Job Demands, not Resources, Predict Worsening Psychological Distress During the Early Phase of the COVID-19 Pandemic

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Abstract

The COVID-19 pandemic forced many workers globally to work from home, suddenly, and often without choice, during a highly uncertain time. Adopting a longitudinal, person-centered approach, we explored patterns of change in employees' psychological distress over three months following the early phase of the pandemic. We investigated how change in distress unfolded for different latent subgroups. We modelled whether and how work characteristics, and individuals' degree of detachment from work, predicted membership of different distress trajectories. Growth mixture modelling revealed two distress profiles: (i) a declining distress profile where employees experienced reduced distress over time, suggesting adaptation and/or improved coping; (ii) a rising distress profile where distress increased and eventually plateaued, suggesting a stress reaction process followed by adaptation. Employees with high workload, underload, or close monitoring, were more likely to belong to the rising distress profile. Detachment from work buffered the negative effect of workload and close monitoring on distress profile membership. Scheduling autonomy and colleague support did not predict profile membership. Contrary to predictions, manager support predicted membership in the rising distress profile. Our findings extend theoretical understanding of how distress unfolds over time, and show the importance of particular job demands in explaining these change processes.

Keywords: COVID-19 pandemic; working from home; psychological distress trajectories; job demands; job resources; detachment from work

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Despite repeated calls for understanding change over time (e.g., Aguinis & Bakker, 2020), most analyses of mental health in the work context have so far failed to investigate dynamic change processes, especially how and why people's individual mental health fluctuates or remains stable over time. The COVID-19 pandemic abruptly and vastly changed how and where work is carried out, on a global scale and over a long period of time. Social distancing forced many to work from home indefinitely, whether or not they would have chosen to or were prepared, with work-related challenges including simultaneously working and caring for children, negotiating workspaces with partners, and lack of support (Tomczak et al., 2018). This challenging context provides a unique opportunity to understand not only people's level of mental ill health (which multiple studies have already shown significantly worsened during this time, e.g., O'Connor et al., 2020; Pierce et al., 2020), but how and why levels of mental ill health changed during the pandemic for different individuals.

Specifically, the aim of this research is to understand how different groups of individual workers' psychological distress changed over the initial three months of the pandemic (April – July 2020). In so doing, we extend theoretical understanding of how distress unfolds over time as well as the drivers of different patterns. Currently, scholars agree that reactions to major stressors change over time, but disagree as to how. Some argue that mental ill health increases over time in response to stressors (e.g., Diener et al., 1999), whereas others suggest it decreases (e.g., Hobfoll, 2001). Theory is also vague with respect to the speed of change: some stress reactions occur rapidly and cause temporary state changes ("stress reaction model"); other stress reactions are slower and more similar to trait-like changes ("stressor strain model") (Frese & Zapf, 1988). Given the paucity of research on the topic, there is little understanding of how or why, or for whom, various patterns of change in distress emerge in the context of a major event. Yet, understanding such patterns will help develop theory and enable organisations to respond effectively to workers' needs following stressful events.

We adopted two approaches to understand how individual workers' psychological distress changed over time during the challenging context of the pandemic. First, we model how change in distress unfolds over time in different ways for different people. There is a vast literature on work stress, with a recent shift towards longitudinal studies. However, the overwhelming majority of these studies have been restricted to two measurement points and have focused on assessing variable-centered causal relationships between stressors and strain (e.g., Ford et al., 2014; Lesener et al., 2019). Although this is important research, these variable-centered methods primarily focus on questions concerning the stability of certain variables over time amongst an entire population as a whole, or amongst predefined subgroups (Mauno et al., 2016). Individual differences in how change unfolds over time are masked by these approaches, which rely on single stability or change coefficients for a whole population. They tell us little about the heterogeneity of dynamic change processes amongst individuals, such as patterns of changes in mental health over time, whether there are linear, recovering, or accumulating effects (Ployhart & Vandenberg, 2010), or whether change evolves differently for different groups of people. Therefore, we adopt a person-centered approach to understand change, which assumes that the population is heterogeneous in terms of the phenomenon of interest and change processes over time, and allows the identification of natural subgroups that have similar stability or change patterns in a specific phenomenon over time (Mauno et al., 2016). Specifically, we used growth mixture modelling (Morin et al., 2011) to explore the development of heterogeneous dynamic change patterns in distress within individuals over time. In so doing, we determine how many meaningful subgroups of workers experienced distinct distress trajectories (i.e. natural subgroups as opposed to pre-determined ones) during the early phase of the pandemic.

Second, having identified different subgroups of people who experience different distress trajectories, we model work design factors and a key individual difference variable (detachment from work) as predictors of those subgroup profiles. We thus assess the key drivers of patterns of change in psychological distress. We focus on work design because work was dramatically altered for many workers during this time, with large variations in workers' experiences. Consequently, we expect work design factors in the early phase of COVID-19 to be a significant determinant of people's general distress and how distress changes over time, in accordance with the job demands-resources model (Bakker & Demerouti, 2007). Although there is much research which links job demands and resources as predictors of well-being outcomes using cross-sectional and longitudinal designs (e.g., Lesener et al., 2018), much less research has investigated job demands and resources as predictors of changing mental health patterns, or distress trajectories, over time. Understanding work design predictors will help us understand whether and how psychological distress evolves differentially following a sudden and impactful change according to individuals' experience of work characteristics. Since work design is an aspect of the environment that is potentially malleable (unlike, for example, demographic predictors), our research paves the way for intervention.

As well as work design, we investigate a key individual difference factor, detachment from work, and assess how this factor interacts with relevant job demands to affect change in distress over time. Detachment from work as a recovery process has been strongly linked to employee outcomes and the stressor-strain relationship (Sonnentag & Fritz, 2015), albeit not within the context of a major external stressor such as COVID. During the pandemic, many of the usual coping mechanisms that individuals might employ to manage stress were restricted or not possible at all (e.g. team sports, visiting friends). Continuing to find ways to detach oneself from work during nonwork time is therefore likely to have been particularly important for buffering the negative effect of job demands.

