MASTERARBEIT | MASTER'S THESIS

Titel | Title

The psychological effects of precarious crowdwork

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2025

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 840
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Psychologie
Betreut von | Supervisor:	Univ.-Prof. i.R. Dr. Christian Korunka

Abstract

This study examines the psychological impact of precarious crowdwork on Amazon Mechanical Turk (MTurk) workers, applying the Job Demands-Resources (JD-R) model to assess key stressors such as financial dependency, work pace, job insecurity, and perceived influence. Situating these findings within the expanding role of crowdwork in AI training data production, the study highlights how workers frequently engage in repetitive, cognitively demanding tasks under conditions of algorithmic management. An online survey of n = 456 MTurk users, conducted using selected scales of the Copenhagen Psychosocial Questionnaire, revealed that individuals who relied primarily on crowdwork as their main source of income experienced significantly higher stress levels than those for whom it was a supplementary source of earnings. Interestingly, although these primary income earners reported a greater perceived influence over task selection, this increased autonomy did not yield the expected stress buffering effects. Job demands, particularly task variation, work pace, and insecurity, were strong predictors of burnout. These findings challenge prevailing narratives of autonomy in gig work, suggesting that algorithmic control and platform-induced precarity erode the psychological benefits typically associated with flexible employment. The study emphasizes the urgent need for policy interventions to address structural inequalities in crowdwork and improve working conditions for platform-based labor.

Introduction

Historical Foundations of Labor

For most of history, working was regarded as a means to an end. Only recent developments in the working culture made workers aware that work could serve other functions than just providing the basic needs for living. The harsh conditions faced by workers in the factories of the 19th century led to illness, accidents, and loss of life, as they were treated like machines. Taylorism introduced an approach that sought to incorporate Enlightenment ideals and rationality into the workplace (Taylor, 1911). Taylor aimed to reorganize labor from an engineering perspective. Production processes were meticulously defined and standardized, following a rigorous scientific process. Every worker had to perform their tasks exactly to the specifications of the management's conducted time and motion studies. Taylorism and the associated assembly line that Henry Ford developed increased productivity in the factories, and it arguably made the modern way of living in the 20th century possible, where heightened commodity consumption started to become accessible to the masses of western workers (Cross, 1993; Wilson, 2010). Although Taylorism seemed like a step forward, it was criticized by numerous scholars at the time, as the strict division of manual and mental labor led to alienation from one's own work. Many of those scholars wanted to introduce the active participation of workers in management to the workplace. The human-relations theory, which was driven by the relations between the workers themselves and the relations between workers and management, seemed like an opportunity to further this goal. However, the human-relations style of management arguably failed to give workers more power, as Bruce and Nyland (2011) point out. It led to a monopolization of authority and a justification of the status quo, as workers did not have the education or realistic chance to participate in executive processes. The paradigm shift following this insight seemed to be lasting regardless, as it diverged into different schools of management that were informed by both the human-relations movement and Taylorism. In the following decades, workers in the West generally became better skilled and able to complete a broader variety of tasks (Kehm & Teichler, 1995). During that time period, the so-called standard employmet relationship came to be regarded as the ideal model of good employment, and to remain competitive companies began offering full-time, permanent positions, a family-sustaining wage, social benefits, strong regulatory safeguards, consistent working hours, and opportunities for career advancement, at least this was true for the US and the European labor-market (Vanroelen et al., 2021). In the late 20th century, workers who lacked higher education found themselves in an economy where low-skilled jobs that nonetheless provided a decent standard of living became increasingly scarce, often due to outsourcing to countries like China or India, where labor costs were cheaper (Standing, 2011). Doeringer and Piore (1975) observed in the seventies that the US labor market split into two sectors and postulated a theory of economic dualism for advanced capitalist economies. The primary sector holds secure and established jobs, which provide a decent standard of living and social prestige. Employees in the primary sector typically exhibit a stronger sense of institutional identification. The secondary sector jobs are described as dead-end, low-paying, and unstable employments that tend to be self-determining.

The term "gig economy" was first popularized by Tina Brown in 2009, during the aftermath of the financial crisis. In an article that year, Brown observed a significant shift in the labor market, one that had been unfolding over time but was exacerbated by the economic downturn (Brown, 2009). She remarked that the loss of jobs pushed the now unemployed workers into a state of pseudo-self-employment. The workers had to take on spontaneous working engagements, which she referred to as gigs, borrowing from the word musicians used, for impromptu musical performances in 1920s nightclubs (Cloonan & Williamson, 2023). These so-called gigs are often low-paying, insecure, and undignified engagements that were necessary for workers who were out of work, as these allowed them to meet their financial obligations. Gig work is not a novel development of the 21st century but rather a continuation of the second labor market sector, which arguably is the theoretical continuation of precarious work. Crises which entail an economic downturn, like the COVID-19 pandemic, emphasize the prevalence of the conditions workers face when their employment is non-standard (Han & Hart, 2021). Although gig work itself is not a novel phenomenon, its increasing significance in modern economies makes it essential for research to critically examine its implications

Conceptualizing Precarious Work

Precarious work can be described by different factors that researchers of the International Labour Organization (ILO) (2012) proposed as following. Precarious employment is characterized by uncertainty regarding the duration of employment. Workers often enter into contracts that lack clear specifications regarding the duration of employment, but rather contracts that might only last for a short period of time, or considering gig work, for the duration of the gig. Additionally, employment relationships may be obscured by complex management structures, such as temporary employment agencies that assign workers to various employers, further complicating accountability and job stability. A key feature of precarious work is the absence of social protections and employment benefits. Employers strive to reduce costs wherever possible by utilizing vague contracts and exploiting unclear legal frameworks. Employees are misclassified as independent contractors, to avoid fiscal and social responsibility (Slone et al., 2021). Workers of temporary agencies therefore oftentimes face troubles in insuring themselves, even when a national health insurance plan becomes more accessible to others. Berdahl and Moriya (2021) point out that US part-time workers, temporary workers, and freelancers still lag behind their full-time employed colleagues when it comes to health insurance. Workers that have to insure themselves are often confronted with the inability to pay for their insurance, as the ILO describes the pay for precarious work as being so low that it is not sufficient for a normal standard of living. Standing (2011) argues that precarious work should also be understood from a subjective perspective, as workers frequently experience a lack of security across multiple domains. The absence of employment security arises from ambiguous contracts that fail to specify the duration of employment, working hours, or requirements for overtime labor. Workers lack employment security if they are not protected against arbitrary dismissal, and if employers are not sanctioned for failing to meet firing and hiring regulations. Standing differentiates between employment and job security. Job security refers to the ability to maintain a position in a field that aligns with the worker's skills and expertise. In temporary work agencies, workers are not necessarily able to get a job that matches their skill set but rather are assigned jobs that mostly do not require specific skills. Additionally, precarious employment limits skill reproduction security, as workers often receive minimal training, restricting their ability to develop professionally. Workers in precarious positions might further work in places that are harmful and unsafe, resulting in work insecurity. Beyond individual job conditions, precarious work is also characterized by a lack of representation security. Standing therefore claims that those securities cannot be achieved through a social process. Workers struggle to unite and advocate collectively through union bargaining. As membership in unions decreases steadily (Ebbinghaus & Göbel, 2014), workers tend to rationalize their materialistic realities through cognitive restructuring instead of pursuing change. As Trappmann et al. (2023) point out, young workers are adopting different frames through which precarious work is legitimized. In interviews the young workers claimed that they see precarious work as unavoidable, as a driver of entrepreneurialism, as a stage within life, or as the price to pay to find meaningful work later. If the authors are right in their assessment, the justification of precarious conditions, fueled by social “bootstrapping” narratives (MacDonald & Giazitzoglu, 2019), could lead to a normalization, and with that, the segment of the employment market that consists of precarious jobs could grow even further with fewer workers to object to those conditions.

The gig economy consists of jobs that are often criticized by professionals and laborers as being de facto precarious. Numerous scholars equate the gig economy with precarious employment; however, it is important to distinguish gig work from other forms of insecure, non-platform-based labor. Non-gig employment, which does not exhibit the defining characteristics of gig work, may also be subject to deregulation and associated insecurities. (Montgomery & Baglioni, 2021). Watson et al. (2021) describe in a meta-study the three approaches to a definition commonly found in the gig work literature. The first approach is to define gig work as platform-dependent work. Workers who work on crowdworking platforms such as Amazon Mechanical Turk (MTurk) are to be considered gig workers. Although adequate for the purposes of this thesis, a platform-based definition excludes many informal, non-platform jobs, such as spontaneous “help wanted” postings or traditional gigs like babysitting, which most researchers would still classify as gig work. Another definition that can be found in the literature is based on the arrangement of work. Gig workers do not have long-term contracts, and they do not earn a steady wage. A third definition of gig work identifies workers according to their taxation and legal status. Gig workers do not have the same benefits and legal protections as their non-gig counterparts. Watson and his colleagues propose a split definition, with primary characteristics of gig work that every gig shows and secondary characteristics that describe specific forms of gig work that are not applicable to all jobs. The primary characteristics of gig work are the project-based compensation, the temporary nature in opposition to long-term employment, and the level of flexibility in the when, how, and where of working. Secondary characteristics include the aforementioned platform-based work, the partitioning of labor using crowdsourcing, the ability to work remotely, and the use of an agency or an intermediary to receive work engagements. Amazon Mturk, the platform used for surveying in this study, meets both the primary and secondary characteristics of platform-based and crowdsourced labor. The authors classify platforms like Amazon Mturk and comparable services like Google Surveys, TaskRabbit, or Shorttask as gig data providers, as workers do not produce a tangible service or goods for consumers but rather information. A facet of gig data providers that the ILO (2012) specifically criticizes is the disguised employment relationship. The individual worker never has direct contact with the client but instead only with the intermediary platform, which puts the workers in a disadvantageous relationship, which facilitates an inherent negative power dynamic between worker and requester. The status of platform workers is therefore analogous to that of subcontracted labor.

Defining Crowdwork and Microtasks

One mode of labor that is an integral part of the gig economy is crowdwork (Schulte et al., 2020). Crowdwork is characterized by tasks broken down into discrete segments that individuals can complete independently, with minimal or no communication among them. This allows companies to outsource tasks that would otherwise need to be performed in-house, potentially posing challenges for dynamically scaling operations. (Zhao & Zhu, 2014). Micro-work represents a more specific form of crowdwork, though the terms are occasionally used interchangeably. Large scale projects are split up into elementary tasks, which are characterized through their simplicity and short duration. Micro-work tasks might only take a few seconds and clicks to be completed (Webster, 2016). Amazon Mturk provides default options for requesters to create tasks where workers can select from a multitude of requests. Workers can answer surveys for researchers and marketers and aid in the accumulation and the rating of different websites. They can choose to classify, describe, and tag images and videos or objects that are contained within them. More complex tasks mostly involve language-based ones, where workers may be asked to rate texts based on factors such as the emotionality of their content, the intent that is expressed, whether the conversation is relevant or not and whether two texts are semantically similar. High-skilled work includes the transcription of audio and the rating of translation quality.

