efficient attention and time management strategies to relieve IT pressure and strain.

Our results indicate that OLM strain is associated with negative affective well-being. Therefore, platforms must identify workers experiencing high levels of negative or low levels of positive emotions to reduce stressors and discourage discontinuation, for example, allow workers to take frequent breaks without a pay penalty, provide resources and troubleshooting assistance and arrange regular community/forum events. However, our research is not aimed at criticising these technological work environments. Instead, our research sets a starting point to examine platform workers' health and well-being, so that necessary interventions can be designed. By recognising the sources of technostress and taking steps to mitigate its effects, platforms can help the transition to this new form of work, reduce the strain it causes and maintain worker well-being.

7. Limitations and future research

Like all research, this study is not without limitations that need to be addressed in future studies. The sample may have been biased because the participants were limited to a single platform at a single point in time. The focus of this research is MTurk, but the presence and importance of the factors identified in the model may differ in other platforms. MTurk is a platform with varying tasks, from simple to complex. Some microtasks are short, and a worker may not be exposed to technology for longer than a few minutes, but to earn a decent income they need to spend a long time working on several tasks. As there are many forms of work within the gig economy, the stressors in one context will not necessarily apply in another context. Therefore, the model must be tested in other macro-platform settings for validation, cautiously using results when generalising from one context to another.

Our study is cross-sectional in nature which limits the inferences we can make about causal mechanisms. To advance our causal understanding of how technostressors interact with work characteristics to alter worker outcomes, future research could adopt an experience sampling approach where data are gathered multiple times a day over multiple days. Such an approach would not only move our understanding from correlation towards causation but also reveal how daily changes in technostress are linked to changes in state well-being.

Technostress is an established research topic in the IS field. Technostressors may not necessarily always act as a hindrance. In certain situations, they bring personal development and goal attainment through challenge stressors (Benlian, 2020; Tarafdar *et al.*, 2019a). Thus, examining how beneficial outcomes can emerge from technostress is worthwhile. Such a line of enquiry is particularly relevant in a gig environment because of the contradictory atmosphere in which it operates. Future research can extend our model by considering job characteristics as antecedents to other technostressors, especially distinguishing between challenge and hindrance technostressors. Another area of future exploration could be to delve into the characteristics of gig workers as they differ in their platform use depending on their motivation (e.g. financial dependence, full-time job, hedonic reasons). Specifically, examining gig worker demographics, personality profiles and computer efficacy as a moderator variable might also provide valuable insights. We recommend that researchers establish measurement items specific to work environments that better represent OLMs with their unique technostressors.

Notes

1. MTurk is an online labour market where employers (called requesters) recruit employees (called workers) to complete HITs (Human Intelligence Tasks) for remuneration (called a reward) (Hunt and Scheetz, 2019).
2. An MTurk Master Worker is someone who has consistently demonstrated a high degree of success in performing a wide range of HITs across a large number of requesters.

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Appendix

Construct	Source and response scale	Items and their codes
IT complexity†	Ayyagari *et al.* (2011) 1 – Strongly Disagree and 7 –Strongly Agree	ITC1. Learning to use ICTs is easy for me. ITC2. ICTs are easy to use ITC3. It is easy to get results that I desire from ICTs
IT presenteeism	Ayyagari *et al.* (2011) 1 – Strongly Disagree and 7 –Strongly Agree	ITP1. The use of ICTs enables others to have access to me ITP2. ICTs make me accessible to others. ITP3. The use of ICTs enables me to be in touch with others. ITP4. ICTs enable me to access others
Job Autonomy	Ahuja *et al.* (2006) 1 – Strongly Disagree and 7 –Strongly Agree	AU1. I control the content of my job. * AU2. I have a lot of freedom to decide how I perform assigned tasks. * AU3. I set my own schedule for completing assigned tasks AU4. I have the authority to initiate projects at my job
Feedback	Steelman *et al.* (2004) 1 – Strongly Disagree and 7 –Strongly Agree	UF1. When I do not meet deadlines, my requesters let me know. UF2. My requesters tell me when my work performance does not meet standards. UF3. On those occasions when my job performance falls below what is expected, my requesters let me know. UF4. On those occasions when I make a mistake at work, my requesters tell me
Work overload	Ayyagari *et al.* (2011) 1 – Strongly Disagree and 7 –Strongly Agree	WO1. ICTs create many more requests, problems or complaints in my job than I would otherwise experience. WO2. I feel busy or rushed due to ICTs. WO3. I feel pressured due to ICTs