In sum, we contribute theoretical understanding to the literature on mental health at work by investigating, during a unique time of challenge, the patterns by which workers' psychological distress change over time, namely, whether there are different patterns for different people, and the work design and individual difference drivers of these patterns. We elaborate these ideas next.

Understanding patterns of change in distress

There is a lack of longitudinal research that investigates how change in mental health unfolds. For instance, longitudinal studies have observed correlations between stressors and strain over time (e.g. Brauchli et al., 2013), but they do not consider how change unfolds over time. In studies that do consider patterns of change over time, the possibility of subgroups with different change patterns is rarely explored. For example, in one of the most rigorous studies of its kind, Garst et al. (2000) applied latent growth curve modelling to six data points collected over five years and found support for a stressor-strain model in which average changes in a stressor over time were associated with average changes in strain. However, assessing the average effect in the population can obscure variation in effects amongst different subgroups, thus this research failed to consider whether different subgroups change in distinct ways. We argue that, by investigating patterns of change in distress during a challenging context in which people had to adjust to a new way of work, we further develop theory about how and why people's stress reactions change over time.

Our research builds on longitudinal studies conducted during COVID-19 that tracked shifts in mental health. As with the wider literature, these studies have not investigated heterogeneous change processes for latent subgroups. For example, Pierce et al. (2020) investigated mean changes in mental health via an epidemiological study with repeated measures of mental health over time. Although they looked at differences in mental health between predefined subgroups such as age, they did not look at latent subgroups, or investigate relationships with work stressors. O'Connor et al. (2020) tested for changes in mean scores over three points in time during the early phase of COVID-19 (April-May 2020) in a national UK sample, but did not look at different change patterns for latent subgroups. The consequences of this neglect is that we know little about whether and for whom distress improves, worsens, or adopts an alternative trajectory.

Psychological Distress Profiles

In April 2020 when our study began, national lockdowns, severe social distancing protocols, and work from home policies had been in place for at least one month in most countries worldwide. Fear, uncertainty, and psychological distress were high (e.g. Pierce et al, 2020). We therefore expect that, on average, our sample will have high levels of psychological distress at Time 1. As time progresses, we expect two patterns of change to be experienced by different subgroups, as follows.

Declining distress profile

We propose that, although the COVID-19 crisis worldwide acted as a constant stressor during the period we focused on, for some people, levels of psychological distress reduced over time, indicating adaptation. We further expect that, over a longer period, this reduction in distress slowed down, and levels plateaued, consistent with the idea that individuals slowly return to baseline levels of well-being. This predicted curvilinear pattern of lowering distress that plateaus over time is based on two theoretical perspectives. First, the adjustment model of strain proposes that, although stressors can cause ill-health initially, over time, some people develop coping strategies such that mental ill-health is reduced even if those stressors are still present (Frese & Zapf, 1988). This perspective recognizes that people are agentic (Bandura, 1989): they learn to cope with situations, such as by seeking support or managing demands, reducing their distress. Second, hedonic adaptation theory suggests that, following major positive or negative life changes, individuals experience specific emotions more intensely, such as distress after a divorce, or job satisfaction after moving jobs, but that these emotions lose intensity over time as people become used to their new life situation (Frederick & Loewenstein, 1999). From this perspective, irrespective of one's initial reaction to a major change, emotions resulting from the change will lessen as people change their expectations about their lives, resulting in a gradual return to one's baseline well-being.

We also expect, because our initial assessment occurred after the onset of the pandemic and associated changes (e.g., lockdowns, working from home), that those individuals who experience a pattern of reduced distress will start with relatively lower levels of distress at Time 1 (the intercept of the profile) compared to others in the sample, consistent with the notion that these individuals have already begun to cope and adapt with the situation. Altogether, we propose:

Hypothesis 1*:* Some individuals will experience a pattern of declining psychological distress which plateaus over the longer-term, with these individuals starting with lower distress relative to others in the sample at Time 1. We refer to this as a 'declining distress' profile.

Rising distress profile*.*

Not all individuals are exposed to the same challenges when experiencing a stressful situation, and individuals adapt in different ways. We therefore expect that some individuals will become overwhelmed by the situation and will experience an increase in distress that sustains over time but then slows down as people habituate to the situation. Two theoretical perspectives inform this predicted curvilinear pattern of increased distress. First, a strain reaction process that occurs as a result of continued exposure to stressors can cause increased psychological distress (Frese & Zapf, 1988). More specifically, the allostatic load model of strain suggests that continued exposure to stressful situations, despite efforts to cope, can have negative consequences which cause dysregulation in physiological and psychological systems (Ganster & Rosen, 2013). Physiologically, when distress is experienced, the body adapts by releasing stress hormones, which manifests in the form of biological and psychological markers such as raised insulin or cortisol, and increased symptoms of depression and anxiety. Usually, these processes work quickly and dampen when the stressor is no longer present or is successfully managed. However, through continued exposure to a stressor, the stress reaction can become dysfunctional, resulting in allostatic overload, whereby the expression of physical and psychological distress become manifest. We suggest that for some people, the pandemic may have triggered stress responses which they could not adapt to over time, resulting in allostatic overload and hence rising distress over time.

Second, hedonic adaptation theory suggests that any increases in distress will not be infinite, but will gradually slow down and plateau over time as people habituate to the situation (Frederick & Lowenstein, 1999). This applies to both positive and negative responses. Thus, although the situation remains and causes distress, individuals become more used to living with the pressures, and alter their expectations, resulting in the stress reaction described above tailoring off. Similar to our argument above, we also expect those who experience a pattern of increasing distress over time will start with higher distress at Time 1, consistent with the notion these people have already had exposure to pandemic-related stressors prior to the starting point. In sum, we propose:

Hypothesis 2. Some individuals will experience a pattern of rising psychological distress, with this increase plateauing over the longer-term and with these individuals starting with higher distress at Time 1. We refer to this as a 'rising distress' profile.