Human Intelligence Tasks (HITs) refer to tasks that necessitate human cognitive abilities for completion, typically involving judgment, interpretation, or decision-making that cannot be easily performed by automated systems. HITS can be woven into an algorithmically controlled workflow. HITs are employed in situations where computers are incapable of fully understanding the context, nuances, and complexities of human sentiment and emotion, or when it is crucial for the generated data to align with human judgment and decision-making (Chen et al., 2023; Retzlaff et al., 2024). AI models are trained through an iterative learning process that necessitates large quantities of data, which have to be vetted by real human workers like the self-called “Turkers”, workers which offer up their time and attention on Mturk. Mturk seemingly markets primarily to requesters, who use it for human in the loop validation for the output of generative AI and the creation of training datasets (Muldoon et al., 2024). The direct marketing quote for the new AWS service Sage Maker Ground Truth, which is displayed first when opening the Mturk requester site says: “Through SageMaker Ground Truth, you can access the MTurk workforce and implement additional validation and quality checks for a scalable and cost-effective way to train and improve ML models. Use cases include data annotation and human data verification. SageMaker Ground Truth also offers curated workforces for Generative AI use cases including content generation, image captioning, human evaluation, prompt engineering, human feedback, and more” (Amazon Mechanical Turk, 2025). Amazon Mturks pool of crowdworkers is therefore accessible to research the effects that this AI-Training might have on the workers itself, although in all likeliness only a portion of the data created by the “Turkers” is used in the big Silicon Valley AI models. Instead, a significant share of the labor force involved in AI training comes from specialized third-party service providers, many of which are located in regions such as South America and Africa (Miceli & Posada, 2022; Le Ludec et al., 2023; Gray & Suri, 2019). These providers are often preferred by tech companies due to their ability to deliver higher-quality data, which is essential for refining AI systems. This outsourcing of business processes to lower-income regions underscores the globalized and inequitable nature of AI development, where the burdens of data annotation and content moderation are disproportionately borne by workers in the Global South.

Platform Labor and AI Training

The working conditions faced by these AI trainers are often exploitative, mirroring the challenges experienced by platform-based crowdworkers. Both groups typically contend with low wages, lack of job security, and minimal labor protections (Bergvall-Kåreborn & Howcroft, 2014). However, there are notable differences between the two. Workers employed by third-party providers often work on-site, which allows them to collaborate with colleagues and potentially organize for better working conditions. This sense of community can provide a crucial buffer against the isolating and psychologically taxing nature of the work. In contrast, platform-based crowdworkers, such as those on MTurk, typically work in isolation, which can exacerbate feelings of alienation and make it more difficult to advocate for improved treatment (Wood et al., 2019). A particularly distressing aspect of AI training labor is the exposure to highly sensitive and traumatizing content. Workers employed by third-party providers are frequently tasked with reviewing and labeling materials such as child abuse imagery, extreme violence, or hate speech to develop content moderation algorithms (Roberts, 2019; Gillespie, 2018). As platform workers are rarely tasked with such content, the psychological burden falls more heavily on third party annotators. Despite the emotional toll of this work, employers often provide inadequate mental health support or fail to implement robust safeguards to protect workers from the long-term effects of exposure to such content (Steiger et al., 2021).

The AI industry is rapidly moving towards automating the tasks that currently rely on human labor. The ultimate goal of many tech companies appears to be the complete replacement of low-skilled AI trainers with AI systems themselves. Models like DeepSeek leverage techniques such as reinforcement learning from human feedback (RLHF) and self-supervised learning to minimize or even eliminate the need for human evaluation (Brown et al., 2020; Ouyang et al., 2022; DeepSeek-AI, 2025). In self-supervised learning, the model generates its own training data by predicting missing parts of input data, such as filling in blanks in text or reconstructing images. These advancements are not only reducing the volume of required but also enabling AI systems to operate with greater autonomy. While this represents a significant technical achievement, it also raises profound ethical and societal questions. The displacement of human workers by AI systems threatens to exacerbate job insecurity and economic inequality, particularly for low-skilled workers in the Global South who currently form the backbone of the AI training workforce. Tech companies often emphasize the sophistication and autonomy of their AI models, but the reality is that these systems are built on the foundation of countless hours of human effort performed under precarious and exploitative conditions. Critical scholars use the term digital Taylorism to describe this specific form of work as the reiteration of the practices outlined in 20th century scientific management. The authors claim that control in crowdwork in the global south is especially tight, and that through the algorithmic tools workers are systematically surveilled and discriminated against. (Anwar & Graham, 2022; Degryse 2016)

The decision of workers to engage in crowdworking is influenced by a range of push and pull factors. (Keith et al., 2019). Pull factors are positives that attract workers to engage with the platform, while push factors are the conditions that compel workers to seek employment. Push factors seem to motivate workers, whose primary income is Mturk. The authors note that, for Mturk, both push and pull factors are at play. Pull factors seem to be the main driver for workers whose main income is not dependent on crowdwork. These factors include the enjoyment of task completion, the opportunity to help researchers, and the perceived flexibility. Workers might appreciate the flexibility to choose when, where, and how to work, and theoretically, they can select jobs that align with their skill sets, earning additional income on the side. However, when crowdwork becomes a primary source of income, workers are often forced to take low-paying jobs for which they are overqualified. The flexibility offered by platforms often leads to a blurring of boundaries that impact the work-life balance of gig workers. “Behind the ‘anytime and anywhere’ motto is an ‘always and everywhere’ working model that attracts and retains precarious workers” (Bérestégui, 2021). This dynamic seems to encourage workers to remain on standby, constantly waiting for the next gig to show up. Push factors, on the other hand, describe circumstances that force workers into a specific type of work. A significant portion of workers are pushed into the gig economy by economic factors, like financial crises, but geographical differences also play a role. European crowdworkers, for instance, are more likely to report crowdwork as a secondary income source, rather than a primary income source in comparison to their counterparts in South America or Africa (Margaryan & Hofmeister, 2021). For gig work, these push factors primarily include a lack of stable income and limited opportunities in the traditional job market. Workers who were economically dependent on crowdwork were less satisfied with their current lives and did not express a belief that their life satisfaction would be higher in the future (Keith et al., 2019). The low and irregular pay associated with many gigs results in workers living paycheck to paycheck, which might cause significant stress in their day-to-day lives (Glavin & Schiemann, 2022). Whether crowdwork is a viable employment option for laborers is therefore dependent on a multitude of factors, including their geography, their skillset, and their access to information technology. For some workers, such as those with disabilities or those needing flexible work arrangements, crowdwork may offer the opportunity to take on an engaging form of work (Harpur & Blanck, 2020). However, empirical evidence suggests that, for most workers, crowdwork is not a sustainable long-term employment solution.

The JD-R Model and its Application to Crowdwork

The job demands-resources model (JD-R) describes an evaluative approach to occupational stress (Bakker & Demerouti, 2007). Job demands are, generally speaking, the costs that a job entails. Job resources are aspects that are functional in achieving task completion, which reduce the costs associated with job demands and that lead to personal development. Bakker and Demerouti (2017) however point out that demands and resources are activating two different processes. Demands are part of a health impairment process, and resources are part of the motivational process of work. While adequate resources can reduce the negative effects of demands, they cannot entirely eliminate them. The authors also propose that personal resources like self-efficacy beliefs can have a similar effect as job resources. Applying the JD-R model to micro-work suggests it is an undesirable employment form for many workers due to the imbalance between a plethora of demands and limited resources gained. Job demands can vary in complexity and abstraction and are influenced by socio-economic factors. While the aim of the study is not a cultural comparison, it is important to keep in mind that due to the high globalization of crowdwork, especially the financial risks and opportunities might differ significantly. For instance, initial investment and upkeep costs might pose a significant hurdle for some workers while being negligible for others (Behl et al., 2022). Workers in the global south might profit more from the financial resources of microwork and therefore experience less financial uncertainty, as they are subjectively comparing the platform economy to their national labor market. The inherent demands of the work seem to be better generalizable. Microwork can be mentally demanding, as the repetitiveness of the tayloristic tasks can lead to cognitive strain and therefore to a lessened well-being while the platforms benefit from the enhanced performance which repetitiveness also tends to bring (Häusser et al., 2014). The main concern with the fact that crowdworkers are seen as disposable independent contractors not tied to the company is that platforms do not have much motivation to keep demands and resources balanced. Workers in traditional employment have the benefit that companies tend to care more about not stressing the workers up to a breaking point where they burn out and have to take sick days, because they have a monetary incentive to keep workers engaged but not overwhelmed, especially in countries with strong labor laws where workers can't be easily dismissed because of their disability to work. The objective of this study is to identify the specific demands that most significantly affect the somatic and psychological health of micro-workers through the effect of stress, offering insights into how these challenges can be addressed within the framework of the JD-R model.

Understanding the psychological and somatic impacts of precarious work requires a multidimensional approach. Models developed in multiple meta-studies highlight financial, socio-relational, behavioral, and physical dimensions, often intersecting with experiences of instability, uncertainty, and marginalization (Allan et al., 2021; Blustein et al., 2023; Rönnblad et al., 2019). Irvine and Rose (2022) encountered in their meta-study of qualitative studies multiple facets of economic experiences that workers in precarious employment faced. Interviewees tended to describe their situation as a material hardship. The household budget is insufficient to accommodate social activities, and complex budgeting decisions need to be made as workers face financial uncertainty. Crowdwork platforms like MTurk and Clickworker institutionalize financial precarity by design, paying workers per task, often below minimum wage, with studies showing median hourly wages as low as 2–3$ in the U.S. and even less for workers in the Global South (Hara et al., 2018; Graham et al., 2017). Behavioral responses to the uncertainty of finance and employment include working overtime and performing more tasks than required. Workers in precarious situations tend to be in constant search for work, and they tolerate poor conditions (Allan et al., 2021). Negative socio-relational impacts were described as the unavailability of time for their family, their partner, children, and friends, which coincides with a feeling of isolation, marginalization, and withdrawal from social networks. Physical experiences and responses include a subjectively poor diet, poor sleep, a lack of exercise, and a feeling of exhaustion. Instability describes the perceived volatility of the existence of the current job. Crowdworkers face instability as the HITs they take on are usually one-time-piece work contracts that become unavailable as soon as the contract is completed, either by themselves or by another worker, leading to further competition to accept and complete work as rapidly as possible. Instability worsens the attitudes that workers hold about the job and the organization they work for. It also impacts the mental and the physical health of workers and has been found to be comparable to that of unemployment (Kim & Von dem Knesebeck, 2015; Sverke et al., 2002). The term “algorithmic insecurity” describes the instability that crowd workers regularly perceive on crowdwork platforms (Wood & Lehdonvirta, 2021). Algorithmic insecurity entails the instability of reputation-based contract allocation. Workers tend to feel more insecure if the rating systems of the platform are opaque and the weight the reputation holds is significant, as one bad rating could lead to worse and less frequent HIT requests. Paradoxically, while algorithmic insecurity exacerbates worker precarity, reputation systems simultaneously function as one of the few available governance mechanisms in these weakly regulated spaces. Benson et al. (2015) point out that, on the other hand, employer reputation can be utilized as a form of security to mitigate opportunistic behavior, like requesters not paying, when contract enforcement ability is otherwise lacking. While job uncertainty is related to job instability, it is described here as a lack of predictability about future job-related outcomes, such as tasks or role expectations.

Marginalization describes the structural hinderance factors, like racism, sexism, ableism, or ageism, that workers experience in the hiring process, permitting them to take on decent work (Allan et al., 2021). As HIT requests are, per se, anonymous, marginalized groups might make up a larger portion of crowdworkers in comparison to the regular employment market. (Glavin & Schieman, 2022) The models of precarious work still differ in their explanations of the mechanisms that underlie the relationship between the predictors and the outcomes of precarious work. The most common outcomes measured in studies that looked at the mental health effects of precarious work were depressive symptoms, psychological distress, anxiety, and psychotropic drug use (Rönnblad et al., 2019).