(*continued*)

Table A1. Construct and items

Construct	Source and response scale	Items and their codes
Job insecurity	Ayyagari *et al.* (2011) 1– Strongly Disagree and 7 –Strongly Agree	JI1. ICTs will advance to an extent where my present job can be performed by a less skilled individual. JI2. I am worried that new ICTs may pose a threat to my job. JI3. I believe that ICTs make it easier for other people to perform my work activities. *
Strain	Ayyagari *et al.* (2011) 1 – Never and 7 Daily	STR1. I feel drained from activities that require me to use ICTs. STR2. I feel tired from my ICT activities. STR3. Working all day with ICTs is a strain for me STR4. I feel burned out from my ICT activities
Cognitive well-being	Diener *et al.* (1985) 1 – Strongly Disagree and 7 – Strongly Agree	CW1. In most ways my life is close to my ideal. CW2. The conditions of my life are excellent. CW3. I am satisfied with my life. CW4. So far, I have gotten the important things I want in life. CW5. If I could live my life over, I would change almost nothing
Positive affective well-being	Anderson *et al.* (2015) 1 – Never and 5 – Extremely often or always	PA1. My job made me feel at ease. PA2. My job made me feel grateful. PA3. My job made me feel enthusiastic. PA4. My job made me feel happy. PA5. My job made me feel proud
Negative affective well-being	Anderson *et al.* (2015) 1 – Never and 5 – Extremely often or always	NA1. My job made me feel frustrated NA2. My job made me feel angry NA3. My job made me feel anxious NA4. My job made me feel fatigued NA5. My job made me feel bored
Discontinuous intention	Turel (2014) 1 – Not at all and 7 – To a very large extent	DI1. I intend to stop using MTurk in the next 3 months DI2. I predict I would stop using MTurk in the next 3 months DI3. I plan to stop using MTurk in the next 3 months
Instructed-response item	Aguinis *et al.* (2021) 1 – Strongly Disagree and 7 – Strongly Agree True or False	Please select neither agree nor disagree to demonstrate your attention This HIT you are working on is an audio transcription HIT
Data quality	Brawley (2017) Yes – my data is good! or no	Were you serious and honest about your responses? (Answer will not affect payment)

Note(s): *Indicates the items removed from analysis
†Note that “IT complexity” measures are reverse coded (i.e. higher scores on these items imply lower complexity)
Participants were instructed that for the purpose of this study references to your ‘job’ and your ‘work’ referred to the use of MTurk. Therefore, each set of questions started with “Considering MTurk work”
Source(s): Author’s own creation/work

Table A1.