Predictors of distress profiles

Large numbers of people were working from home more intensively than prior to the pandemic, which has important implications for people's work design. Consequently, we focused on job resources and job demands that are particularly pertinent for predicting patterns of change in psychological distress during the pandemic. Job demands-resources (JD-R; Bakker & Demerouti, 2007) theory defines job resources as physical (e.g., comfortable work environment), psychosocial (e.g., autonomy, support), or organisational aspects of work (e.g., flexible work practices) that promote achievement of work goals, and stimulate learning and development. Work high in job resources is motivating and predicts good mental health and well-being. Job demands refers to aspects of work that require persistent effort (e.g., high workloads) and have psychological and physiological costs, such as burnout, psychological distress, and ill-health. A wealth of evidence supports these suppositions (e.g., Gonzalez-Mulé et al., 2020; Lesener et al., 2019). However, little research has investigated how job demands and resources affect *change* in distress over time, especially in response to major adverse events. This means we do not know how job demands and resources affect patterns of mental health change, or whether indeed such aspects are even relevant during a major crisis such as a pandemic.

We propose that during the pandemic, job resources and demands are important for adjusting to work changes. In line with recent meta-analytical evidence, we expect demands and resources to be additive (i.e., independent main effects on psychological distress; Gonzalez-Mulé et al., 2020). Those who perceived high resources or low demands initially are likely to have adapted to their new working circumstances better leading to distress decreasing over the first few weeks. Those with low job resources or high demands initially would have lacked the job resources to adapt to the situation, or needed to expend considerable energy to manage their demands, instigating a stress response and increased distress (Bakker & Demerouti, 2007). We theorise that three job resources (scheduling autonomy, manager support, colleague support), and three job demands (workload, underload, close monitoring from the supervisor), are particularly pertinent during the pandemic. Some of these resources and demands have been highlighted in remote working literature as related to well-being while working from home (Charalampous et al., 2019; Oakman et al., 2020). We build on this literature and apply it to the unique context of the pandemic to advance theory and provide novel insights into working from home under this context.

Job resources

First, job autonomy is consistently associated with better mental health and well-being as it allows individuals to meet their own work goals, needs, and desires, leading to self-fulfilment (Parker, 2014). Golden et al. (2006) found that scheduling autonomy allowed individuals working virtually to manage home and work demands better because they could choose their own hours and plan work around non work commitments. Scheduling autonomy is likely especially important during the pandemic because it allows flexibility for coping with unusual pressures such as a lack of access to childcare, and because it gives workers a sense of agency during a time when one's general sense of control may be reduced due to the wider uncertainty of the pandemic.

Second, social support refers to the help that workers receive from colleagues and managers

(Morgeson & Humphrey, 2006). The JD-R model theorises that social support promotes work engagement and well-being by stimulating goal achievement and learning (Bakker & Demerouti, 2007) and increasing belonging to a work team or group (van den Broeck et al., 2016). When working remotely, workers are at increased risk of social isolation and distress such as anxiety or depression (Knight et al., 2022). Isolation is likely to be enhanced during the pandemic due to decreased face-to-face interaction. Managers have a key role in providing practical and emotional support which can help individuals feel valued and cared for by the organisation, fostering a sense of well-being (Grant & Parker, 2009). Colleague support is particularly helpful for reducing uncertainty and solving work or non-work problems, for example, by reducing workload, role conflict or role ambiguity (Chiaburu & Harrison, 2008). Colleague and manager support during the pandemic is likely to facilitate adaptation, allowing individuals to experience greater social connection, gain more support with work challenges, and, experience less psychological distress over time.

Job demands

Much literature has linked high workload to negative well-being outcomes such as burnout, stress, anxiety, and depression (e.g., Lesener et al., 2018). According to the JD-R, when workload is high, individuals must invest more time, effort and energy into completing their work. This can mean working extra hours, and taking fewer breaks, depleting individuals' cognitive and psychological resources, making them more susceptible to ill-health (Bakker & Demerouti, 2007). When forced to work from home during the pandemic, people had to adapt their work tasks to the home and online environment, which for some will have created extra work. The pandemic is thus a unique context for exploring what happens when individuals are suddenly faced with higher workloads, such as due to having to carry out their work in a new environment for which they were not prepared.

On the other hand, during the pandemic, underload, which refers to not having enough work to do, may have also been salient for many. Underload may be considered a demand as it requires individuals to expend effort to self-regulate their behaviour to focus their attention on work when they do not have enough to do, or are faced with unstimulating tasks (Cham et al., 2021). In contrast to workload, underload creates a lack of job stimulation and engagement, leading to boredom (Fisher, 1993), fatigue (Cham et al., 2021), increased distress and depressive symptoms (van Hooff & van

Hooft, 2014), and lack of job fulfilment and meaning (Spreitzer, 1997). During the pandemic, some people may not have had jobs that could be easily transferred to the home environment. Some tasks may have become redundant (e.g., health and safety checks), replaced by other, more monotonous or repetitive tasks (e.g., data entry), and some tasks could not be carried out from home at all (e.g., due to business closures), driving boredom and fatigue. To our knowledge, no research has explored how peoples' well-being is affected over time when they are suddenly not able to carry out some of their work tasks and their load is radically reduced. We propose that underload is a pertinent job demand during the pandemic associated with worsening psychological distress.

Finally, during the pandemic, managers were suddenly thrust into managing employees from a distance irrespective of whether they were confident and prepared for this style of management. Initial evidence suggests managers monitored their employees closely to keep control over them and track their productivity and performance (Parker et al., 2020). Close monitoring may be considered a job demand as employees can feel obliged to respond to work messages immediately and expend effort to prove they are working (Day et al., 2018). This can prevent employees from carrying out their work in the way that works best for them. Remote working literature has consistently found that monitoring is associated with lower job satisfaction (Tomczak et al., 2018), lower trust (Staples, 1999), and increased stress (Aiello & Kolb, 1995) in employees. Charalampous et al. (2019) reported that, even when employees were trusted, supervision increased when employees transitioned to remote working. During the pandemic, increased monitoring may cause greater distress over time.