Stress has been identified by numerous studies to be a contributor to both psychological and somatic complaints such as anxiety, depression, cardiovascular disease, and immune dysfunction (Theorell et al., 2015). Occupational stress, also referred to as job strain, arises during the workday as individuals respond to various job-related stressors (Chen, 2023). Job stressors may refer to stressful events or inherent qualities of the labor. Stressors can be divided into chronic and acute stressors and challenge and hinderance stressors, which reference the idea of Eustress, which is helpful and energizing, and Distress or hinderance stressors, which are tiring and exhausting. Individuals can experience stressors differently, as a stressor can be energizing to one and exhausting to another. Bakker and Demerouti (2017) highlight the ambiguous nature of certain job characteristics, which can be perceived either as demands or resources, depending on individual circumstances. Crowdworkers face a constellation of stressors that reflect the unique precarity of platform labor. Quantitative overload, driven by the need to complete high volumes of microtasks to earn subsistence wages, is endemic, with studies showing workers often laboring 10–14 hours daily to offset low piece-rate pay (Hara et al., 2018; Wood et al., 2019). This overload intersects with workplace telepressure, a form of technostress where workers feel compelled to remain perpetually online to secure tasks, leading to disrupted sleep cycles and an inability to disengage from work (Tarafdar et al., 2007; Barber & Santuzzi, 2015). While crowdwork is often framed as flexible, the autonomy of crowdworkers in how they approach their tasks is not. Algorithmic management systems impose rigid task protocols that inhibit creative problem-solving, while simultaneously enforcing continuous monitoring. This creates an environment in which workers are perpetually observed and evaluated, profoundly shaping their behavior and decision-making processes (Bérastégui, 2021). Algorithmic management degrades professional identity by reducing workers to commodified labor inputs rather than recognizing their expertise, resulting in both alienation and diminished self-efficacy (Gandini, 2021). Perceived unfairness further compounds stress, particularly when clients reject completed tasks without transparent justification, effectively nullifying labor without compensation, as platforms permit requesters to withhold payment for arbitrary reasons, leaving workers with little recourse (Gray & Suri, 2019; Bergvall-Kåreborn & Howcroft, 2014). Moreover, crowdworkers are subject to job insecurity, the subjectively perceived threat of job loss and the worries related to that threat. Job insecurity is closely tied to contractual flexibility, as it serves as the subjective counterpart to the objective employment contract. This form of insecurity, which is a prevalent concern for many crowdworkers, exacerbates stress and is linked to various aspects of ill-being, including decreased motivation and engagement. Studies indicate that job insecurity acts as a hindrance stressor, depleting energy and exhausting workers rather than motivating them or spurring growth (De Witte & Van Hoote, 2021). The absence of collective bargaining mechanisms exacerbates power imbalances, leaving workers isolated in negotiating disputes or advocating for fair treatment (Glavin et al., 2021; Veen et al., 2020). Within the framework of the JD-R theory, it is imperative to identify the demands that are most impactful to the stress experienced by the crowdworkers and to explore potential avenues to reduce stress.

Study Objectives and Hypotheses

Prior research suggests that the financial dependency on platform work has a significant impact on workers' psychological well-being. For example, Glavin and Schieman (2022) found that platform workers who relied on such work as their primary source of income reported higher levels of psychological distress compared to those who viewed platform work as a secondary or supplementary income. However, their study was based on a Canadian sample and included a variety of platform-based occupations, such as ride-sharing, delivery services, on-site task services, and crowdwork. Given the broader focus of the previous research, it is essential to isolate crowdwork as a specific category to examine whether the observed relationship between income dependency and psychological distress still applies to this particular subset of platform labor. Furthermore, expanding the analysis to a global sample can provide a more comprehensive understanding of how this dynamic varies across different contexts.

This leads to the following hypothesis:
H1: Crowdworkers who depend on MTurk for their primary income exhibit significantly higher levels of stress symptoms compared to those workers that use MTurk as a secondary source of income.

Job crafting, as described by Bakker and Demerouti (2017), is a valuable resource that allows workers to shape their workplace to align with personal preferences, needs, and goals. Theoretically, crowdworkers possess significant autonomy in selecting tasks, deciding when and where to work, and determining how to approach their tasks. However, this autonomy may be limited in practice, particularly for workers who are economically dependent on crowdwork, as described above. Job crafting can be further understood through the lens of approach and avoidance crafting, as elaborated by Tims et al. (2022). Approach crafting involves proactive efforts to enhance positive aspects of work, such as seeking more complex tasks, whereas avoidance crafting entails minimizing exposure to negative elements, such as rejecting tedious or overly demanding tasks. Dependent crowdworkers, who rely on platforms like MTurk as their primary source of income, often face constraints that undermine their ability to choose tasks freely. Economic necessity may compel these workers to accept any available task regardless of its alignment with their skills or preferences, and to remain on standby for new opportunities (Bérestégui, 2021). This reality raises questions about the extent to which job crafting is feasible for such individuals. However, it remains unclear whether this dependence translates into a lesser sense of perceived influence over their work. While the theoretical flexibility of the platform model suggests that all crowdworkers have similar opportunities for job crafting, the lived experiences of dependent and independent workers may diverge significantly.

H2: Crowdworkers who rely on Mturk as their primary income report lower levels of perceived influence over their work then workers who view crowdwork as a secondary income

Perceived influence over one’s own work constitutes a fundamental factor in enhancing psychological well-being, particularly in environments characterized by high demands. Autonomy acts as a vital resource that can alleviate the negative effects of job-related stress (Bakker & Demerouti, 2017). In crowdwork, however, the structure of tasks, often dictated by platforms and algorithms, may limit this sense of control, reducing workers' ability to exercise autonomy over their workflows. The relationship between limited influence over work and stress might be particularly significant in the context of crowdwork, where workers frequently operate under conditions of unpredictability and competitive task allocation. This relationship between diminished influence over one's work and elevated stress levels is anticipated to apply to both dependent and non-dependent workers, as the psychological impact of limited autonomy affects all workers, regardless of their reliance on crowdwork for income.

H3: Crowdworkers who report lower levels of influence over their work experience higher levels of stress

Exploring the relationship between work pace and stress is important for understanding the psychological toll of fast-paced work environments, particularly in the context of crowdwork. In these settings, workers are often tasked with completing high volumes of work in a short time frame, which can create significant pressure. The urgency to perform tasks quickly, coupled with financial incentives or platform demands, may contribute to heightened stress and a sense of overwhelming workload.

H4: Workers who have a high work pace experience more stress

The degree to which this stress impacts workers may be influenced by their sense of control over their work. Influence, or the ability to make decisions about how tasks are approached, could play a moderating role in this relationship. Workers who feel they have more control over their pace or task choices may be better equipped to manage the stress that comes with high work demands. Workers with higher levels of control might be more likely to engage in approach crafting, such as reshaping their tasks to align with personal strengths or seeking out activities that bring a sense of accomplishment. This proactive behavior could buffer against the negative effects of high work demands by fostering a sense of agency and purpose. Similarly, avoidance crafting, the ability to avoid overly demanding or monotonous tasks, might mitigate stress by reducing the exposure to elements that contribute to cognitive overload. Workers with a high degree of influence over their tasks may use avoidance crafting to maintain balance, effectively managing their workload to prevent exhaustion. (Tims et al., 2022)

H5: Perceived influence is moderating the relationship between work pace and stress

Burnout, characterized by emotional exhaustion, cynicism, and reduced professional efficacy, has been extensively linked to high job demands in various occupational settings (Bakker & Demerouti, 2017; Schaufeli & Taris, 2014). The JD-R model suggests that excessive job demands, such as high work pace, monotonous tasks, and job insecurity, function as chronic stressors that deplete workers' psychological and physical resources.

Recent studies highlight the association between key job demands, such as work pace, job insecurity, and variation of work, and burnout among crowdworkers in platform-based labor settings. Algorithmic control in gig work, which dictates work intensity and limits autonomy, exacerbates stress and emotional exhaustion (Wood & Lehdonvirta, 2021), key components of burnout. For example, the lack of task predictability and the pressure to meet algorithm-driven demands often lead to sustained cognitive and emotional overload, particularly in precarious work environments. Research suggests that perceived job instability further amplifies these effects, as workers are forced to remain constantly available to secure tasks and income. It has been shown that workers who experience instability in their employment, uncertain income streams and inconsistent task availability, are more prone to stress and emotional exhaustion (Jiang & Probst, 2017; Jiang et al., 2021). As such, examining these factors within crowdwork offers critical insight into the psychological toll of platform-based labor.

H6: Job demands commonly associated with crowdwork such as work pace, little variation in tasks, and job insecurity, are positively related to burnout.

Method

Data Collection Procedure

Data collection was conducted between January 3, 2025, and January 6, 2025. To systematically control for potential response biases and enhance sample representativeness, participant recruitment was executed in six sequential batches. The first batch (n=20) served as a pilot to assess survey clarity and technical functionality. The second batch included n=80 participants, followed by four additional batches of n=100 each. To mitigate potential temporal biases and capture participants across different geographical regions, batch release times were systematically varied. This approach was based on the assumption that participants would primarily complete the survey during standard working hours within their respective time zones. Despite those efforts, the sample should be seen as a convenience sample. The task was published to Mturk with the title “~ 4 min survey about your work on Mturk”. The Survey link redirected participants, when accepted, to the online survey.

On Socisurvey the questionnaire was introduced to participants via a concise explanation of its objectives, which centered on examining the demands and resources experienced by MTurk workers. This introductory section emphasized that participation was entirely voluntary and that all responses would remain anonymous. Although the overview provided a general outline of the questionnaire’s content, specific hypotheses were not disclosed to avoid biasing responses. Participants were then given the option to provide informed consent to proceed or to withdraw from the study. Key demographic variables such as age, gender, country of origin, highest level of formal education, employment, profession, and income were assessed using the recommended questions of Socisurvey. A Socisurvey link was embedded within the Mturk research framework and only the initial recruitment via the HIT-link and the approval of payment were handled within the Mturk ecosystem. Each participant received a unique ID at the end of the survey, that they had to enter into the Mturk task window, to ensure that only eligible participants were paid for their work. It was ensured that workers would only answer the questionnaire once by tracking the Mturk Worker IDs.

Measures and Scales

Facets of the Copenhagen Psychosocial Questionnaire (COPSOQ-III) were used to explore psychosocial demands, resources, and outcomes pertinent to crowdworkers. Given the unique nature of platform-based labor, only dimensions with clear applicability to an isolated, task-focused work environment were included, in order to keep the item amount parsimonious, and the used scales relevant. Social dimensions requiring interaction with management or colleagues were excluded, as such connections are rare in crowdwork, as only professional crowdworkers, seem to regularly communicate with others via online forums (Wood et al., 2018), and it was unlikely that crowdworkers in business process outsourcing centers, which are physically together at location, would answer the questionnaire.

Work pace refers to the speed and intensity of work demands, particularly relevant in the algorithm-driven environment of crowdwork. High work pace is often imposed by the individual need to complete a certain number of tasks or to earn a certain amount of money, platform expectations that encourage workers to set their completion goals as high as humanly possible, and competition among workers to work on the most lucrative HITs. The scale includes items such as “Do you have to work very fast?”, measured on a 5-point Likert-Type scale (Always, Often, Sometimes, Seldom, Never/Hardly ever). Prior research has demonstrated good internal consistency for this dimension, with Cronbach’s $\alpha = 0.80$ in international samples (Burr et al., 2021). Given the fast-paced nature of many crowdwork tasks, this subscale provides valuable insights into potential stressors affecting platform workers.

