TPM

THE COSTS OF TECHNOSTRESS WHEN WORKING REMOTELY: A MULTI-METHOD INVESTIGATION OF TECHNOSTRESS CREATORS, JOB AUTONOMY, AND STRESS BIOMARKERS IN A PERSPECTIVE OF JOB DEMANDS AND RESOURCES

DAMIANO GIRARDI
LAURA DAL CORSO
ELVIRA ARCUCCI
UNIVERSITY OF PADOVA, ITALY

ACHIM ELFERING
UNIVERSITY OF BERN, SWITZERLAND

ISABELLA PIVIDORI
UNIVERSITY OF UDINE, ITALY

ALESSANDRO DE CARLO
UNIVERSITY OF MESSINA, ITALY

TANIA BOATTO
XYLEM INCORPORATED, VICENZA, ITALY

DORA CAPOZZA
ALESSANDRA FALCO
UNIVERSITY OF PADOVA, ITALY

Building on the Job Demands-Resources (JD-R) theory, in this study we investigated the association between technology-related risk factors — referred to in the literature as technostress creators (TCs) —, job autonomy (JA), and the ratio of cortisol to dehydroepiandrosterone sulfate (DHEA(S)) in hair as possible biomarker of work-related stress. A total of 85 remote workers (i.e., smart workers) in a private metalworking company completed a self-report questionnaire (i.e., psychological data) and contextually provided a strand of hair (i.e., biological data). Results from moderated multiple regression analysis showed that techno-insecurity was positively associated with log cortisol/DHEA(S) ratio at average levels of job autonomy. Additionally, JA exacerbated — rather than buffered — the association between techno-overload/-invasion/-insecurity and log cortisol/DHEA(S) ratio. Our results suggest that hair cortisol/DHEA(S) ratio is a promising biomarker of technostress, and that remote workers may not necessarily benefit from traditional job resources such as JA. Theoretical and practical implications are discussed.

Keywords: Remote working; Technostress creators; Hair cortisol; Hair dehydroepiandrosterone sulfate; Biomarker.

Correspondence concerning this article should be addressed to Damiano Girardi, Department of Philosophy, Sociology, Education, and Applied Psychology, Section of Applied Psychology, University of Padova, Via Venezia 14, 35131 Padova (PD), Italy. Email: damiano.girardi@unipd.it

Over the last two decades, digitalization, accompanied by a widespread increase in the pace of technological and economic growth, has significantly changed several aspects of life (Kraus et al., 2021), including the nature and characteristics of work, in both the public and private sectors. The integration and advancement of information and communication technology (ICT) in everyday workplace activities has changed the way employees work and communicate with each other, creating both challenges and new risks that require the attention of researchers and practitioners (Wang et al., 2021).

On the one hand, in terms of opportunities, ICT have significantly improved work by increasing functionality, accuracy, speed of information processing, reporting, and access to more effective tools and platforms (Zhu et al., 2023). Furthermore, technological advancements have resulted in the emergence of alternative work arrangements, such as remote working — also known as smart working (SW) in Italy — which have provided employees with greater flexibility in terms of when and where to perform work activities (Eurofound, 2020). In particular, before the COVID-19 pandemic, remote working was mainly used by highly skilled workers who did most of their work on computers and had a high degree of autonomy over their work (e.g., managers, professionals; Joint Research Centre of the European Commission, 2020). It is widely recognized that with the pandemic, this trend has become the norm for many workers, including those who previously had little or no experience of it (Wang et al., 2021).

However, despite its facilitation of work, the increased use of ICT has created new risk factors for workers and exacerbated existing ones (Karimikia et al., 2021). These risks include overwhelming inherent complexity (Zhu et al., 2023), work intensification due to remaining connected for work during personal time, and managing significant amounts of data from multiple sources, which can lead to isolation and ineffective communication (Allen et al., 2015; Wang et al., 2021). In addition, employees may be expected to be available for work outside of their regular working hours (European Agency for Safety and Health at Work et al., 2021), which may lead to difficulties in disengaging from work and negative consequences for work-life balance (Senarathne Tennakoon, 2021). As a consequence, the extensive use of ICT, especially when working remotely, can have a significant impact on workers' health (Ayyagari et al., 2011; Eurofound, 2020; Singh et al., 2022).