Item	*t*-statistic	*p*-value	95% confidence low-bound	95% confidence high-bound
ITC1	0.106146	0.9159	−0.35864	0.398644
ITC2	−0.82246	0.414798	−0.55094	0.230938
ITC3	−1.44769	0.154073	−0.52539	0.085389
ITP1	0.889001	0.378346	−0.2521	0.652097
ITP2	−0.18884	0.850995	−0.46566	0.385657
ITP3	1.196903	0.237103	−0.19011	0.750114
ITP4	0.449281	0.65521	−0.27783	0.437829
AU1	0.281638	0.779407	−0.49082	0.650824
AU2	1.875486	0.066691	−0.03432	0.994318
AU3	0.821479	0.415353	−0.34711	0.827109
AU4	1.457256	0.151425	−0.20467	1.284667
UF1	1.099944	0.276731	−0.33079	1.130792
UF2	−0.19381	0.847129	−0.68214	0.562141
UF3	−0.36062	0.71993	−0.7887	0.548698
UF4	0.82945	0.410872	−0.34147	0.821467
WO1	1.11378	0.270807	−0.32171	1.121713
WO2	−0.20938	0.835023	−0.84784	0.687836
WO3	0.897992	0.373581	−0.42087	1.100871
JI1	0.898332	0.373402	−0.39584	1.035843
JI2	0.541676	0.590496	−0.54198	0.941984
JI3	−1.07034	0.289712	−0.97836	0.298356
STR1	1.779812	0.081309	−0.07487	1.234875
STR2	0.652753	0.516966	−0.41572	0.815723
STR3	0.449163	0.655294	−0.48637	0.766366
STR4	0.86607	0.390672	−0.36969	0.929694
CW1	0.553207	0.582637	−0.47387	0.833867
CW2	0.988252	0.327884	−0.33071	0.970708
CW3	0.671334	0.50516	−0.47842	0.958417
CW4	1.101877	0.275898	−0.29656	1.016559
CW5	1.643727	0.106635	−0.16025	1.600252
PA1	0.000001	0.999998	−0.36313	0.363133
PA2	0.498729	0.620202	−0.30294	0.502939
PA3	0.632535	0.529978	−0.30478	0.584783
PA4	0.192377	0.848242	−0.37784	0.45784
PA5	0.090003	0.928652	−0.42656	0.466558
NA1	0.735147	0.465754	−0.20803	0.448028
NA2	0.100525	0.920338	−0.37982	0.419818
NA3	1.088434	0.281728	−0.20311	0.683112
NA4	−0.17786	0.859568	−0.49195	0.411952
NA5	−0.10266	0.918649	−0.41149	0.371486
DI1	1.420142	0.161898	−0.21583	1.255827
DI2	1.237437	0.221822	−0.24959	1.049593
DI3	1.531414	0.132098	−0.16236	1.202362

Note(s): Out of 43 comparisons, just that for PA1 was found to be significant, suggesting that in general there is no difference between these two groups
Source(s): Author's own creation/work

Table A2.
Results of independent *t*-test on first 50 and last 50 responses

Table A3. Cross-loadings between items and constructs

	IT complexity	IT presenteeism	Autonomy	Feedback	Work overload	Job insecurity	Strain	Cognitive well-being	Positive affective well-being	Negative affective well-being	Discontinuous intention
ITC1	0.891	−0.514	−0.161	−0.009	0.182	0.109	0.240	−0.083	−0.152	0.155	0.140
ITC2	0.914	−0.520	−0.165	0.016	0.189	0.150	0.251	−0.104	−0.146	0.164	0.183
ITC3	0.879	−0.472	−0.207	0.004	0.195	0.171	0.269	−0.099	−0.143	0.199	0.225
ITP1	−0.436	0.728	0.145	0.012	−0.054	0.032	−0.053	0.008	0.102	−0.052	−0.086
ITP2	−0.508	0.833	0.155	0.028	−0.126	−0.062	−0.107	0.015	0.097	−0.100	−0.171
ITP3	−0.537	0.902	0.125	−0.012	−0.210	−0.102	−0.199	−0.041	0.033	−0.075	−0.308
ITP4	−0.423	0.889	0.113	0.029	−0.179	−0.058	−0.163	−0.023	0.046	−0.074	−0.142
AU3	−0.192	0.176	0.852	−0.022	−0.058	−0.026	−0.036	0.111	0.150	−0.133	−0.100
AU4	−0.158	0.088	0.885	0.095	−0.060	−0.037	0.003	0.239	0.165	−0.127	−0.002
UF1	0.059	−0.113	0.081	0.825	0.341	0.212	0.279	0.247	0.289	0.072	0.317
UF2	−0.016	0.089	−0.011	0.81	0.146	0.169	0.132	0.056	0.076	0.091	0.094
UF3	−0.082	0.134	0.039	0.808	0.112	0.084	0.058	0.157	0.150	0.044	0.079
UF4	−0.025	0.092	2E-04	0.821	0.138	0.128	0.086	0.065	0.111	0.082	0.108
WO1	0.254	−0.248	−0.058	0.275	0.889	0.524	0.632	0.084	0.129	0.369	0.500
WO2	0.140	−0.129	−0.032	0.237	0.924	0.582	0.609	−0.014	0.023	0.410	0.377
WO3	0.182	−0.157	−0.094	0.231	0.939	0.599	0.676	−0.027	−0.021	0.475	0.409
JI1	0.095	−0.026	0.051	0.17	0.485	0.870	0.435	−0.012	−0.027	0.261	0.253
JI2	0.187	−0.109	−0.098	0.193	0.614	0.923	0.575	−0.053	−0.021	0.375	0.371
STR1	0.280	−0.198	−0.001	0.215	0.674	0.543	0.937	−0.091	−0.034	0.509	0.478
STR2	0.243	−0.143	−0.006	0.21	0.659	0.541	0.951	−0.130	−0.076	0.491	0.431
STR3	0.241	−0.158	−0.015	0.181	0.643	0.507	0.939	−0.093	−0.069	0.529	0.431
STR4	0.303	−0.175	−0.045	0.191	0.644	0.551	0.928	−0.092	−0.060	0.531	0.492
CW1	−0.114	−0.018	0.181	0.165	0.007	−0.075	−0.089	0.942	0.559	−0.333	0.117
CW2	−0.102	−0.002	0.237	0.137	−0.010	−0.079	−0.139	0.914	0.505	−0.332	0.124
CW3	−0.118	−0.013	0.157	0.146	−0.007	−0.059	−0.122	0.931	0.563	−0.364	0.122
CW4	−0.105	0.042	0.203	0.169	−0.011	−0.031	−0.111	0.883	0.484	−0.328	0.132
CW5	−0.047	−0.091	0.150	0.218	0.087	0.063	−0.031	0.815	0.483	−0.251	0.213
PA1	−0.120	0.024	0.195	0.134	−0.016	−0.003	−0.063	0.515	0.810	−0.393	0.128
PA2	−0.140	0.08	0.148	0.215	0.025	−0.019	−0.050	0.414	0.788	−0.285	0.050
PA3	−0.177	0.093	0.164	0.184	0.010	−0.045	−0.109	0.485	0.891	−0.390	0.011