Variation of work assesses the degree of diversity in tasks and skill requirements. Crowdwork platforms may offer tasks ranging from simple, repetitive microtasks to complex problem-solving assignments, leading to differing levels of variation among workers. Although this subscale has exhibited lower reliability ($\alpha = 0.24$) in previous studies (Rahimi et al., 2024) , it was retained to capture a distinct aspect of crowdwork that may moderate the effects of job demands and resources. The scale included the items “Is your work varied” and “Do you have to do the same thing over and over again?”.

Job insecurity reflects workers’ concerns about the stability and continuity of their income and employment prospects. In the context of platform labor, job insecurity is assumed to be heightened due to fluctuating task availability, opaque algorithmic decision-making, and the absence of traditional employment protections. The scale has demonstrated acceptable internal consistency ($\alpha = 0.72$) in international samples (Burr et al., 2021). Capturing perceptions of job insecurity is particularly relevant for understanding the precariousness of gig-based work and its potential impact on worker well-being. Example items such as “Are you worried about becoming unemployed?” were evaluated on a 5-Point Likert-Type scale.

Influence refers to the degree of control and autonomy workers have over their tasks, decision-making, and work schedules. In traditional employment settings, influence is typically associated with decision latitude (Karasek, 1979), encompassing workers’ ability to set their own pace, choose their methods, and participate in organizational decision-making. However, in the context of crowdwork and platform labor, influence is shaped by task availability, selection mechanisms, platform policies, and algorithmic management. Workers may have the freedom to select tasks, but this autonomy may be constrained by platform-imposed restrictions, such as task rejection rates, opaque qualification criteria, and automated performance assessments, which can significantly limit their actual control over work conditions. This subscale has been found to have good internal consistency ($\alpha = 0.80$) (Burr et al., 2021). To assess perceived influence, participants responded to a series of items evaluating their subjective sense of control over their work. The scale was prefaced with: "The following questions are about your subjective influence over the tasks you take on. Please answer the questions with your personal feelings about your perceived influence." This preface was included to encourage workers to reflect on their personal experiences of influence, rather than the theoretical autonomy implied by the platform model, in which workers ostensibly have complete control over their task selection. Participants then rated statements such as “Do you have any influence on what you do at work. These items were designed to capture the degree of autonomy workers feel they have, considering the structural constraints imposed by platform-based employment.

Stress was assessed using a composite score derived from general stress and cognitive stress subscales, which capture both physiological and mental strain associated with work. Stress is a core psychological outcome in the JD-R model, reflecting the extent to which job demands exceed workers’ coping capacities. The stress measure demonstrated strong internal consistency in a previous validation in an Australian sample ($\alpha = 0.88$ for Stress, $\alpha = 0.92$ for Cognitive Stress) (Rahimi et al., 2024). Items were rated on a 5-point Likert scale (All the time, A large part of the time, Part of the time, A small part of the time, Not at all).

Burnout refers to a state of emotional exhaustion, mental fatigue, and reduced professional efficacy, often resulting from prolonged exposure to high job demands and insufficient resources. It is particularly relevant in crowdwork, where long working hours, financial uncertainty, and lack of social support may contribute to burnout. The burnout scale demonstrated high internal consistency ($\alpha = 0.91$) in previous studies (Rahimi et al., 2024). Responses were measured using the same 5-point Likert scale as the stress measure, assessing the frequency of burnout-related symptoms experienced by participants.

The assessment of income dependence was conducted using a single-item measure that distinguished between crowdwork as a primary and crowdwork as a supplementary income source. Participants were asked to indicate whether their work on MTurk constitutes their “main source of income” or whether it “provides additional income”. Respondents selecting the former were classified as dependent platform workers, while those selecting the latter were categorized as secondary platform workers. However, as highlighted by Glavin and Schieman (2022), conceptualizing income dependence as a binary variable presents limitations. A more comprehensive assessment would account for the sufficiency of earnings in relation to a decent standard of living, rather than solely identifying whether platform work constitutes a primary or secondary income source. Additionally, income dependence should be contextualized by comparing earnings to national median income levels and considering other economic dependencies, such as household composition and alternative income streams. Many platform workers may supplement their earnings through multiple gig economy platforms, further complicating a strictly dichotomous classification. Despite the limitations of a binary classification, this approach was chosen for its practical advantages in statistical analysis as a dichotomous measure allowed for better interpretability.

Methodological Challenges and Approaches in working with Mturk

Research on precarious work within the gig economy remains insufficient due to several methodological challenges that are difficult to overcome (Iphofen et al., 2022). One primary obstacle is the limited access to the population of gig workers. These workers are often difficult to engage with through traditional industrial-organizational psychology research methods, such as closely collaborating with a company and sharing the results with the business and the public. Platforms frequently exhibit reluctance or unwillingness to collaborate with researchers, particularly when research questions could be critical of their practices. Even in cases where platforms are willing to cooperate, the quasi-anonymous and unstructured nature of platform work may prevent them from effectively facilitating access to participants. To address these challenges, this study adopts a methodological approach that circumvents direct collaboration with platforms by recruiting participants through the platform itself. While this approach has been piloted successfully in prior studies, such as by Schlicher et al. (2021) or Keith et al. (2019), the use of Mturk itself poses several challenges, such as technical ones like integrating Mturk into existing research architectures, but more so dealing with the humans on the other side of the wire. Researchers have to make assumptions about their willingness to fill out the questionnaire to their best knowledge and about their ability to stay attentive to the questions while answering numerous surveys a day. Simultaneously, it is essential to approach this population with compassion, empathy, and trust.

Saravanos et al. (2021) suggest injecting logical tautologies, where only one answer is applicable to assess the attentiveness of the crowdworkers on Mturk as research has shown that a general inattentiveness is nearly always present. This inattentiveness might skew results and cannot be solved with higher rewards or the usage of the provided Mturk qualifications. The statement “At some point in my life, I have had to consume water in some form” (Saravanos et al. 2021) was used as a logical check to check for inattentiveness in the middle of the questionnaire, with the same 5-point Likert-Type scale, as in the COPSOQ-III. An additional honesty check, which asked the participants if they completed the tasks according to the instructions, with the additional mention that it would have no consequences for them and the reply options (never, sometimes, and often) were used at the end of the questionnaire in the debriefing section. Furthermore, the survey platform's internal monitoring function hitherto provided by Socisurvey was used to ensure that participants did not complete the questionnaire in an unreasonable amount of time. A minimum completion time of one minute was established as a threshold. Participants who completed the survey in less time were redirected back to the start, ensuring that data collection met a minimum standard of attentiveness and engagement.

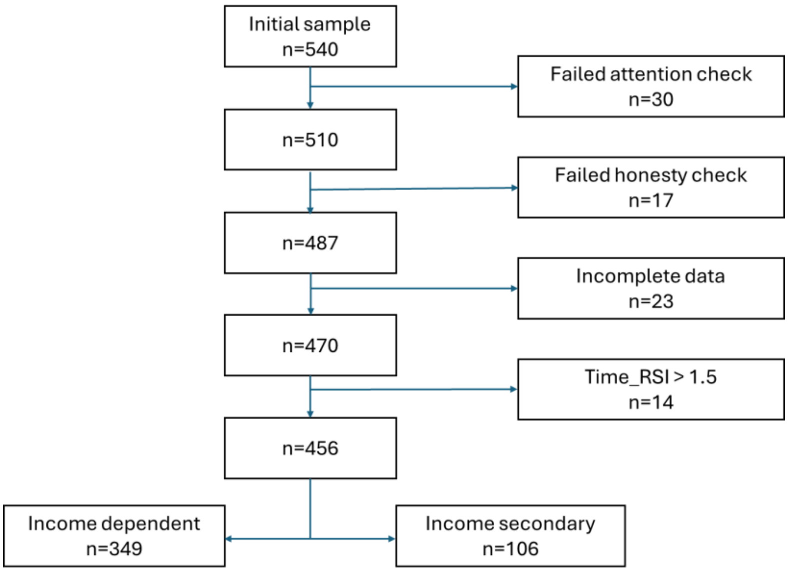
An a priori power analysis was conducted to determine the required sample size. Based on a significance level of $\alpha = .05$ and a statistical power of $\beta = .8$, the analysis indicated that a minimum of n = 462 participants was necessary to reach a sufficient probability in detecting the suspected effect. Among the tested hypotheses, Hypothesis H2 was identified as the most demanding in terms of testing with enough statistical power, given its estimated effect size and group distribution. Specifically, the ratio of dependent to secondary platform workers was estimated at 1:5, based on Glavin and Schiemann (2022), with an expected effect size of $d = .35$ for differences in perceived influence.

To mitigate the effects of potential dropouts and incomplete datasets, n = 500 participants was ultimately chosen as a target sample size, because Saravanos et al. (2021) reported that inattentiveness failure would exclude between 5 and 22 percent of the sample.

Participants were excluded if they failed to correctly respond to the tautological control item requiring them to either answer “strongly agree” or “agree,” or if they self-reported inattentiveness, by answering with the options (“I have often clicked something, so I am quickly done” or “I was distracted by my environment several times”). Additional exclusion criteria included incomplete responses, defined as failing to answer more than 30% of the total questionnaire or omitting more than 50% of items within any single scale. Furthermore, participants whose completion times were implausibly short were excluded. Multiple test runs established that reading and responding to all questionnaire items within 70 seconds was infeasible.

Figure 1

Dropout flow chart



A total of n = 540 participants initially completed the questionnaire. As depicted in Figure 1, n = 30 participants were removed for failing the tautological attention check, followed by n = 17 exclusions due to honesty check failures, resulting in n = 487 remaining cases. Additionally, n = 23 participants were excluded for insufficient data completeness. Reducing the sample to n = 470. A further n = 14 participants were excluded due to implausibly short completion times. This means that a total of n = 84 participants had to be excluded from the study. Following these exclusion criteria, the final analytical sample comprised 456 participants, categorized into income-dependent (n = 349) and income-secondary (n = 106) groups based on self-reported reliance on platform work (Figure 1).

All participants received compensation irrespective of their performance on the attention and honesty checks. Those in the pilot batch were rewarded with 0.20€, while participants in subsequent batches received 0.11€ for their involvement.

Microsoft Excel was utilized for the initial data cleaning, including the identification and removal of incomplete responses, the calculation of composite scale scores, and preliminary descriptive statistics. For statistical analyses, JASP, an open-source software for Bayesian and frequentist statistical modeling, was employed. JASP was used to conduct inferential statistical tests. Additionally, JASP provided diagnostic tools to assess the assumptions of normality, homogeneity of variance, and multicollinearity where applicable.