Hypothesis 3. Workers perceiving higher job resources (scheduling autonomy, manager support, colleague support) at Time 1 will be more likely in the declining distress profile, and less likely in the rising distress profile.

Hypothesis 4. Workers perceiving higher job demands (workload, underload, close monitoring) at Time 1 will be more likely in the rising distress profile, and less likely in the declining distress profile.

Detachment from work and job demands

Psychological detachment refers to being able to "switch-off" from work during non-work time such that an individual is not thinking about work or work-related issues and is able to focus on other activities (Sonnentag et al., 2010). Detachment is a form of coping which facilitates recovery from work, allowing individuals to replenish cognitive, emotional, and physical resources depleted through work. Those able to detach are more likely to experience better recovery, higher work engagement, and lower exhaustion and psychosomatic complaints. Those unable to detach are likely to experience elevated stress levels during non-work time, with little opportunity for these levels to reduce before the next working period. We therefore expect that those who report lower detachment from work during the pandemic are likely to belong to the rising distress profile.

We further predict that there will be an interaction between two of these work demands and detachment from work. Firstly, we propose that the negative impact of higher workload will be moderated by the ability of individuals to detach from work, with those able to detach more successfully experiencing lower distress levels over time. The stressor-detachment model (Sonnentag & Fritz, 2015) proposes that job stressors, such as work demands, prevent detachment as they cause physiological and psychological human systems to remain activated. According to the allostatic load model of strain (Ganster & Rosen, 2013), this can lead to the chronic depletion of resources over time, as there are inadequate opportunities for resources to recover, resulting in more serious health issues in the longer term (Meijman & Mulder, 1998). Being able to detach from work is therefore important for recovery when job demands are high. When detachment is low, work spills over into non-work time as people have too much to do in the time available, and may ruminate about work whilst doing non-work tasks and activities, consuming energy and hindering recovery (Brosschot et al., 2007).

Secondly, we predict that the negative effect of distress on close monitoring will be attenuated by successful detachment from work. Constant monitoring can be emotionally draining, as individuals feel pressure to be constantly available, meet work demands, and perform to a high standard (Parker et al., 2020). This can lead to time pressure, work spilling over into non-work time, and constant rumination about work tasks or problems. Individuals who are not able to detach when faced with such pressure are likely to experience persistently depleted resources, meaning they cannot recover.

Hypothesis 5a. Workers perceiving higher detachment from work at Time 1 will be more likely in the declining distress profile, and less likely in the rising distress profile.

Hypothesis 5b. The likelihood of those with high demands (workload and close monitoring) being in the rising distress profile is reduced for those with higher detachment.

Method

Participants and Procedure

A longitudinal study was launched on April 22, 2020, six weeks after the WHO declared the COVID-19 pandemic and during the height of the COVID-19 restrictions worldwide. The target population were participants working from home at least some of the time. Participants were recruited internationally via social media, industrial organisation websites (e.g., US Academy of Management), contacts, and alumni of the authors' institutions. Participants completed four weekly surveys followed by two surveys each a month apart (i.e., weeks 8 and 12). These time intervals capture dynamic short-term change early in the pandemic and help manage survey fatigue over longer periods. The study continued beyond this point, however, our research questions focused on the early period of the pandemic when lockdown restrictions were more stringent. Participants received a personalised feedback report at Time 4. The first survey was open to new participants for seven weeks to maximise sample size. Each survey was automatically emailed to participants. The study was fully approved by the first author's University Ethics board, approval number (*to be added post review*).

Initially, 589 participants responded. Following data cleaning to remove participants with missing data on all or most variables, who were not working from home all or most of the time (i.e., four or more days a week), or became unemployed between Time 1 and Time 6, 412 participants remained. At Time 6, 177 participants remained (30.1% retention). To assess non-response bias we conducted a dropout analysis. Those who responded at Time 6 reported significantly lower home-work conflict (M=2.11, SD=1.01) than those who dropped out (M=2.41, SD=1.08; t=-2.89, df=414, p=<.01). There were no other significant differences between responders and non-responders on any of our research variables. At Time 1, participants comprised 70.4% female, ranged between 20-72 years (M=41.87 years, SD=10.78). The mean number of working hours was 36.45 (SD=13.87), average experience of working from home was 3.83 years (SD=1.94), and average job tenure was 5.89 years (SD=6.86). Participants were employed in a wide range of industries, including education (29.3%), professional and scientific industries (19.3%), and government services (9.5%). 72.7% were located in Australia, with the remaining participants from a wide variety of countries such as the Netherlands (6.7%), the US (3.3%), and the UK (1.6%).

Measures

Job resources and demands

Job characteristics were measured with three items each using established scales using a 5-point agreement scale (1=*strongly agree* to 5=*strongly disagree*). Example items are as follows: scheduling autonomy, "This week, the job allowed me to make my own decisions about how to schedule my work" (α=.87; Morgeson & Humphrey, 2006); colleague support, "This week, I got the help and support I needed from colleagues" (α=.87; Cousins et al., 2004); manager support, "This week, my line manager gave me supportive feedback on the work I do" (α=.87; Cousins et al., 2004); workload, "This week, my job required me to work very hard" (α=.78; Spector & Jex, 1998) and underload, "This week, I had very little work to do" (α=.95; Fisher, 1987). Close monitoring was assessed with two items from George and Zhou (2001), "My supervisor/manager kept very close tabs on me by frequent checking", and "It sometimes feels like my supervisor is always looking over my shoulder", and one item from Holman (2006) "I was monitored too much" (α=.88).