In this perspective, this study examined the relationship between technology-related risk factors — referred to as technostress creators (TCs) — and the strain response among smart workers (SWs), with a focus on the protective role of job autonomy. We focused on SWs because they use ICT extensively to perform work-related tasks and communicate with colleagues/supervisors, possibly experiencing several technology-related stressful situations at work (De Carlo et al., 2022). In doing so, we think that our study would provide a valuable contribution to the field by examining the physiological mechanisms potentially involved in the association between TCs and stress-related health impairment in a population of workers who are particularly at risk (Nastjuk et al., 2023). Additionally, our study aims to shed light on the role of job autonomy in the relationships between technology-related job demands and the strain response, a topic which has not been extensively explored in literature (Karimikia et al., 2021) especially with respect to alternative work arrangements, such as SW (De Carlo et al., 2022). We also believe that the results of our study would be robust due to the multimethod approach, which integrates different measurement methods and represents a significant contribution to the field (Fischer & Riedl, 2017). It provides a more comprehensive understanding of the relationship between technology-related subjective stress experiences and physiological responses, which has not been extensively explored in literature.

Technostress and the Job Demands-Resources Theory

Technostress is the term commonly used to describe the stress experienced by workers due to the use of ICT (Ragu-Nathan et al., 2008). From a theoretical perspective, the literature on technostress is primarily based on the transactional models of stress (Lazarus & Folkman, 1984). According to this model, technostress is a process that involves a transaction between the individual and the technological conditions of the environment, which are appraised by workers as demands. In the work context, ICT can be perceived as demanding in many ways. In particular, technostress research has identified five typical stressors, known as techno-stressors or technostress creators (Ragu-Nathan et al., 2008). According to Ragu-Nathan et al. (2008), these include techno-overload, the perception that technology forces employees to work harder and faster ("too much"); techno-invasion, the perception of being invaded by technology, which blurs the boundaries between work and social life domains ("always connected"); techno-complexity, the perception that the need to constantly update one's skills in order to adapt to changing technologies can be perceived as difficult ("too difficult"); techno-insecurity, the concern that job security may be threatened by technological advancements ("being replaced"); and techno-uncertainty, the perception that changes to the system are occurring too rapidly, and individuals are uncertain about their ability to keep up ("too many changes"; Nastjuk et al., 2023). Technostress creators are associated with several psychological, physical, and behavioral outcomes for the individual over time, such as exhaustion (a core component of job burnout; Maslach et al., 2001), reduced job satisfaction, or increased stress hormones secretion (Fischer & Riedl, 2017; Tarafdar et al., 2019). Although technostress is a process that depends on individual experience and appraisal, it is often conceptualized as the "dark side"' of technology, emphasizing the negative consequences of ICT use (Nastjuk et al., 2023).

Recent research (Pansini et al., 2023) has investigated the role of technostress within the Job-Demands Resources (JD-R) theory, which provides a flexible and unifying framework for studying work-related stress, motivation, and job performance (Demerouti et al., 2001; for a review see Bakker et al., 2023). In this perspective, TCs can be considered as job demands, defined by the JD-R as those aspects of the job that require effort from workers and may result in psychological and/or physiological costs for individuals (i.e., risk factors). Accordingly, the prolonged or chronic exposure to TCs, coupled with inadequate recovery opportunities, depletes individuals' physical and mental resources (e.g., energy, concentration, or time) which may result in negative stress-related outcomes, such as job burnout and psycho-physical symptoms (La Torre et al., 2019; Nastjuk et al., 2023).

It is important to note that while the definition of job demands includes physiological costs, research into the physiological processes that link chronic or prolonged stressful situations at work, psychophysical symptoms associated with work-related stress (i.e., strain; Nixon et al., 2011), and more serious long-term outcomes (Bakker & Demerouti, 2017; Schaafsma et al., 2021) is still limited. Similarly, past research on technostress primarily relied on self-report data, which undermines our understanding of the physiological processes involved in the association between TCs and negative health consequences (Nastjuk et al., 2023).