Results

Table 1

Sociodemographic Charateristics of Participants

Variable	Dependent Platform Work		Secondary Platform Work	
	n	%	n	%
Gender				
Male	251	72.5	83	78.3
Female	95	27.5	23	21.7
Type of Employment				
In School	0	0	1	.9
University Student	16	4.6	6	5.7
Employee	229	66.7	72	67.9
Civil Servant	4	1.2	1	.9
Self employed	93	27.1	25	23.6
Unemployed	1	.3	0	0
Employment				
Employed	339	98.8	103	99
Unemployed	0	0	1	1
Homemaker	4	1.2	0	0
Highest educational level				
No qualification	2	.6	1	.9
Secondary school	3	.9	2	1.9
High school diploma	74	21.3	23	21.7
Apprenticeship	41	11.8	5	4.7
Vocational baccalaureate	44	12.6	6	5.7
A - levels	77	22.1	42	39.6
University degree	100	28.7	25	23.6
Country				
USA	328	94	103	97.2
Other	21	6	3	2.8
Income				
100-250	14	4	1	1
250-500	13	3.7	3	2.9
500-1000	41	11.7	12	11.4
1000-1500	51	14.6	16	15.2
1500-2000	49	14	17	16.1
2000-3000	55	15.8	21	20
3000-4000	47	13.5	13	12.4
4000-5000	44	12.6	11	10.5
5000$ or more	34	9.7	11	10.5

Note. n = 456 (n = 346 for dependent platform worker and n = 106 for secondary platform workers). Participants were on average 34.1 years old (SD = 4.8), and participant age did not differ by condition

Descriptive Statistics

Table 1 presents the sociodemographic composition of the sample, distinguishing between income-dependent platform workers (n = 346) and income-secondary platform workers (n = 106). The gender distribution was similar across groups, with the majority identifying as male (72.5% vs. 78.3%). In terms of employment status, nearly all participants reported to be employed (98.8% vs. 99%), with dependent platform workers primarily engaged as employees (66.7%) or self-employed (27.1%), while secondary platform workers showed a comparable distribution (67.9% employees, 23.6% self-employed). University students comprised a small fraction of both groups (4.6% vs. 5.7%), whereas unemployment was negligible. Regarding educational attainment, dependent platform workers were a bit more likely to hold a university degree (28.7%) compared to secondary platform workers (23.6%), although A-levels (22.1% vs. 39.6%) and high school diplomas (21.3% vs. 21.7%) were common in both groups. The vast majority of participants were from the United States (94% vs. 97.2%), with only a small fraction (6% vs 2.8%) reporting to be native to another country. Income levels varied considerably, with dependent platform workers displaying greater representation across lower-income brackets (≤$2,000/month), while secondary platform workers were more evenly distributed across income categories. However, both groups exhibited a notable proportion earning between $1,000 and $3,000/month, with 12.6% of dependent and 10.5% of secondary workers earning above $4,000/month. Participants had a mean age of 34.1 years (SD = 4.8), with no significant age differences observed between the groups.

Table 2

Descriptive Statistics and Correlations for Study Variables

Variable	M	SD	1	2	3	4	5	6
1. Stress	61.881	19.661	-					
2. Burnout	65.205	18.415	0.630	-				
3. Influence	66.164	16.813	0.409	0.355	-			
4. Insecurity	64.930	18.162	0.502	0.431	0.344	-		
5. Variance	67.023	16.916	0.502	0.544	0.450	0.465	-	
6. Work Pace	68.768	15.656	0.345	0.491	0.421	0.404	0.498	-

Note. n=456. The variable Stress is a combination of the COPSOQ-III scales cognitive stress and stress

Hypothesis Testing

Hypothesis 1 (H1) proposed that income-dependent platform workers would report significantly higher stress levels compared to those who engage in crowdwork as a secondary income source.

To test this hypothesis, a one-tailed independent samples t-test was conducted, comparing the self-reported stress scores of the two groups. The analysis revealed a statistically significant difference in stress levels, $t(453) = 4.13$, $p < .001$, $d = .46$, supporting the hypothesis. Income-dependent workers reported a higher mean stress score ($\bar{x} = 63.89$, SD = 18.95) compared to secondary income workers ($\bar{x} = 55.05$, SD = 20.49), suggesting that reliance on platform work as a primary source of income is associated with greater occupational stress. Given the significant result, the null hypothesis, stating that there is no difference in stress levels between the two groups, was rejected. The dependent workers therefore experienced more stress.

Before conducting the independent samples t-test, the assumption of normality was assessed using the Shapiro-Wilk test. The results indicated a significant deviation from normality ($W = .944$, $p < .001$). However, given the large sample size, the Central Limit Theorem ensures that the sampling distribution of the mean approximates normality, making the t-test robust to this violation (Ghasemi & Zahediasl, 2012).

Hypothesis 2 (H2) was, as well, tested using a one-tailed independent samples t-test, based on the assumption that dependent workers would report lower levels of perceived influence compared to secondary workers. The analysis did not yield a statistically significant result in the expected direction, $t(453) = 2.27$, $p = .988$. Additionally, the assumption of normality was violated, as indicated by the Shapiro-Wilk test ($W = .914$, $p < .001$). Notably, an exploratory post-hoc analysis in the opposite direction revealed a significant effect, indicating that secondary income workers reported significantly lower levels of perceived influence ($\bar{x} = 62.89$, SD = 18.65) than income-dependent workers ($\bar{x} = 67.1$, SD = 16.11).

Hypothesis 3 (H3) proposed that workers who perceive lower influence over their tasks would experience higher levels of stress. However, this hypothesis was contingent on the significance of both H1 and H2. Given that H2 did not yield a significant result in the expected direction, the proposed relationship in H3 was also not supported. Contrary to expectations, the analysis revealed that workers who reported higher perceived influence also experienced greater stress. Although stress and influence were moderately correlated ($r = .409$), the direction of this relationship was opposite to what was hypothesized (Table 2). The statistical test yielded a non-significant result ($p = 1.00$), further indicating that perceived influence does not predict lower stress levels in this sample.

Hypothesis 4 (H4) posited that an increased work pace would be linked to higher stress levels among crowdworkers. To examine this association, a correlation analysis was performed, yielding a moderate positive correlation (r = .345, $p < 0.001$). This statistically significant result suggests that as work speed demands rise, workers tend to experience greater stress.

Hypothesis 5 (H5) examined whether perceived influence over work moderates the relationship between work pace and stress, potentially buffering against the negative effects of a higher work pace. A moderation analysis was conducted using a classical process model, with bootstrapping set to 1,000 replications and a diagonally weighted least squares (DWLS) estimator applied to account for non-normality. To reduce multicollinearity, all predictor variables were mean centered prior to analysis.

The analysis revealed a significant direct effect of work pace on stress, β = .336, p = .012, 95% CI [.197, .476], as well as a significant direct effect of influence on stress, β = .361, p = .002, 95% CI [.207, .487]. However, the interaction term representing the moderating effect of influence did not reach statistical significance, β = .010, p = .074, 95% CI [.004, .014], suggesting that perceived influence did not significantly buffer the impact of high work pace on stress levels. The overall model explained R^2 = 24.1% of the variance in stress levels.
To further explore the nature of this relationship, a simple slopes analysis was conducted, examining the effect of work pace on stress at low (16), average (50), and high (84) levels of perceived influence. The results indicated that the relationship between work pace and stress remained significant across all levels of influence, with no evidence of a buffering effect. Additionally, model comparison metrics, including Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), did not indicate superior model fit when including the interaction term, further supporting the lack of moderation.

Table 3

Hierarchical Regression Analysis Predicting Burnout

Model	*R*	R^2	Adjusted R^2	RMSE	R^2 Change	*F* Change	df1	df2	*p*
M_0	0.000	0.000	0.000	18.415	0.000		0	455	
M_1	0.544	0.296	0.294	15.472	0.296	190.617	1	454	< .001
M_2	0.600	0.360	0.357	14.765	0.064	45.521	1	453	< .001
M_3	0.618	0.382	0.378	14.526	0.022	15.980	1	452	< .001

Note. n = 455, in Model 1 work variation was entered as a predictor, in Model 2 work pace and finally in Model 3 job insecurity. M_0 is the null model; M_3 is the final model.

Hypothesis 6 (H6) examined whether work variation, work pace, and job insecurity significantly predict burnout levels among platform workers. To test this, a hierarchical multiple regression analysis was conducted using a stepwise inclusion approach. The dependent variable was burnout, while the predictors were introduced sequentially to assess their incremental explanatory power (Table 3). Burnout was positively correlated with work variation ($r = .544$, $p < .001$), work pace ($r = .491$, $p < .001$), and job insecurity ($r = .431$, $p < .001$), indicating that each of these factors is associated with increased stress levels. Variance inflation factors (VIFs) were below the standard threshold of 10, indicating no concerns regarding multicollinearity. Residual plots indicated no substantial deviations from homoscedasticity, and normality tests suggested that residuals were approximately normally distributed. The relationships between predictors and burnout were confirmed to be linear.

The baseline model (M_0), which included no predictors explained no variance in burnout (R^2 = 0.000). In model M_1, work variation was entered as the first predictor, yielding a significant model improvement ($R^2 = 0.296$, $F(1,454) = 190.617$, $p < .001$), explaining approximately 29.6% of the variance in burnout. This suggests that fluctuations in task variety, work routines, or unpredictability contribute substantially to worker strain. However, the low internal consistency of the work variation measure ($\alpha = 0.32$) raises concerns about its reliability. A Cronbach's alpha below 0.70 suggests that the items may not be measuring a coherent construct, increasing the risk of measurement error. Although a low alpha (<0.50) often indicates random error, removing a theoretically relevant predictor may also risk oversimplifying the model. This limitation nonetheless warrants caution in interpreting the effect of work variation on burnout.

In Model M_2, work pace was added to the model, further improving model fit ($\Delta R^2 = 0.064$, $F(1,453) = 45.521$, $p < .001$). Work pace was a significant predictor of burnout, indicating that higher work speed is associated with increased occupational strain.

Finally, in Model 3 (M_3), job insecurity was incorporated, resulting in a further significant improvement in model fit ($\Delta R^2 = 0.022$, $F(1, 452) = 15.980$, $p < .001$). The final model accounted for 38.2% of the variance in burnout ($R^2 = 0.382$), demonstrating that work variation, work pace, and job insecurity collectively contribute to heightened stress and exhaustion. The final regression equation was as follows:

Burnout = 8.78 + (0.37 × Work Variation) + (0.30 × Work Pace) + (0.17 × Job Insecurity)

Discussion

Summary of Findings

The findings provide robust support for several of the study's central hypotheses. H1 was confirmed, indicating that income-dependent platform workers reported significantly higher stress levels than those who rely on crowdwork only as a secondary income source. This underscores the psychological toll of financial dependency in precarious gig work. H2, which predicted that income dependent workers would feel less influence over their tasks, was not supported. On the contrary, these workers reported significantly higher perceived influence than their secondary earning counterparts. Because of this unexpected direction, H3, which proposed that lower perceived influence would be associated with higher stress levels, was also not supported. Instead, the data showed a moderate positive correlation between perceived influence and stress suggesting that greater perceived control does not necessarily buffer against strain and may even coincide with higher pressure or responsibility. H4 found clear support, that a higher work pace was associated with increased stress, highlighting how demands for a high work pace in digital labor amplify stress. H5 explored whether perceived influence moderates the relationship between work pace and stress. Although both variables independently contributed to stress, no significant moderating effect was detected. The stress inducing impact of a fast work pace remained consistent regardless of perceived control, indicating that influence alone cannot offset the burdens of accelerated task demands. Finally, H6 was supported through hierarchical regression analysis. Work variation, work pace, and job insecurity each emerged as significant predictors of burnout, cumulatively explaining a substantial proportion of the variance in stress outcomes. While work variation had the strongest explanatory power, its low internal consistency suggests caution in interpretation. Nonetheless, the final model confirmed that a combination of fluctuating task structure, performance pressure, and instability contribute meaningfully to psychological exhaustion among MTurk workers.