(*continued*)

Table A3.

	IT complexity	IT presenteeism	Autonomy	Feedback	Work overload	Job insecurity	Strain	Cognitive well-being	Positive affective well-being	Negative affective well-being	Discontinuous intention
PA4	−0.113	0.067	0.143	0.203	0.038	−0.041	−0.085	0.543	0.898	−0.395	0.105
PA5	−0.151	0.012	0.128	0.233	0.154	0.004	0.049	0.502	0.868	−0.259	0.170
NA1	0.175	−0.074	−0.118	0.034	0.343	0.264	0.432	−0.337	−0.448	0.853	0.253
NA2	0.261	−0.155	−0.170	0.130	0.454	0.316	0.478	−0.221	−0.223	0.832	0.414
NA3	0.132	−0.069	−0.141	0.102	0.416	0.306	0.447	−0.256	−0.233	0.815	0.282
NA4	0.154	−0.053	−0.097	0.127	0.374	0.322	0.522	−0.341	−0.332	0.850	0.229
NA5	0.038	−0.003	−0.072	−0.064	0.232	0.246	0.307	−0.285	−0.450	0.671	0.181
DI1	0.189	−0.215	−0.043	0.225	0.413	0.297	0.435	0.156	0.121	0.293	0.929
DI2	0.186	−0.22	−0.040	0.23	0.472	0.354	0.475	0.136	0.084	0.359	0.942
DI3	0.206	−0.241	−0.072	0.193	0.433	0.344	0.460	0.155	0.099	0.297	0.936

Source(s): Author's own creation/work

About the authors

Azka Umair is a doctoral candidate at the University of Galway. Her research interest includes online labour markets, worker well-being in digital platforms, computer-human interaction and technology induced stress. Specifically, her research focusses on examining the use of emerging digital technology and its impact on individual behaviour and work outcomes. Her research is multi-disciplinary combining concepts and theories from organisational behaviour, management research, and information systems. Her work has been published in leading conferences such as European Conference on Information Systems and International Symposium on Open Collaboration. Azka Umair is the corresponding author and can be contacted at: a.umair1@nuigalway.ie

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