The Current Study

To shed light on the psychophysiological mechanisms underlying the relationship between TCs, the strain response, and long-term consequences of work-related stress, in this study we combined psychological and biological measures. Specifically, we build on the allostatic load (AL; McEwen, 1998) model as an integrative framework that explains the long-term impact of chronic/prolonged psychosocial stress on workers' physical and mental health through cumulative physiological dysregulation over time (Juster et al., 2010). According to the AL model, the exposure to repeated/chronic technology-related demands — such as SWs facing prolonged TCs — may be associated with a sustained physiological activation of stress systems, including the hypothalamic-pituitary-adrenal (HPA) axis (Steptoe et al., 2000; van der Meij et al., 2018). Over time, this sustained activation, coupled with inadequate recovery opportunities (Geurts & Sonnentag, 2006), may result in a dysregulation of the HPA axis and negative health outcomes (Bellingrath et al., 2008; Juster et al., 2010; Zänkert et al., 2019).

Against this background, in this study we focused on hair cortisol/DHEA(S) ratio as a biomarker of work-related stress (Qiao et al., 2017; Theorell et al., 2021). On the one hand, cortisol, a biomarker of allostatic load (McCrory et al., 2023), is the primary effector hormone of the HPA axis stress response system (O'Connor et al., 2021). In response to a stressor, cortisol is involved in energy mobilization — by stimulating glucose production — as well as the suppression of the immune-system by inhibiting pro-inflammatory cytokines (Schaafsma et al., 2021). On the other hand, DHEA(S) is an anabolic steroid that plays a regenerative role in the body (Dutheil et al., 2021). Previous research has suggested that DHEA(S), as an antagonist to the effects of cortisol, may have a protective role during stress (Lennartsson et al., 2013). In this study we focused on the ratio between cortisol and DHEA(S), which reflects an imbalance in the HPA axis associated with prolonged/chronic stress (Goulter et al., 2019; Kimonis et al., 2019) and has recently been considered as a biomarker of mental stress in healthy humans (Ahmed et al., 2023).

Furthermore, concentrations of both cortisol and DHEA(S) can be measured using a variety of matrices, each reflecting a specific timeframe of HPA axis activation. For example, previous research has mainly examined cortisol/DHEA(S) in saliva, blood, and urine, which provides a useful insight into the short-term physiological responses to work stressors (Stalder et al., 2017). However, in this study we focused on biomarker concentrations in hair, as hair steroid hormone measurement is a useful research method for describing long-term, retrospective endogenous steroid hormone concentrations (Schaafsma et al., 2021; Wright et al., 2015). The dosage of hormones in the hair reflects their average concentration over months because endo- and exogenous compounds are continuously incorporated from blood to hair follicles during hair growth. In addition, hormones captured inside the hair are stable (Eisenbeiss et al., 2020; Peng et al., 2022). Accordingly, a strength of hair measurement is that — in line with the AL model — it allows the retrospective assessment of cumulative hormone concentrations over an extended period of time (typically one month per cm, assuming an average hair growth of 1 cm/month; Abell et al., 2016), reflecting an individual's physiological activation in response to the exposure to chronic/prolonged stressful events over the same time period (Herr et al., 2018; Ibar et al., 2021).

Hence, building on the AL model (McEwen, 1998) applied to the health impairment process of the JD-R (Bakker, 2015; Ilies et al., 2015), we assume that TCs — in terms of techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty — require effort and are associated with psycho-physiological costs for the individual (Riedl, 2013). We therefore hypothesized that TCs would be positively associated with the hair cortisol/DHEA(S) ratio as a biomarker of work-related stress.

Hypothesis 1 (H1): Technostress creators, in terms of techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, will be positively associated with hair cortisol/DHEA(S) ratio.

In addition to job demands (i.e., factors that create stress), job resources are other aspects of the job that can lead to employees' health and well-being by nurturing both extrinsic and intrinsic motivation (i.e., the motivational process of the JD-R; Bakker & Demerouti, 2017). Additionally, job resources have the potential to reduce the psycho-physiological costs associated with job demands including TCs, which is the buffer hypothesis of the JD-R (Bakker et al., 2005). Specifically, job autonomy (JA) refers to the "extent to which a job allows freedom, independence, and discretion to schedule work, make decisions, and choose the methods used to perform tasks" (Morgeson & Humphrey, 2006, p. 1323). Research in the field of technostress has shown that employees with greater JA are more resilient to technology-related demands (Suh & Lee, 2017). For example, employees whose supervisors promote autonomy may perceive reduced interruption overload (Tams et al., 2020) and be better equipped to manage the demands of a digital work environment (Rademaker et al., 2023), which results in less work-related stress and increased work engagement (Bošković, 2021). Conversely, lack of autonomy may pose challenges for employees when adopting new software or dealing with ICT (Barrett, 2018).