Moderator variable: detachment from work

Detachment from work was measured with three items (α=.85; Sonnentag et al., 2007), using a 5-point scale (1=*strongly agree* to 5=*strongly disagree*). An example item is "This week, I forgot about work".

Psychological distress

Psychological distress was measured with five items (K5; Kessler et al., 2003) with response options ranging from 1=*none of the time* to 5=*all of the time*. An example item is, "Over the past week, about how often did you feel depressed?".

Control variables

We included four control variables in our models: i) Country of location ("Which country or region are you in?", coded, 1=*Australia,* 0=*all other countries*); ii) Degree of lockdown, measured with the item, "Which of the below best describes how much your home is in lock-down (i.e. not going outside of the home)" and coded, 1=*not at all (we are going out as much as before COVID-19)* to 5=*full lock down (e.g., not going out at all, or going out only with permission from authorities)*; in places where the degree of lockdown was severe, psychological distress is likely to have been higher due to uncertainty and health fears; iii) Job tenure, measured with the item, "How many years have you worked in total in your main job?"; evidence suggests that those working remotely with shorter job tenures experience worse job outcomes (Akkirman & Harris, 2004), and are less likely to have developed trusting relationships with immediate managers; and iv) Home-work conflict, measured with three items which focused on the interference of home activities with managing work responsibilities (e.g., "This week, due to all the pressures at home, sometimes it was hard for me to do my job well"; α=.88; Carlson et al., 2000). During the pandemic, heightened home-work conflict was likely, with, for example, the closure of childcare facilities and schools necessitating that parents home-school and care for children whilst working. Working virtually has been found to increase home-work conflict (Golden et al., 2006), and lead to higher stress when undertaken involuntarily (Lapierre et al., 2016), hence it is an important control in our analyses.

Statistical Procedure

Confirmatory factor analyses (CFA) were carried out in MPlus (v8.4; Muthén & Muthén, 1998-2019) using the robust maximum likelihood estimator (MLR). Model fit was assessed using recommended fit indices and statistical cut-offs (Hu & Bentler, 1999). Growth mixture modelling was used to explore natural subgroups in psychological distress profiles over time. We tested models where the means of the distress indicators differed across profiles but variances were set to equality. Following best practice recommendations (McLarnon & O'Neill, 2018), we modelled linear and quadratic psychological distress profiles, starting with one profile and increasing the number of profiles until model fit did not improve or statistical inadequacy was reached. Lower values on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), and sample-adjusted BIC (SABIC), and higher entropy values, indicate better fitting models (Masyn, 2013). Elbow plots helped determine where the slope of the information criteria plateaued, indicating the optimal solution. The Lo, Mendell, and Rubin's Likelihood Ratio (LMR) and the Bootstrap Likelihood Ratio (BLRT) tests indicate that the *k* profile model is a better fit than the *k*-1 profile model when *p*-values are <.05. The final model retained was informed by both model fit and theoretical expectations. Predictors were assessed using the AUXILIARY R3STEP function in M*plus*

(Asparouhov & Muthen, 2014). This function calculates odds ratios (OR) from multinomial regression coefficients which indicate the likelihood of individuals belonging to a profile. ORs >1 indicate increased likelihood of membership in the target profile; ORs <1 indicate decreased membership. In step 1, we tested the direct effects of predictors on profile membership. In step 2, we added our hypothesised interactions to the model and tested their effect on profile membership.

Results

A table of means, standard deviations, and bivariate correlations of all study variables can be obtained from Figshare (*link to be provided*). CFA revealed good model fit for the Time 1 study variables (χ^2=435.537, *df*=314, *p*<.01; RMSEA=.03; CFI=.98; SRMR=.04). For all predictor analyses, we focus on Time 1 work design predictors because our analyses showed that these predictors are constant, with no mean change over time (results available from the corresponding author). A key methodological advantage of this approach is that, rather than correlating change in work variables with change in distress, we use Time 1 variables as predictors of change profiles, which means we introduce a time element, and therefore strengthen the research design. We confirmed scalar invariance of psychological distress across the six time points (results available upon request).

Growth mixture modelling revealed the five-profile linear solution was statistically inadequate, likely due to over-parameterization (McLarnon & O'Neill, 2018; see Table 1), so we did not explore solutions with more profiles. Beyond the two-profile quadratic solution, there were too few people assigned to some profiles to warrant validity. Elbow plots suggested two profiles captures the key variance; a conclusion supported by other fit indicators. We therefore retained the two profile quadratic solution as optimal. Lower fit statistics for the quadratic solutions suggested better fitting models, hence we investigated these further (see Table 1 and Figure 1).

The two-profile solution revealed a significant quadratic slope factor mean for a profile in which distress rose and then plateaued ('rising distress that plateaus' profile; *M*=<-.01; *SE*=<.01, p=.04), but was non-significant for a profile in which distress declined ('continually declining distress' profile, see Table 2). The continually declining distress profile comprised 335 people (81%) who reported lower distress at Time 1 and who gradually decreased in distress over the first eight weeks (Time 1 – Time 5). The rising distress that plateaus profile comprised 77 people (19%) who reported relatively high distress at Time 1, and whose distress increased over the first eight weeks before plateauing over the final four weeks. These results fully support Hypothesis 2, and partially support Hypothesis 1 due to the lack of curvilinear effect in the continually declining distress profile.

In terms of predictors of profile membership, there were no significant differences between profile membership for the job resources of scheduling autonomy or colleague support, but those reporting higher manager support were 0.5 times less likely to belong to the declining distress profile (Table 3). These results do not support Hypothesis 3. In terms of job demands, people experiencing high underload, and high close monitoring, were 0.6 times, and 0.5 times, respectively, less likely to belong to the declining distress profile. There were no significant differences in profile membership for workload. Hypothesis 4 was partially supported. Detachment from work predicted membership in the declining distress profile, supporting Hypothesis 5a. Significant interactions between detachment from work and workload, and detachment from work and close monitoring, predicted membership in the rising distress profile. As workload or close monitoring increased and detachment decreased, individuals were 0.36 times less likely, and 0.5 times less likely, respectively, to belong to the declining distress profile. This supports Hypothesis 5b. There were no significant effects of the controls, country, degree of lockdown, and job tenure on profile membership. However, home-work conflict predicted membership in the rising distress that plateaus profile. To rule out the possibility of a buffering effect of demands on resources which is predicted by JD-R theory, we also tested for interactions between job resources and job demands, but found no significant effects. This is consistent with previous research (e.g., Gonzalez-Mulé et al., 2020).