Interpretation of Results

Approximately half of the tested hypotheses aligned with existing research on platform workers, reinforcing prior findings within the field of crowdwork. H1 mainly replicated the results of Glavin and Schieman (2022), demonstrating that platform dependency, defined in this study as deriving one's primary income from Mturk, was associated with higher levels of stress compared to those for whom crowdwork served as a secondary income source. This finding underscores the heightened pressures experienced by workers who rely on crowdwork as their main source of livelihood. However, the results remain noteworthy given that crowdworkers, who primarily engage in data-related gig tasks, differ in several ways from service-based gig workers . Contrasting MTurk-users with delivery drivers, the differences in their respective lifestyles are striking, as the sedentary lifestyle, the cognitive demanding tasks, and the isolation from others during work, are expectedly leading to completely different demands than for ride hailing service workers who are much more prone to physical demands (Watson et al., 2021). These differences suggest that resources, stressors, and coping mechanisms may manifest distinctively across various sectors of the gig economy, warranting further comparative investigation.

H2 produced unexpected results, as primary income crowdworkers reported greater perceived influence and autonomy over their work than those who engaged in crowdwork as a supplementary income source. This contrasts with initial expectations that income dependence would correlate with reduced autonomy, given that workers who rely on MTurk as their primary income source are theoretically more constrained in their ability to reject unprofitable tasks. Prior research, such as that by Bérestégui (2021) or Keith et al. (2020) suggests that the financial necessity, that de facto exists, when workers mostly rely on the revenue stream crowdwork provides, should compel workers to accept a broader range of tasks and a larger quantity, thereby limiting their perceived control. However, several countervailing factors may explain why full-time crowdworkers experience greater influence over their work. First, extended engagement with the platform likely fosters increased expertise, allowing workers to optimize their task selection enabling them to increase their efficiency, and their feeling of being in control. More experienced workers may possess a better understanding of which tasks offer the best returns, how to schedule their work to align with peak task availability that usually is highest during the standard US working hours, and how to navigate the financial backend of MTurk more effectively. Additionally, long-term engagement with the platform may encourage participation in online worker communities, where collective knowledge-sharing provides strategies for securing higher-paying or less tedious tasks. Second, platform algorithms may privilege more active users, granting them access to a superior selection of tasks. Given that crowdwork platforms often implement reputation-based systems, workers with higher completion rates, positive task reviews, and consistent activity may be algorithmically favored, effectively granting them a degree of influence over the work, which they accept, that is unavailable to less active or newer users (Wood & Lehdonvirta, 2021). This dynamic could make full-time workers more selective in the tasks they accept, increasing their perceived autonomy even as financial necessity pressures them to maintain a steady workflow. Workers who depend on MTurk as their primary income source may develop structured routines that enhance their sense of control. However, this autonomy does not necessarily translate to reduced stress levels. On the contrary, the heightened responsibility of managing one’s own workflow under economic constraints could contribute to greater psychological strain. The autonomy afforded by crowdwork is likely to influence the extent to which workers engage with their tasks, potentially leading to overwork. When workers perceive that they have discretion and freedom in choosing their tasks, they may experience fewer mental barriers to participation, resulting in a deeper cognitive or emotional investment in their work (Bush & Balven, 2021). Unlike traditional employment structures that enforce regulated working hours and mandated breaks, crowdwork operates on a task-by-task basis, meaning that workers must independently manage their workload, rest periods, and overall work-life balance. This self-regulation can lead to a paradoxical effect: instead of using their autonomy to maintain a healthy work-life balance, crowdworkers may feel compelled to work longer hours, continuously accepting new tasks in pursuit of a better earning-quota. The lack of a clear stopping point, combined with the knowledge that more work is always available, can lead to the "always-on" mentality, which was originally proposed, where crowdworkers struggle to disengage from work. This tendency may be especially pronounced among dependent workers, who rely on crowdwork as their primary source of income and feel constant pressure to maximize their earnings. Moreover, the task-based nature of crowdwork makes it easy for workers to rationalize continued engagement. Unlike traditional jobs where extended work hours may require supervisor approval or clear overtime policies, crowdworkers face no such external constraints. The flexibility of crowdwork may thus encourage excessive labor, as workers tell themselves they will "just complete one more task," a mindset that can quickly escalate into chronic overwork. Ultimately, while autonomy is generally perceived as a benefit, in the context of crowdwork, it can contribute to self-imposed overwork, leading to burnout, cognitive fatigue, and heightened stress levels. Instead of serving as a protective factor, autonomy in this case may act as a double-edged sword, fostering conditions where workers push themselves beyond healthy limits, while maintaining a feeling of control.

This suggests that autonomy in online piecework may not function as a stress buffer (H5) in the same way it does in traditional employment contexts. Another possible explanation is that, despite instructions to report their subjective sense of autonomy, workers may have instead described the objective nature of control in crowdwork, where task selection, scheduling, and work location are theoretically unrestricted. This distinction is crucial, as it implies that while workers recognize their freedom to choose tasks, they may not perceive this autonomy as affording them greater influence over their well-being. The notion of control, therefore, remains unchanged, but the introspection necessary to recognize how this autonomy translates, or rather how it does not translate, into personal agency may be lacking. This interpretation is further reinforced by the finding that perceived influence did not significantly moderate the relationship between work pace and stress. Although an increased work pace was positively associated with stress (H4), the anticipated buffering effect of autonomy was not observed, suggesting that in crowdwork, autonomy does not necessarily alleviate occupational strain, but may instead exacerbate it.

H6 examined which job demands most significantly contribute to burnout among crowdworkers. The findings revealed that task variety accounted for the greatest proportion of variance among the considered predictors. This result was unexpected, given the prevailing assumption, rooted in the scholastic criticisms of Tayloristic principles, that repetitive tasks are detrimental to mental health and well-being (Häusser et al., 2014). Conversely, the regression analysis indicated a positive relationship between task variety and burnout, suggesting that increased variation in work tasks may not be as beneficial as traditionally assumed, at least within the sample studied, and rather leads to a higher degree in burnout. While more limited empirical research supports this perspective, Bush and Balven (2021) provide a possible explanation, arguing that an increase in task variety may lead to feelings of inadequacy among workers who perceive themselves as insufficiently equipped to meet diverse task requirements. This misalignment between task demands and worker competencies can foster frustration and reduce cognitive and emotional investment in the job. Although prior research has generally found that task variety enhances job engagement in traditional employment settings (Christian et al., 2011), the distinct nature of cognitive piecework, where tasks can vary widely in complexity, required skill sets, and mental demands, suggests that excessive variation may undermine well-being and contribute to burnout. However, it is important to note that the internal consistency of the task variety measure in this study did not fully meet reliability standards, necessitating cautious interpretation of these results. The second most influential predictor of burnout was work pace, aligning with prior expectations. A heightened work pace was associated with increased burnout levels, suggesting that sustained pressure to complete tasks rapidly may contribute to cognitive overload and exhaustion. This relationship is well-supported by the JD-R theory which posits that excessive job demands, such as high work intensity, deplete personal resources and heighten burnout risks (Bakker & Demerouti, 2007). Crowdworkers who engage in continuous, high-speed task completion may experience prolonged strain, making them more susceptible to burnout. Finally, job insecurity was the weakest predictor of burnout in the model, though still relevant. The precarious nature of platform-based work, characterized by inconsistent income streams, lack of employment protections, and dependence on platform algorithms, contributes to technostress (Tarafdar et al., 2007) and persistent job uncertainty. While job insecurity and unpredictable task availability were expected to be strong contributors to burnout, their relative explanatory power in this study was lower than that of work pace and task variety. Nevertheless, the cumulative effects of uncertainty, such as concern over account suspension, fluctuating pay rates, and ever-changing platform policies, likely play a role in increasing mental strain over time. Taken together, these findings suggest that burnout in crowdwork is not solely driven by traditional workplace stressors but is uniquely shaped by the structural characteristics of digital labor platforms. Unlike conventional jobs, where task variety is often linked to engagement and skill development, in the context of crowdwork, excessive variation may introduce new forms of stress, particularly when workers lack the necessary skills or resources to adapt to diverse tasks efficiently. Similarly, while high work pace is a well-documented predictor of occupational burnout, its effects may be amplified in the gig economy due to the absence of regulated work schedules and mandated rest periods. Although job insecurity remains a concern, its relative impact on burnout may depend on individual coping strategies, external financial support, or workers adaptability to the unpredictable nature of crowdwork.

The expected ratio of American to international workers was initially estimated to be far lower, yet the observed distribution was approximately 15 American workers to one international worker. This discrepancy aligns with findings from Hornruf and Vrankar (2022), who reported that 86% of tasks specifying a country requirement explicitly request US workers, further restricting opportunities for non-American participants (Lehdonvirta, 2018). However, this raises the possibility that some crowdworkers from lower-income countries may be circumventing these restrictions by using Virtual Private Networks to appear as if they are located in the US. If so, this could have significant implications for data validity, as workers might misreport their country of residence out of fear that disclosing their true location would lead to task rejection and loss of compensation. In addition to concerns about geographic representation, the findings of this study suggest shifting patterns in employment status and the role of crowdwork as a source of income. The income distribution observed approximated a bell curve, with the modal earnings cluster falling between 2,000 and 3,000$ per month. While this range may initially suggest financial stability, contextualizing these figures within poverty thresholds reveals significant precarity. The US Census Bureau (2023) defines the federal poverty level for a single as 15,480$ annually rising to 24,230$ when there are two additionally dependent people in the household. Based on these thresholds, 33.2% of surveyed workers earned incomes below the poverty line, a conservative estimate that excludes taxes, healthcare costs, and regional cost-of-living disparities. Considerably more than the 11.1% reported for the total population of the US. For example, in high-cost states such as California, the MIT Living Wage Calculator estimates that a single adult is required to earn at least 7.52$ to meet basic needs, rendering even median earners economically vulnerable (Glasmeier, 2025). The precariousness of these earnings is further exacerbated by the gig economy's opaque taxation structures. Unlike traditional employment, MTurk workers are classified as independent contractors, responsible for self-employment taxes (15.3% of income) and ineligible for employer-sponsored benefits (IRS, 2023). Gig workers underreport taxes due to complexity or fear of audits, risking penalties that deepen financial instability. Additionally, income volatility undermines budgetary planning. Algorithmic task allocation and client discretion make consistent earnings nearly unattainable. While 10% of workers reported monthly earnings exceeding $5,000, this cohort represents outliers most likely reliant on unsustainable practices, such as 10–14 hour workdays (Wood et al., 2019), boting or specialized technical skills like programming. However, even high earners remain vulnerable to platform precarity: sudden account deactivations or opaque soft bans can erase income overnight.

Limitations and Future Research

Many workers identified themselves as employed even when they also reported that most of their income came from dependent crowdwork. This raises concerns about how workers perceive their employment status and whether crowdwork is increasingly being treated as a primary occupation rather than a supplemental gig. Most strikingly, the observed ratio of dependent to secondary platform workers in this study was nearly the reverse of that found by Keith et al. (2019). While

Keith et al. reported that for every one worker relying on crowdwork as a primary income source, there were 3.5 workers using it as a secondary source, this study found a ratio of approximately 3:1 in the opposite direction. This unexpected shift suggests that a growing proportion of workers are relying on platform work as their main source of income, raising important questions about the broader labor market and economic conditions driving this trend. One potential explanation is that the COVID-19 pandemic forced more workers into crowdwork, as traditional employment opportunities became more precarious or unavailable. Alternatively, crowdwork itself may be evolving, with fewer workers viewing it as a side hustle and more treating it as a full-time occupation. However, the underlying reasons for this shift remain uncertain. Future research should investigate whether this trend reflects an erosion of standard employment opportunities, a structural change in platform work, or broader economic pressures forcing individuals into less secure forms of labor. Additionally, as discussed above, the binary classification of dependent versus secondary platform workers may not fully capture the complexity of income dependency. Workers' financial stability is influenced by multiple factors, including cost of living, household income composition, and access to social safety nets. (Glavin & Schieman, 2022). A worker relying on crowdwork as a primary income source in a high-cost region may face greater financial precarity than one doing the same in a lower-cost area, if their earnings are comparable. Similarly, workers with additional forms of informal income or financial support may not experience the same degree of dependency, despite deriving most of their earnings from platform work. Understanding the nuances of income dependency requires a more comprehensive approach that accounts for material hardship, job stability, and long-term financial security.