Furthermore, previous research indicates that greater JA is associated with increased opportunities to cope effectively with stressful situations at work among SWs (Bakker & Demerouti, 2007). For example, providing SWs with control over their work can increase their flexibility in adapting to unexpected situations (e.g., computer or system failures) or can help them in developing new strategies to overcome temporary challenges (e.g., using technology to perform tasks more efficiently), thus reducing fatigue and exhaustion associated with TCs (Barrett, 2018; Jamal et al., 2021). In this perspective, JA is expected to attenuate the association between technology-related demands and the strain response. However, it should be noted that previous research has also found an inverse effect (Andreassen et al., 2017; Meier et al., 2008), which is known as the "autonomy paradox" (Mazmanian et al., 2013). Accordingly, an excess of autonomy may not be helpful and may even exacerbate the negative effects of stressors (for more information, please see the Discussion section). However, in line with the JD-R theory (Bakker et al., 2023) and the Job Demand-Control model (Karasek, 1979), as well as consistent with previous empirical research (Cianci et al., 2024), in our study we hypothesize that autonomy has a buffering — rather than an exacerbating — effect. In the light of this reasoning, we hypothesized that JA would moderate the positive association between TCs and hair cortisol/DHEA(S) ratio, which is expected to be weaker when JA is high.

Hypothesis 2 (H2): Job autonomy will moderate the association between technostress creators, in terms of techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, and hair cortisol/DHEA(S) ratio, which is expected to be weaker when job autonomy is high.

Method

Participants and Procedures

The study participants were employees of a private company in the metalworking sector who worked remotely for all or part of their working time (i.e., smart workers). A total of 85 workers agreed to participate in a research project focused on fostering workers' well-being amidst the COVID-19 pandemic.

In June 2022 participants were invited to complete a self-report questionnaire (i.e., psychological data) designed to determine technostress creators as well as sociodemographic variables including sex and age. At this stage, employees were provided with a personal identification code that was required to match psychological data with biological data, namely the concentrations of cortisol and DHEA(S) in hair. Next, a hair strand was collected noninvasively from each participant (i.e., biological data). Prior to completing the questionnaire, employees were informed that their involvement in the study was voluntary and confidential, and that they could withdraw at any time. Participants also provided written informed consent before data collection. The project was approved by the Ethical Committee for the Psychological Research of the University of Padova, Italy (protocol n. 4632).

The sample included 29 females (34.1%) and 56 males (65.9%) with the majority of respondents being under 50 years of age (67.1%). With respect to their occupation, 68 participants were white-collar workers (80%) and 17 were middle or top managers (20%). Finally, most of the participants had children (56.5%; three missing values, 3.5%) and had been with the company for more than five years (73%; three missing values, 3.5%). With respect to SW, participants on average worked remotely 21.7 hours per week (SD = 11.2).

Psychological Measures

With respect to psychological data, the self-report questionnaire included the following self-report measures:

Technostress creators were measured using a shortened Italian adaptation of the scale developed by Ragu-Nathan et al. (2008). This instrument included 14 items aimed at detecting techno-overload (two items; e.g., “I am forced by this technology to work with very tight time schedules”), techno-invasion (three items; e.g., “I feel my personal life is being invaded by this technology”), techno-complexity (three items; e.g., “I often find it too complex for me to understand and use new technologies”), techno-insecurity (two items; e.g., “I feel constant threat to my job security due to new technologies”), and techno-uncertainty (four items; e.g., “There are always new developments in the technologies we use in our organization”). The response scale ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). In this study, Cronbach’s alpha ranged from .76 (techno-invasion) to .92 (techno-overload).

Job autonomy was assessed using a scale taken from the Q_u-Bo Test (De Carlo et al., 2008). The scale comprised of three items that measured the general level of JA (e.g., “Your job allows you to autonomously decide the pace of work”). The response scale ranged from 1 (*strongly disagree*) to 6 (*strongly agree*), and higher scores reflected a greater level of autonomy. Cronbach’s alpha was .88 in this study.