Discussion

We set out to understand how psychological distress changes over time, and the role of work in that process, in the context of a pandemic that meant large numbers of people were working from home. Largely consistent with our predictions, we found two very different psychological distress profiles: a profile in which distress was relatively low, and gradually decreased, consistent with an adjustment to strain process; and a profile in which distress was relatively high and increased over time before plateauing, consistent with a stress reaction process involving allostatic overload followed by hedonic adaptation. Examination of distress sum scores for the latter group showed that 67% of this group had levels of distress at Time 1 that suggested clinical intervention would be beneficial (for benchmarks, see ABS, 2012), with this percentage rising to 100% after two months (Time 5). For the declining distress profile, 83% scored below 12, rising to 93% after 3 months. This suggests meaningful differences in distress between the two groups. We also showed a clear role for work design and individual differences in predicting profile membership, with workload, underload, close monitoring, and poor detachment from work predicting membership of the rising distress profile.

Theoretically, our results provide insight into how distress evolves over time. Previous approaches to understanding change in distress, including in the context of COVID-19, are overwhelmingly variable-centered and thus assume a single average trend amongst a population. These analyses do not assess whether people experience different distress trajectories, whereas person-centered analyses are highly suited to exploring whether there are different patterns of change for different latent subgroups (Mauno et al., 2016). Our study therefore addressed a different question to previous research on changes in mental health over time. We identified meaningful subgroups, suggesting that there is no "one size fits all" in terms of distress response, but neither are there many different change patterns in distress. This finding is important for understanding who is likely to struggle in the face of major stressful events, and who is likely to adapt and cope. From a practice and policy perspective, our results suggest potential targets for intervention.

More generally, our research has broader theoretical implications for understanding how mental health unfolds over time in the context of a major event. Contrary to our expectation of hedonic adaption, the reducing distress profile did not plateau over time: instead, workers in this group continued to experience improved mental health, consistent with the idea they were adjusting to the situation and / or learning how to cope. It is likely that, were the study extended further, the reduction in distress may have slowed down and plateaued when individuals reached their baseline level of mental health. On the other hand, the rising distress group increased in distress but then plateaued after a few weeks, suggesting recovery processes may take longer for these people than those in the declining distress profile. This could be because, for some people, continuous effort and energy investment is needed to improve psychological health and learn to cope with work and life in response to major and persistent stressors.

Our findings partially concur with research which has investigated recovery trajectories following other types of stressful events. For example, Bryant et al. (2015) observed that some people recovering from traumatic events such as life altering injuries experienced a trajectory in which symptoms of traumatic distress are initially high, and then decline, similar to our declining distress profile, and consistent with an adjustment to strain theory. They also observed that other groups of people experienced worsening distress, similar to our rising distress profile. However, in a departure from our findings, this study suggested that yet other groups of people experience consistently low or high symptoms, or high stability in their mental health. These findings suggest that there are similarities and differences in how people react to different major adverse events over time. Given that the pandemic affected everybody, unlike an individual trauma such as injury, it may be that our findings are best generalized to other naturally occurring events which impact whole populations, such as environmental disasters (e.g., flooding, bushfires) or economic downturns.

Further, we extend previous research into why mental health changes over time by demonstrating, in the context of a major stressor, the importance of job demands and recovery from work on adaptation. Work design influences change in people's psychological distress, even when there are many other sources of stress besides work. Importantly, profile membership was largely determined by job demands, the presence of which fostered distress, and the absence of which supported recovery. Resources had no unique effect. This contrasts with prominent theorizing and previous findings from longitudinal research. For example, Lesener et al. (2019) meta-analysed longitudinal JD-R studies and found that, as predicted by the JD-R model, job resources negatively predicted burnout while job demands positively predicted burnout. This two wave meta-analysis was based on variable-centered studies and did not analyse change in burnout, so cannot tell us about patterns of change in wellbeing. It also categorised all demands together and all resources together, preventing nuanced relationships between specific demands and resources from being explored.

Other reviews have also demonstrated associations between job resources, job stressors, and mental health (e.g., Herchovis & Barling, 2010; Lee & Ashforth, 1996; Nixon et al., 2011). However, these rely on cross-sectional research, limiting causal inferences. Our findings go beyond these previous reviews to suggest that relationships between job resources, demands, and outcomes, are more nuanced than suggested by work stress models such as the demand-control model (Karasek, 1979) or JD-R (Bakker & Demerouti, 2007). These models and previous reviews do not theorise around trajectories of distress or wellbeing, and so are less useful for predicting membership of distress profiles, or explaining why some people experience increasing distress following a major stressful event, while others experience decreasing distress. Our findings clearly show that job resources, at least those assessed here, are not as important for predicting change in distress over time relative to job demands. This is important as previously, research has demonstrated that demands may cause distress, but has not established what predicts patterns of change in distress. Practically, understanding predictors of patterns of change over time is important for targeting interventions more specifically to those who will benefit most (i.e., those in the increasing distress profile).