A concerning possibility is that an increasing proportion of MTurk users are employing automated bots to complete tasks, generating responses that appear superficially plausible but ultimately consist of statistical noise (Kennedy et al., 2020). More troubling still is the prospect of an entire network of bots systematically exploiting paid participation. As artificial intelligence advances and chatbots become increasingly difficult to distinguish from human participants, what assurances do researchers have that the rewards they offer are not being collected by sophisticated AI rather than genuine human respondents? The financial incentive for deploying bots is clear. Users stand to benefit monetarily with minimal effort, making it a highly attractive strategy for those looking to generate a passive income stream. While rudimentary bots producing random or nonsensical answers can often be filtered out through techniques such as redundancy checks, time limits, and logical consistency tests (Saravanos et al., 2021), as employed in this study, a more advanced AI specifically engineered to mimic human response patterns, would be far more challenging to detect. Such an AI could be programmed to respond within human-like time frames, incorporate minor errors to avoid suspicion, fake browser history and cookies, and even adjust responses based on prior answers to maintain internal consistency (Plesner et al., 2024). The primary logistical hurdle for bot operators remains the need to register multiple accounts on MTurk, but given the potential financial rewards, this obstacle is far from insurmountable. The rise of AI driven automation in crowdwork thus represents a significant and growing threat to the integrity of research conducted through gig-based platforms. This issue is particularly alarming in light of the ongoing replication crisis in psychological and social sciences, which has already undermined confidence in the reliability of many research findings (Maxwell et al., 2015). If responses collected via MTurk and similar platforms become increasingly uncertain, blurred between genuine human input and algorithmically generated noise, then the very foundation of empirical research is at risk. In the most extreme case, the research process itself could be reduced to little more than an elaborate form of data fabrication, with public funds and research grants effectively being funneled into studies that produce no meaningful knowledge. The "publish or perish" culture exacerbates this issue further, as the pressure to continuously generate research articles leads to an influx of low quality, minimally peer reviewed publications. Paper mills, groups that mass-produce research papers, are already a significant concern in academia, and the proliferation of AI generated data could accelerate their ability to churn out studies that are neither reproducible nor scientifically valid. The strategic self-citation practices often observed in such networks further distort citation metrics, allowing for artificial inflation of their academic influence while contributing little to genuine scientific progress.

Beyond concerns regarding AI generated responses and data integrity, another fundamental issue with gig-based research platforms is the persistent problem of WEIRD (Western, Educated, Industrialized, Rich, and Democratic) samples (Henrich et al., 2010), which has long plagued psychology and social science research. Despite claims that MTurk provides access to a globally diverse participant pool, structural barriers to entry and platform restrictions mean that these samples often remain far from representative of the broader population. As Newlands and Lutz (2021) highlight, structural barriers restrict access to crowdwork, limiting its economic benefits for disadvantaged populations. Technical literacy is essential, excluding those with limited digital skills or unreliable internet access. Geographic restrictions further favor US-based workers, while workers from lower-income countries face payment barriers and lower compensation. Workers of the global south might be pushed to work for platforms as job offers in their region might be deficient and pay in other fields might be significantly lower. Breasemann et al. (2022) highlight that remote work is predominantly available in cities, where infrastructure is accommodated for information technology. They also argue that workers in the Global North are more likely to access higher paying gigs, while workers in the Global South often compete for lower-paying, and less skilled jobs. The flexibility promised by gig work is consequently highly dependent on regional factors. Device disparities also shape economic outcomes. Mobile phone users, particularly in lower income regions, struggle with usability challenges such as data entry difficulties and inefficient task management, reinforcing digital inequalities. This “mobile underclass” faces limited earning potential compared to those using personal computers (Newlands & Lutz, 2021). These structural inequalities undermine the perception of crowdwork as an accessible economic opportunity, necessitating a deeper examination of digital divides and labor market inclusion.

This study’s findings are constrained by several interrelated limitations. First, the exclusive focus on Amazon MTurk limits generalizability to other crowdwork ecosystems. Platforms like Prolific or Appen differ structurally: Prolific enforces minimum hourly wages, and Appen has managed outsourcing contracts for AI training tasks, which often include nondisclosure agreements that obscure labor conditions (Le Ludec et al., 2023). These workers, invisible to researchers due to corporate gatekeeping, may experience distinct precarity dynamics, such as hourly pay with productivity quotas that are being achieved through the constant surveillance and monitoring of the workers (Gray & Suri, 2019; Roberts, 2019). The absence of managed crowdworkers in this sample thus precludes insights into how platform labor diverges from outsourced microwork, a critical gap given the rapid growth of AI data annotation companies (Miceli & Posada, 2022). Second, methodological simplifications risk misrepresenting workers realities. The binary classification of income dependency overlooks material hardship shaped by debt, caregiving costs, or regional inequality. Crowdworkers with secondary income might be pushed to crowdwork, as well as, their primarily dependent counterparts, through monetary need, like being unable to pay for their bills with their primary income. For example, a worker reporting crowdwork as secondary income may still depend on it to avoid eviction (Schor et al., 2020). The study’s operationalization of worker autonomy may inadvertently conflate structural features of the platform with subjective experiences of control. MTurk explicitly markets itself as offering workers flexibility in selecting tasks, setting schedules, and determining work methods, a cognitive framing that likely influenced participants objective self reports. For example, workers might truthfully report having full control over working time because the platform technically allows them to log in at any hour, yet this ignores constraints such as unpredictable task availability, algorithmic deprioritization for sporadic workers, and the need to work during peak hours to secure viable tasks (Gray & Suri, 2019). Similarly, the ability to choose tasks (procedural flexibility) does not equate to meaningful agency over payrates, task design, or dispute resolution (substantive control), as platforms rigidly enforce client-dictated terms (Chen et al., 2023). Prior research demonstrates that crowdworkers internalize platform rhetoric to rationalize precarity, reframing exploitative practices as entrepreneurial self-determination (Trappman et al., 2023; MacDonald & Giazitzoglu, 2019). This gap between advertised and experienced autonomy underscores that responses may reflect the platforms ideological framing of freedom rather than the true material conditions of the workers. Third, when using gigified research data, quality concerns are always an issue. N = 30 participants failed attention checks, and demographic anomalies, like gender distribution diverging from other studies, suggest sampling bias or platform population shifts (Difallah et al., 2018). Reliance on self report data from workers incentivized to minimize survey time raises risks of inattention and carelessness. Motivated misrepresentation, such as underreporting unemployment to align with societal norms of stable employment or obfuscating their true country of origin to get approved more often, might also play a significant role when collecting data through those research platforms (Chmielewski & Kucker, 2020).

The psychological dynamics revealed in this study warrant deeper inquiry into the mechanisms driving stress and burnout in crowdwork, particularly the paradoxes of autonomy and the role of task design in digital labor environments. The finding that dependent workers report greater perceived influence over their work yet experience heightened stress suggests a need to reconceptualize autonomy in platform labor. Future studies should distinguish between objective autonomy, the technical freedom to select tasks or set schedules, and subjective autonomy, such as meaningful control over income stability. A validated psychometric questionnaire should be developed to systematically assess core psychosocial demands and resources inherent to gig work, including but not limited to perceived autonomy, work pace intensity, possibilities for social interaction, and technostress, thereby providing an empirically grounded framework for comparative studies. Longitudinal survey designs tracking perceived autonomy, financial precarity, and stress over time could clarify whether procedural autonomy initially buffers strain, only to erode as economic pressures intensify. Additionally, mixed methods approaches combining qualitative interviews with quantitative surveys might clarify how workers cognitively reframe perceived control under conditions of income instability, such as attributing financial precarity to personal failure rather than structural constraints.

Cross sectional survey studies comparing workers across platforms with varying task structures could identify thresholds at which diversity transitions from stimulating to depleting. Future studies should examine the role of social support networks by integrating validated measures of online community engagement like perceived emotional solidarity or frequency of strategy sharing. It has been shown that platform work was highly associated with feelings of powerlessness and isolation, therefore new strategies to mitigate these feelings and foster a sense of connectedness should be developed and evaluated (Glavin et al., 2021). Similarly, survey items assessing workers use of self-regulation strategies like time blocking or task batching might reveal whether specific coping behaviors mitigate the stress associated with high work pace demands. The reasons for the stress disparity between dependent and secondary workers might not be fully discovered yet. For instance, dependent workers may experience precarity vigilance a hyper awareness of income instability, which amplifies stress independent of immediate workload (Blustein et al., 2024). Survey instruments measuring financial anxiety should be incorporated into future studies to better understand what role financial uncertainty plays in the manifestation of stress related disorders specifically in crowdwork. Another critical avenue of inquiry is the impact of labor fragmentation on professional identity formation. Many precarious workers lack a stable occupational identity, leading to feelings of detachment from the broader workforce. Studying whether crowdworkers see themselves as freelancers, entrepreneurs, or employees, and how these self-conceptions influence their stress levels and career aspirations, could provide insights into the psychological consequences of gig work. Future research could explore whether stronger identification with online worker communities mitigates stress, fosters collective advocacy, or reinforces precarity through normalization of unstable work conditions. The moderate explanatory power of burnout predictors signals gaps in understanding individual differences. Finally, research should explore policy interventions and worker advocacy efforts aimed at mitigating crowdwork precarity. As traditional labor protections often fail to extend to digital piecework, investigating alternative regulatory approaches, such as portable benefits, minimum task wages, or platform cooperatives, could provide pathways for improving worker conditions. Studies examining the efficacy of emerging labor movements, collective bargaining initiatives, and crowdworker led campaigns could offer valuable insights into the feasibility of structural change within the gig economy.