Biological Measures

Cortisol and DHEA(S) were quantified in the first most proximal centimeter of the gathered scalp hair from a posterior-to-vertex position since it has been found that this area has a greatest growth synchrony (Abell et al., 2016). Each sample was stored in a paper envelope at room temperature and protected from UV rays until processing. Twenty-five milligrams of hair were weighted, and each hair strand was washed twice using H2O for 3′ and then, in agreement with Davenport et al. (2006) twice with isopropanol for 3′. Steroids were extracted by incubating each specimen for 16 h in methanol at 37°C. Next, the liquid in the vial was evaporated to dryness at 37°C under an airstream suction hood. The dried residue was then resuspended in 1.2 mL of ELISA buffer (50 mM phosphate buffer, pH 7.4, 0.4% BSA, 0.5 M NaCl). The concentrations of cortisol and DHEA(S) were measured using an in-house Enzyme-linked Immunosorbent Assay (ELISA) as described by Falco et al. (2023).

Data Analysis

The relationships hypothesized in the study were tested using moderated multiple regression analysis. In Model 1 (M1), the hair cortisol/DHEA(S) ratio was regressed on techno-overload, JA, and the respective interaction term. The other models were similar, except that the technostress creator was techno-invasion in Model 2 (M2), techno-complexity in Model 3 (M3), techno-insecurity in Model 4 (M4), and techno-uncertainty in Model 5 (M5). The models included mean-centered independent variables (excluding dichotomous variables for sex and age, see below) to facilitate result interpretation. If a significant interaction was found, a simple slope analysis was performed to determine whether the specific technostress creator was associated with hair cortisol/DHEA(S) ratio at high (+1*SD*) and low (−1*SD*) levels of JA. Significant interactions were also presented graphically (Cohen et al., 2003). As previous research has shown an association between hair cortisol/DHEA(S) concentrations and sex/age (Binz et al., 2018; Dettenborn et al., 2012; Feller et al., 2014; Qiao et al., 2017; Stalder et al., 2017), they were both included as control variables in all the models tested. Finally, missing values were considered. Data were missing completely at random (Little's MCAR test $\chi^2 = 271.93$, $df = 245$, $p = .11$), and before analyzing data missing values were estimated using the expectation-maximization algorithm (Cox et al., 2014). Overall, 24 missing values (1.3%) were imputed. Statistical analyses were performed using R version 4.3.1 (R Core Team, 2023).

RESULTS

Descriptive Statistics

All variables had univariate skewness and kurtosis that fell within the acceptable range of ±2.0 and ±7.0, respectively (Finney & DiStefano, 2013). Correlations and descriptive statistics are presented in Table 1.

Correlation analysis showed a positive association between log cortisol/DHEA(S) ratio and techno-complexity ($r_{83} = .23$, $p = .03$), techno-insecurity ($r_{83} = .21$, $p = .049$), and techno-uncertainty ($r_{83} = .25$, $p = .02$). Job autonomy was negatively associated with techno-insecurity ($r_{83} = -.38$, $p < .001$) and techno-complexity, although this association was marginally significant ($r_{83} = -.18$, $p < .10$), meaning that JA was associated with reduced TCs, at least in some cases. With respect to control variables, there was a significant difference in log cortisol/DHEA(S) ratio across sex, with higher levels in females ($M = -0.51$, $SD = 0.28$) compared to males ($M = -0.87$, $SD = 0.34$), $t(67.83) = 5.12$, $p < .01$, Cohen's $d = 1.11$ (large effect size; Cohen, 1992). Finally, a significant difference in log cortisol/DHEA(S) ratio across age emerged, with higher levels in workers over the age of 50 ($M = -0.61$, $SD = 0.35$) compared to those under the age of 50 ($M = -0.82$, $SD = 0.35$), $t(52.91) = -2.59$, $p = .01$, Cohen's $d = 0.61$ (medium effect size; Cohen, 1992).

TPM Vol. 31, No. 4, December 2024
465-485 – Special Issue

TABLE 1
Means, standard deviations, and correlations for study variables (N = 85)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Cortisol/DHEA(S) ratio	0.25	0.21	–								
2. Techno-overload	2.09	0.95	.17	–							
3. Techno-invasion	1.66	0.78	.08	.56**	–						
4. Techno-complexity	2.04	1.02	.23*	.41**	.23*	–					
5. Techno-insecurity	1.64	0.84	.21*	.51**	.25*	.59**	–				
6. Techno-uncertainty	2.85	0.81	.25*	.42**	.07	.36**	.29**	–			
7. Job autonomy	4.13	1.14	.03	−.13	−.06	−.18	−.38**	−.12	–		
8. Sex [a]	0.66	0.48	−.47**	−.03	.06	−.16	−.04	−.14	−.14	–	
9. Age [b]	0.33	0.47	.28*	.18	−.03	.41**	.32**	.15	−.18	−.02	–

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Cortisol/DHEA(S) ratio values were log-transformed prior to data analyses, including correlations shown above. DHEA(S) = dehydroepiandrosterone (sulfate). [a] 0 = female, 1 = male. [b] 0 = ≤ 50 years old, 1 = > 50 years old.
$^{*}p$ < .05. $^{**}p$ < .01.