Our findings accord with views that adverse events have a greater impact than positive events (e.g., Hobfoll, 2001) and suggest different aetiologies of rising and declining distress profiles. In addition, the pandemic, or other major adverse events, may act as a background stressor that is more powerful than job resources can offset (Gump & Matthews, 1999). The findings also support those of Garst et al. (2000) who found that job stressors were associated with worry over a period of five years in response to major political change in Germany, again suggesting the important impact of major stressors. Our findings pave the way for building change in mental health over time into work stress models as a focal part. Current models focus on associations, whereas developing models which focus on longitudinal change in outcomes may help unpack more nuanced relationships between demands and mental health and the sustainability of these effects. Practically, work redesign interventions focusing on reducing demands could facilitate adaptation for people with higher demands.

As theorised, the negative impact of high demands appeared to initiate a stress reaction process, causing individuals to suffer until a point at which (high) distress stabilises. This accords with the stressor-detachment model (Sonnentag & Fritz 2015), wherein high demands are theorised to cause persistently raised activation of biological and psychological systems, leading to allostatic overload and preventing recovery. In contrast, low demands predicted a reduction in distress, suggesting that people are more able to cope with the situation when demands are low. Underload has often been overlooked as a demand yet our results suggest its effect on well-being is considerable.

When individuals do not have sufficient stimulating work or a sufficient amount of work, their skills are underutilised and they cannot grow, develop, and take pride in their work (Fisher, 1993). Work loses its meaning, days drag, and individuals are left feeling demotivated. This effect may have been accentuated during the pandemic as many activities were hampered, not just work, so it was not possible to replace work with other activities. Close monitoring by managers also exacerbated distress over time, perhaps because individuals felt 'tethered' to their computers (Parker et al., 2020), whether or not other demands occured (e.g., requests from children / partners). Close monitoring also promotes distrust, which can create performance pressure and distress (Staples, 1999).

Importantly, we found that being able to detach from work moderated the negative impact of workload and close monitoring on distress. This suggests that detachment not only promotes recovery in the immediate term, which has been the focus of previous research to date, but also impacts the trajectory of stress that individuals experience in the longer term. Therefore, in spite of high demands, individuals can use detachment techniques to influence their distress levels, for example, by refocusing their thoughts on activities other than work such as a hobby, learning a new skill, or spending time interacting with friends and family.

Surprisingly, high manager support predicted the rising distress profile. This is inconsistent with previous research which has found manager support beneficial for well-being (e.g., Akkirman & Harris, 2004). We see three explanations for this finding. First, in line with social exchange theory (Emerson, 1976), those who perceived high manager support might have also perceived high pressure to perform and meet the expectations of their manager, causing strain. Second, being offered social support implies that one's individual struggles are visible to managers, yet receiving support may negatively affect self-esteem and trigger worries about insufficient performance and job security, increasing distress (e.g., Lindorff, 2000). Third, we cannot rule out the idea that managers may have observed some employees' distress and offered greater support, with this process starting prior to our first wave of data collection.

Notably, the control variable work-home conflict predicted membership of the rising distress trajectory. The impact of home-work conflict on rising distress is in keeping with emerging COVID-19 research which suggests that when a parent must manage work, children, and domestic life simultaneously, well-being suffers (e.g., Shockley et al., 2021). This contradicts previous research conducted prior to COVID-19, which suggests remote working can improve well-being (Delanoeije et al., 2019). This may be explained because pre-pandemic, those who chose to work from home likely preferred this type of working, which may be associated with certain personality traits, such as introversion. They may also have had the home circumstances which allowed it, such as children who had left home, and a home office. In the context of COVID-19, when usual support networks and coping methods were in limited supply, some people adapted while others struggled, with significant consequences for change in mental health. Importantly, in our study, the significant negative impact of job demands on distress, and the buffering effect of detachment on demands, suggest the critical role of job demands in the evolution of stress reactions over time, even when taking into account external factors such as home-work conflict. It is therefore imperative that organisations support workers to manage these demands, as well as encouraging detachment from work.

Research and practical implications

Research implications include developing theory around how the process of distress evolves over time. We unpack the distress process and how it changes for different groups of people, contributing knowledge around the aetiology of distress in response to major stressors. This progresses stress research which has previously relied on variable centred analyses and causal mechanisms which say little about how and why distress itself changes over time and for different naturally occurring groups of people (e.g., Lesener et al., 2019; Sonnentag & Frese, 2012). Further, we highlight the important impact of work demands, irrespective of job resources, on the aetiology of psychological distress over time. Popular work design and stress models suggest that job resources are crucial for wellbeing, and can buffer the impact of demands (e.g., Bakker & Demerouti, 2007; Karasek, 1979). Our research does not support this view, but suggests that job demands, irrespective of job resources, are key players in the aetiology of distress.

Practical implications include focusing on job demands as potential targets for the design of interventions to reduce demands and positively alter the trajectory of increasing distress. These might include managers refraining from close monitoring, ensuring appropriate staffing levels, reallocating tasks or removing unnecessary tasks, helping employees reprioritise workload, and encouraging employees to detach from work during non-work hours (e.g., by minimising electronic communication outside of work hours). Individuals could also aim to manage their own distress by proactively crafting their work to reduce demands (see Tims et al., 2013), and actively implementing strategies to enable them to detach from work, such as creating boundaries between work and non-work time (e.g. going for a walk before / after work), and planning fun, engaging, activities during non-work time to avoid the temptation to continue working or ruminate over work problems.

Strengths and Limitations

The strengths of our study lie in the six-wave, repeated measures design, which allowed us to model change in psychological distress over time for meaningful subgroups of people, and determine predictors of that change. In addition, data collection commenced during the height of the initial phase of the pandemic, increasing our understanding of the evolution of distress in response to such a severe and catastrophic event. We acknowledge that due to the unforeseen nature of the event, we did not collect data prior to the event and thus do not have a baseline enabling us to compare responses before the pandemic with subsequent responses. We also note that differences in psychological distress were already present at Time 1. This could suggest that caution needs to be applied when generalising conclusions. However, this was not the point of our study - we wanted to understand how people adapted in response to a widescale major change in which many people were forced to work from home and socially distance. Our data shows that we captured workers in a range of industries and job roles which were able to pivot to online work (i.e. as expected, we had minimal respondents from frontline industries such as healthcare, retail, and manufacturing). To test the robustness of our results, we controlled for the two industries representing the largest proportion of respondents using dummy variables, namely, education (29% of participants), and professional, scientific, and technical activities (19% of participants). We re-ran our predictor analyses and observed the same pattern of significant effects as in Table 4, except for underload, which was no longer significant. These results suggest robustness.