Implications for Policy and Practice

The rapid expansion of crowdwork and gig labor is reshaping labor markets, regulatory frameworks, and is affecting worker well-being all around the world. While gig work is often associated with flexibility and autonomy, it simultaneously introduces precarity, income volatility, and an erosion of social protections. As gig work continues to proliferate, policymakers face a fundamental dilemma: how to regulate an industry that thrives on informality, globalized competition, and algorithmic management without stifling its growth or limiting access to flexible employment opportunities. In response to these challenges, the European union has taken legislative steps to improve platform worker protections. The EU directive 2024/2831 of the European parliament and of the council on improving working conditions in platform work seek to extend rights such as minimum wage guarantees, social security access, and collective bargaining protections to gig workers (European Commission, 2024). However, these efforts remain insufficient in addressing the full scope of platform labor precarity. The presumption of employment status in the proposed directive remains difficult to enforce due to ambiguous classification criteria, while the provisions addressing algorithmic management fail to account for the experiences of self-employed platform workers, who remain largely unprotected from client-sided mistreatment, opaque rating systems, and algorithmic pay determination. These regulatory gaps illustrate the persistent struggle to impose labor protections in an industry defined by its decentralization and reliance on nonstandard employment arrangements. One of the defining characteristics of crowdwork is the opacity of task pipelines, which exacerbates worker alienation and disengagement (Miceli & Posada, 2022). Unlike traditional employment, where workers can directly observe the impact of their labor, crowdworkers often complete highly fragmented microtasks with little to no understanding of their broader purpose. Miceli and Posada (2022) argue that task transparency is crucial for mitigating alienation and fostering engagement in crowdwork. When workers understand the significance of their contributions, they report higher levels of motivation, increased attentiveness, and improved task performance. This principle has direct practical implications. On platforms like Amazon Mechanical Turk, requesters should provide clear explanations of study objectives, ensure detailed task descriptions, and acknowledge worker contributions. Transparency not only benefits workers psychologically but also enhances the quality of data collected, as engaged workers are less likely to provide careless or inaccurate responses. Miceli and Posada (2022) further emphasize that crowdworkers should be recognized as critical assets in the data generation process rather than as interchangeable, anonymous laborers. Fair working conditions, including adequate pay, realistic timeframes for completing tasks, and achievable task goals, are not only ethical imperatives but also business incentives. Both workers and data requesters stand to gain from improved transparency. Despite these potential improvements, ensuring high quality data in crowdwork remains a persistent challenge. One of the primary concerns is the presence of automated bots and low effort responses, which can distort research findings and undermine the reliability of data collected from crowdwork platforms. While requesters often rely on qualification filters, approval rate thresholds, and attention checks to maintain data integrity, these mechanisms alone are insufficient (Saravanos et al., 2021). Even highly rated workers may engage in low-effort task completion if conditions incentivize speed over accuracy. Addressing this issue requires platform-level interventions that go beyond simple qualification metrics. One potential solution is the implementation of behavioral analytics to detect suspicious activity, similar to CAPTCHA systems that assess mouse movement trajectories and response latency patterns (Von Ahn et al., 2008), but as Plesner et al. (2024) showed, even sophisticated CAPTCHAs can be overcome, therefore platforms need to keep implementing state of the art checks. By analyzing task completion times, keystroke dynamics, and response variability, platforms like MTurk could develop more advanced fraud detection mechanisms to flag botted or low effort responses. Given these constraints, improving data quality requires a multi faceted approach, including enhanced worker vetting, dynamic fraud detection, and clearer task design standards. Until these structural weaknesses are resolved, the credibility of research relying on crowdwork data remains questionable. Allocating research grants to platforms with unaddressed data quality concerns risks compromising the validity of findings while simultaneously reinforcing exploitative labor practices that undervalue and underpay workers. The question of whether crowdwork represents a viable employment model or a precarity trap does ultimately not yield a simple answer. This study, in conjunction with existing research, underscores the deep-seated structural vulnerabilities of gig work, including income instability, psychological distress, and an absence of formal labor protections.

The findings of this study further the understanding of the structural and psychological demands of crowdwork. As hypothesized, dependent crowdworkers, those who rely on crowdwork as their primary source of income, exhibit markedly higher levels of stress compared to secondary workers who engage in these tasks for supplementary earnings. This supports existing literature on labor precarity. The study could not confirm that dependent workers felt they had less control over how they manage their work, but there might be some explanations for that discussed above.

These findings highlight the urgent need for stronger regulations to prevent platform labor from deepening economic inequality. While crowdwork offers flexibility, its unregulated expansion risks creating a vulnerable workforce with little protection. Existing policies fall short, as platforms continue prioritizing efficiency over worker rights. A sustainable gig economy requires wage stabilization, algorithmic transparency, and stronger collective bargaining protections. Beyond immediate policy interventions, these results provoke broader reflections on the future of work. As artificial intelligence advances, the very crowdworkers who currently train these systems risk being displaced by the technologies they help create. Alternatively, there may be a growing shift in market values, wherein companies and consumers begin to prioritize authenticity and genuine creativity over mechanized efficiency. In this evolving landscape, the value placed on authentic, human contributions could pave the way for a more equitable and innovative labor model. Whether platform labor evolves into a fair employment model, or whether it remains a system of exploitation, depends on the actions of policymakers, researchers, and industry leaders. The choices made now will determine whether gig work becomes a path to opportunity or a driver of structural long-term precarity.

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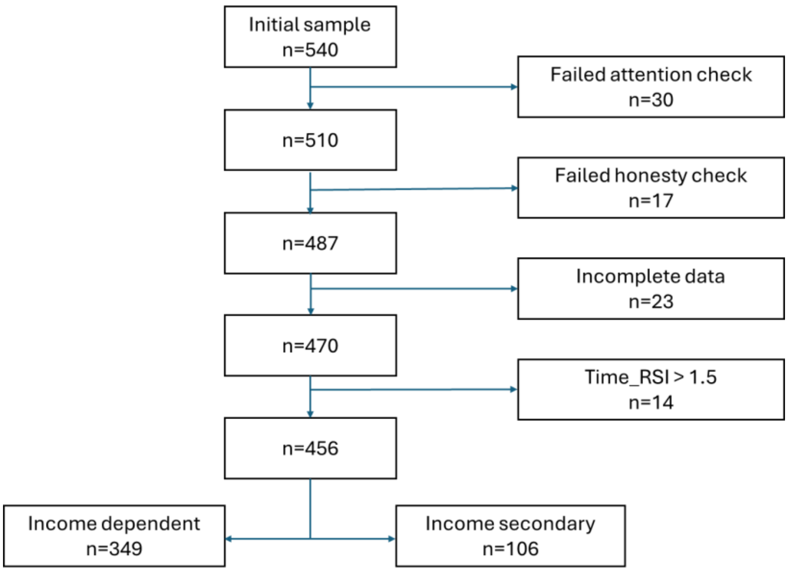
Figures

Figure 1

Dropout flow chart



Tables

Table 1

Sociodemographic Charateristics of Participants

Variable	Dependent Platform Work		Secondary Platform Work	
	n	%	n	%
Gender				
Male	251	72.5	83	78.3
Female	95	27.5	23	21.7
Type of Employment				
In School	0	0	1	.9
University Student	16	4.6	6	5.7
Employee	229	66.7	72	67.9
Civil Servant	4	1.2	1	.9
Self employed	93	27.1	25	23.6
Unemployed	1	.3	0	0
Employment				
Employed	339	98.8	103	99
Unemployed	0	0	1	1
Homemaker	4	1.2	0	0
Highest educational level				
No qualification	2	.6	1	.9
Secondary school	3	.9	2	1.9
High school diploma	74	21.3	23	21.7
Apprenticeship	41	11.8	5	4.7
Vocational baccalaureate	44	12.6	6	5.7
A - levels	77	22.1	42	39.6
University degree	100	28.7	25	23.6
Country				
USA	328	94	103	97.2
Other	21	6	3	2.8
Income				
100-250	14	4	1	1
250-500	13	3.7	3	2.9
500-1000	41	11.7	12	11.4
1000-1500	51	14.6	16	15.2
1500-2000	49	14	17	16.1
2000-3000	55	15.8	21	20
3000-4000	47	13.5	13	12.4
4000-5000	44	12.6	11	10.5
5000$ or more	34	9.7	11	10.5

Note. n=456 (n=346 for dependent platform worker and n=106 for secondary platform workers). Participants were on average 34.1 years old (SD=4.8), and participant age did not differ by condition

Table 2

Descriptive Statistics and Correlations for Study Variables

Variable	M	SD	1	2	3	4	5	6
1. Stress	61.881	19.661	-					
2. Burnout	65.205	18.415	0.630	-				
3. Influence	66.164	16.813	0.409	0.355	-			
4. Insecurity	64.930	18.162	0.502	0.431	0.344	-		
5. Variation	67.023	16.916	0.502	0.544	0.450	0.465	-	
6. Work Pace	68.768	15.656	0.345	0.491	0.421	0.404	0.498	-

Note. n=456. The variable Stress is a combination of the COPSOQ-III scales cognitive stress and stress

Table 3

Hierarchical Regression Analysis Predicting Burnout

Model	*R*	R^2	Adjusted R^2	RMSE	R^2 Change	*F* Change	df1	df2	*p*
M_0	0.000	0.000	0.000	18.415	0.000		0	455	
M_1	0.544	0.296	0.294	15.472	0.296	190.617	1	454	< .001
M_2	0.600	0.360	0.357	14.765	0.064	45.521	1	453	< .001
M_3	0.618	0.382	0.378	14.526	0.022	15.980	1	452	< .001

Note. n=455, in Model 1 work variation was entered as a predictor, in Model 2 work pace and finally in Model 3 job insecurity. M_0 is the null model; M_3 is the final model.

Appendix

Abstract

This study examines the psychological impact of precarious crowdwork on Amazon Mechanical Turk (MTurk) workers, applying the Job Demands-Resources (JD-R) model to assess key stressors such as financial dependency, work pace, job insecurity, and perceived influence. Situating these findings within the expanding role of crowdwork in AI training data production, the study highlights how workers frequently engage in repetitive, cognitively demanding tasks under conditions of algorithmic management. An online survey of n = 456 MTurk users, conducted using selected scales of the Copenhagen Psychosocial Questionnaire, revealed that individuals who relied primarily on crowdwork as their main source of income experienced significantly higher stress levels than those for whom it was a supplementary source of earnings. Interestingly, although these primary income earners reported a greater perceived influence over task selection, this increased autonomy did not yield the expected stress buffering effects. Job demands, particularly task variation, work pace, and insecurity, were strong predictors of burnout. These findings challenge prevailing narratives of autonomy in gig work, suggesting that algorithmic control and platform-induced precarity erode the psychological benefits typically associated with flexible employment. The study emphasizes the urgent need for policy interventions to address structural inequalities in crowdwork and improve working conditions for platform-based labor.

Abstract

Diese Studie untersucht die psychologischen Auswirkungen von prekärem Crowdworking bei Amazon Mechanical Turk (MTurk) Arbeiter*innen. Dabei wird das Job Demands-Resources (JD-R) Modell angewandt, um zentrale Stressfaktoren wie finanzielle Abhängigkeit, Arbeitstempo, Arbeitsplatzunsicherheit und wahrgenommene Beeinflussbarkeit der Arbeitsbedingungen zu bewerten. Die Studie ordnet diese Ergebnisse in die wachsende Rolle von Crowdwork bei der Produktion von KI-Trainingsdaten ein und hebt hervor, wie Arbeiter*innen häufig repetitive, kognitiv anspruchsvolle Aufgaben unter den Bedingungen des algorithmischen Managements übernehmen. Eine Online-Befragung von n = 456 MTurk-Nutzer*innen unter Verwendung ausgewählter Skalen des Kopenhagener psychosozialen Fragebogens ergab, dass Personen, die sich in erster Linie auf Crowdwork als Haupteinkommensquelle verließen, ein deutlich höheres Stressniveau aufwiesen als diejenigen, für die es eine zusätzliche Einkommensquelle war. Obwohl diese Haupteinkommensbezieher angaben, einen größeren Einfluss auf die Aufgabenauswahl zu haben, führte diese größere Autonomie interessanterweise nicht zu den erwarteten stressmindernden Auswirkungen. Die beruflichen Anforderungen, insbesondere die Variation der Aufgaben, das Arbeitstempo und die Unsicherheit, waren starke Prädiktoren für Burnout. Diese Ergebnisse stellen die vorherrschenden Narrative über Autonomie in der Gig-Arbeit in Frage und deuten darauf hin, dass algorithmische Kontrolle und plattformbedingte Prekarität die psychologischen Vorteile, die normalerweise mit flexibler Beschäftigung verbunden sind, aushöhlen. Die Studie unterstreicht die dringende Notwendigkeit politischer Interventionen, um strukturelle Ungleichheiten bei Crowdwork zu beseitigen und die Arbeitsbedingungen für plattformbasierte Arbeit zu verbessern.