Hypothesis Testing

The results of the regression analyses are presented in Table 2, in which unstandardized regression coefficients are reported. In all the models tested, a positive versus negative association between log cortisol/DHEA(S) ratio and predictors would be interpreted as a health-threatening versus protective effect, based on the conceptualization of the ratio as a biomarker of work-related stress. In all the tested models, the log cortisol/DHEA(S) ratio was negatively associated with sex, while age showed a positive association. This is in line with the aforementioned findings indicating that females and workers over the age of 50 had higher levels of log cortisol/DHEA(S) ratio.

Among technostress creators, only techno-insecurity in M4 was positively associated with log cortisol/DHEA(S) ratio at average levels of job autonomy and controlling for the effect of sex and age, $b = 0.10$, $SE = 0.05$, $p = .04$, $sr = .19$. Therefore, H1 was only supported for techno-insecurity.

The interaction term between techno-overload and JA was significant in M1, $b = 0.06$, $SE = 0.03$, $p = .02$, and accounted for an additional 5% of the variance in log cortisol/DHEA(S) ratio, $F_{\text{change}}(1, 79) = 5.53$, $p = .02$, $f^2 = .07$, considered a small to medium effect (Cohen, 1992). Simple slope analysis showed that the association between techno-overload and log cortisol/DHEA(S) ratio was positive and significant when JA was high ($b = 0.12$, $SE = 0.05$, $p = .01$) but not significant when JA was low ($b = -0.02$, $SE = 0.05$, $p = .63$). The interaction between techno-overload and JA is shown in the Figure 1. Techno-invasion in M2 showed a similar pattern of results. The interaction term between techno-invasion and JA was significant, $b = 0.08$, $SE = 0.03$, $p = .03$, and accounted for an additional 4% of the variance in log cortisol/DHEA(S) ratio, $F_{\text{change}}(1, 79) = 4.80$, $p = .03$, $f^2 = .06$, considered a small to medium effect (Cohen, 1992). Simple slope analysis showed that the association between techno-invasion and log cortisol/DHEA(S) ratio was positive and significant when JA was high ($b = 0.14$, $SE = 0.06$, $p = .02$) but not significant when JA was low ($b = -0.03$, $SE = 0.06$, $p = .60$). Next, the interaction term between techno-insecurity and JA in M4 was significant, $b = 0.08$, $SE = 0.03$, $p = .02$, and accounted for an additional 5% of the variance in log cortisol/DHEA(S) ratio, $F_{\text{change}}(1, 79) = 5.53$, $p = .02$, $f^2 = .07$, a small to medium effect (Cohen, 1992). Simple slope analysis showed that the association between techno-insecurity and log cortisol/DHEA(S) ratio was positive and significant when JA was high ($b = 0.18$, $SE = 0.07$, $p < .01$) but not significant when JA was low ($b = 0.01$, $SE = 0.05$, $p = .86$). Finally, neither the interaction term between techno-complexity and JA ($b = 0.03$, $SE = 0.03$, $p = .36$) nor the interaction term between techno-uncertainty and JA ($b = 0.03$, $SE = 0.04$, $p = .42$) were significant in M3 or M5, respectively. Summarizing, JA moderated the association between techno-overload/-invasion/-insecurity and log cortisol/DHEA(S) ratio, but the effect was in the opposite direction: the association between TCs and log cortisol/DHEA(S) ratio was not significant when JA was low, but positive and significant when JA was high. Thus, JA exacerbated — rather than buffered — the association between TCs and log cortisol/DHEA(S) ratio, and H2 was not supported.