Our study suffered some attrition over time, however, our dropout analysis revealed few differences between dropouts and those who continued to participate, suggesting robust results. We also maximised our data by using Full Information Maximum Likelihood (FIML) to analyse our longitudinal data in MPlus, which is the recommended way of taking account of missing data (Newman, 2014; Schafer et al., 2002). In addition, all our measures were self-report, which can increase common method variance However, this is a within-person study and as such, we investigate change over time within individuals. Common method variance is less of a concern in within-person studies as individuals act as their own referent and thus individuals' scores can be compared to each other across time and partitioned to a within-persons component, effectively controlling for individual differences in scores (Pindek et al., 2019). In addition, one of the main objectives of this study was to extract distress profiles. As this involves clustering employees rather than observations, it is less likely that common method variance influenced the relationships between the levels of variables across the profiles (Keller et al., 2016). Finally, it is possible that our sample size limited the extraction of greater numbers of profiles, however, we argue that there is strong theory to suggest the two profiles we uncovered and thus that it is likely these profiles would be uncovered in a larger sample of workers working from home.

Acknowledgements

1. This study was funded by the Australian Research Council Laureate awarded to Sharon K. Parker, FL160100033; and the Western Australian State Government Department of Jobs, Tourism, Science and Innovation awarded to Sharon. K Parker and Caroline Knight, C1128000380.
2. We have no conflicts of interest to disclose.
3. We are grateful to Shannon Chen, Ding Wang, Iustina Armasu and Leah Zoszak for their outstanding and meticulous help with survey administration and data preparation.

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Table 1

Latent Profile Analysis Class Enumeration Fit Indices (N=412)

Model	LL	#parameters	AIC	CAIC	BIC	SABIC	Entropy	LMR *p*	BLRT *p*
Linear models									
One profile	-1066.74	11.00	2155.48	2210.71	2199.71	2164.81	n/a	n/a	n/a
Two classes	-1028.82	14.00	2085.65	2155.94	2141.94	2097.51	0.77	0.00	0.00
Three classes	-1020.32	17.00	2074.64	2159.99	2142.99	2089.04	0.78	0.11	0.00
Four classes	-1004.57	20.00	2049.15	2149.57	2129.57	2066.11	0.74	0.66	0.00
Five classes	Could not be interpreted due to statistical inadequacy/over-parameterization of the solution								
Quadratic models									
One profile	-1052.91	15.00	2135.82	2211.14	2196.14	2148.54	n/a	n/a	n/a
Two classes	-1011.24	19.00	2060.48	2155.87	2136.87	2076.58	0.75	0.05	0.00
Three classes	-988.07	23.00	2022.14	2137.63	2114.63	2041.64	0.83	0.02	0.00
Four classes	-973.23	27.00	2000.45	2136.02	2109.02	2023.35	0.80	0.37	0.00
Five classes	-957.68	31.00	1977.36	2133.01	2102.01	2003.64	0.78	0.07	0.00

Note. For all models, means differed across profiles, respective variances were constrained to equality; LL=Loglikelihood value; AIC=Akaike Information Criterion; CAIC=Consistent AIC; BIC=Bayesian Information Criterion; SABIC=Sample size adjusted BIC; LMR=Lo, Mendel and Rubin LRT test; BLRT=Bootstrapped LRT; *p*=*p*-value

Table 2.

Parameter Estimates of the Quadratic Two Profile Growth Mixture Model (N=412)

Parameters	Profile parameter estimates			
	P1		P2	
	Low, adaptive psychological distress (n=335)	*SE*	High maladaptive psychological distress (n=77)	*SE*
Intercept factor mean	1.71**	.05	2.72**	.14
Slope factor mean	-.05**	.01	.12**	.04
Quadratic factor mean	<.01*	<.01	<-.01	<.01
Intercept factor variance	.34**	.05	.34**	.05
Slope factor variance	.01*	<.01	.01*	<.01
Quadratic factor variance	<.01	<.01	<.01	<.01

Note. ***p*≤.01; **p*≤.05; *n*=sample size; *SE*=standard error.

Table 3.

Multinomial Logistic Regression Results of Predictor Effects on Psychological Distress Profile Membership

Predictor	Profile 1 vs 2			
	Coefficient	*SE*	*p*	OR
STEP 1 - Direct effects				
Scheduling autonomy	0.44	0.30	0.14	1.56
Manager support	-0.75	0.34	0.03	0.47
Colleague support	0.52	0.33	0.11	1.68
Workload	-0.11	0.46	0.81	0.90
Underload	-0.60	0.29	0.04	0.55
Close monitoring	-0.71	0.22	0.00	0.49
Detachment from work	0.55	0.27	0.04	1.73
Country	0.32	0.54	0.55	1.38
Degree of lockdown	0.07	0.28	0.79	1.08
Job tenure	0.04	0.04	0.30	1.04
Home-work conflict	-0.56	0.22	0.01	0.57
STEP 2 - Interactions				
Detachment from work*workload	-1.03	0.48	0.03	0.36
Detachment from work*close monitoring	-0.53	0.17	0.01	0.59

Note. *$p \leq .05$; N=393*;* Listwise deletion was applied to auxiliary variables reducing sample size by n=19; Profile 1=Low, adaptive psychological distress; Profile 2=High, adaptive psychological distress; OR=odds ratio; *SE*=standard error of the coefficient; Country was coded 1=Australia, 0=Every other country; All other scales were ordinal

Figure 1

Final Two Profile Quadratic Growth Mixture Model for Psychological Distress Profiles