Post Hoc Analysis

Post hoc analyses were carried out to address specific issues pertaining to (i) managerial status, (ii) the potential nonlinear association between JA and outcomes, and (iii) possible interaction between sex and the main predictors, in terms of technostress creators as well as JA. First, our sample included 17 (20%) middle or top managers. Managers often have more JA than followers (Karasek et al., 1998), and they often

TABLE 2
Multiple regression analyses for log cortisol/DHEA(S) ratio (N = 85)

Variable	Dependent variable: Log cortisol/DHEA(S) ratio									
	Model 1 Techno-overload		Model 2 Techno-invasion		Model 3 Techno-complexity		Model 4 Techno-insecurity		Model 5 Techno-uncertainty	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Sex [a]	−0.30***	0.07	−0.34***	0.07	−0.33***	0.07	−0.31***	0.07	−0.33***	0.07
Age [b]	0.20**	0.07	0.20**	0.07	0.20*	0.08	0.19*	0.07	0.20**	0.07
Technostress creator [c]	0.05	0.04	0.06	0.04	0.02	0.04	0.10*	0.05	0.07	0.04
Job autonomy	0.01	0.03	−0.01	0.03	0.01	0.03	0.01	0.03	0.01	0.03
Technostress creator X job autonomy	0.06*	0.03	0.08*	0.03	0.03	0.03	0.08*	0.03	0.03	0.04
R^2	.35***		.34***		.30***		.35***		.32***	
ΔR^2	.05*		.04*		.01		.05*		.01	
AIC	45.12		45.89		51.26		44.69		48.93	
BIC	62.22		63.00		68.36		61.79		66.03	

Note The independent variables included in the models (excluding dichotomous variables) were mean-centered, to enable easier interpretations of the results. The values of cortisol/dehydroepiandrosterone sulfate ratio were log-transformed prior to data analysis. Unstandardized regression coefficients are reported in the table. DHEA(S) = dehydroepiandrosterone (sulfate). AIC = Akaike information criterion. BIC = Bayesian information criterion. [a] 0 = female, 1 = male. [b] 0 = ≤ 50 years old, 1 = > 50 years old. [c] In each model, a different technostress creator was analyzed. These were techno-overload in Model 1, techno-invasion in Model 2, techno-complexity in Model 3, techno-insecurity in Model 4, and techno-uncertainty in Model 5.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

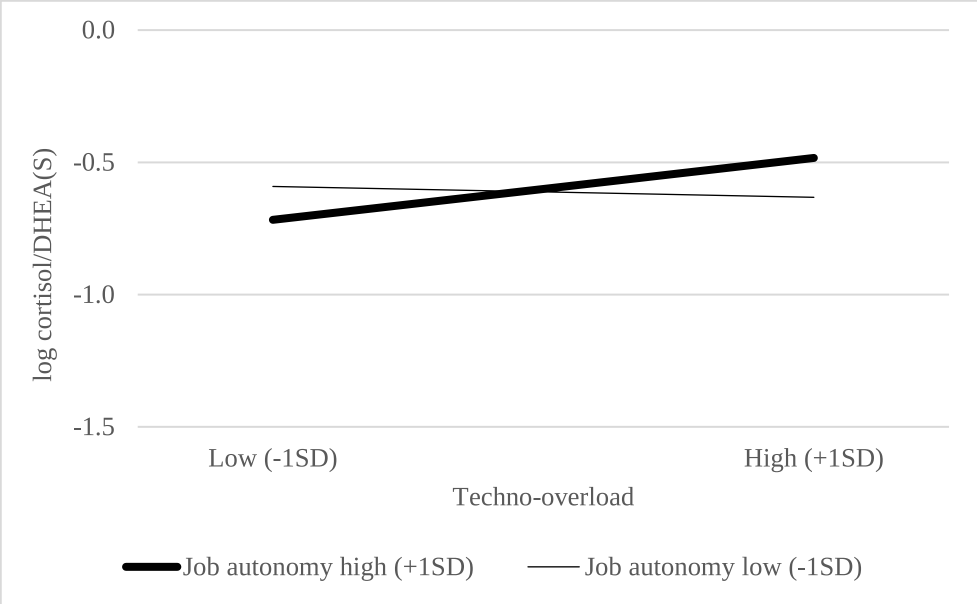

FIGURE 1
The moderating role of job autonomy in the relationship between techno-overload and log cortisol/DHEA(S) ratio

have a lot of other stressors than followers that arise from their supervisor role (e.g., to give critical performance feedback to others). Moreover, managers' higher JA is also bound to a higher responsibility for work processes and outputs, especially when SW is introduced, and supervision tasks have to be done per video/digitally (Delfino & van der Kolk, 2021). Hence, we investigated the role of managerial status in greater depth. The proportion of middle or top managers did not differ by sex, $\chi^2(1) = .01$, $p = .92$. There were no significant differences in focal constructs between middle/top managers and white-collar workers, including log cortisol/DHEA(S) ratio and TCs, with the exception of techno-uncertainty, with marginally higher scores among white-collar workers ($M = 2.93$, $SD = 0.82$) compared to middle/top managers ($M = 2.54$, $SD = 0.70$), $t(28.29) = 1.97$, $p = .06$, Cohen's $d = 0.48$. Interestingly, in our study there was no significant difference in JA between middle/top managers and white-collar workers. To check whether the hypothesized two-way interaction (i.e., between TCs and JA) differs across the levels of a third variable, namely managerial status, five three-way interaction models were estimated, one for each TC, following the same logic as in Table 2. These models did not account for any additional variance in the log cortisol/DHEA(S) ratio compared to the two-way interaction models (Model 1 to Model 5 in Table 2), and the three-way interaction term was not significant in any of the models tested. This implies that the hypothesized two-way interaction did not vary across levels of managerial status.

Next, previous research has suggested a nonlinear association between JA and psychological well-being (e.g., Clausen et al., 2022). To control for possible curvilinear effects of JA, five models were then estimated — one for each TC, following the same logic as in Table 2 — in which the square of JA was entered into the regression equation. The square term of JA was not significant in all the models tested and the interaction term was still significant after its inclusion, suggesting that the moderating effect is supported above and beyond possible curvilinear effects of JA (Dawson, 2014).

Finally, five additional models — one for each TC (see Table 2) — were estimated to check whether the impact of TCs and JA on the log cortisol/DHEA(S) ratio differs by sex. The interaction term between sex and JA was not significant in all the models, meaning that the association between JA and log cortisol/DHEA(S) ratio did not differ by sex. A similar pattern of results occurred for TCs, with the exception of techno-insecurity. Specifically, a simple slope analysis showed that the association between techno-insecurity and log cortisol/DHEA(S) ratio was positive and significant only for females ($b = 0.20$, $SE = 0.07$, $p < .01$) but not for males ($b = -0.01$, $SE = 0.06$, $p = .97$). Summarizing, the association between the main predictors and log cortisol/DHEA(S) ratio did not differ between sexes, with the exception of techno-insecurity.

Discussion

The aim of this study was to examine the relationship between TCs — or technology-related risk factors — and the strain response among SWs, with a focus on the protective role of JA. Building on the JD-R theory (Bakker et al., 2023; Demerouti et al., 2001) and the AL model (McEwen, 1998), we hypothesized that TCs would be positively associated with hair cortisol/DHEA(S) ratio as a biomarker of work-related stress (Qiao et al., 2017; Theorell et al., 2021). We also hypothesized that JA would attenuate the association between TCs and hair cortisol/DHEA(S) ratio, which is expected to be weaker when JA is high (i.e., the buffer hypothesis of the JD-R; Bakker et al., 2005). The results only partially supported our predictions. While zero-order correlations showed positive associations between hair cortisol/DHEA(S) ratio on the one hand, and techno-complexity, techno-insecurity, and techno-uncertainty on the other, only techno-insecurity was positively associated with hair cortisol/DHEA(S) ratio in regression models, that is, at average levels of JA as well as controlling for the effect of sex and age. Interestingly, a post hoc analysis showed that the association between techno-insecurity and log cortisol/DHEA(S) ratio was positive and significant only for females, suggesting possible sex differences in the technostress response. These findings are consistent with recent studies showing that women are less able to adapt to situations requiring intensive use of ICT and report higher levels of ICT-related anxiety (Nimrod, 2022; Solís et al., 2023). This trend may be rooted in broader societal issues, as evidenced by a study conducted by Plan International and Bocconi University (2020). The study highlights the role of cultural stereotypes in perpetuating the notion that the technology sector is unwelcoming to women. These stereotypes, which portray technology as a male-dominated field (at least in some countries), emerge early in life, influencing both educational environments and career choices. For example, gender biases in entertainment (e.g., game choice) and education lead to a systematic underestimation of girls' abilities in quantitative subjects such as mathematics and science. This contributes to women's insecurity in the use of technology and gender inequality in the technology sector. Furthermore, contrary to our expectations, JA exacerbated, rather than attenuated, the positive association between three TCs, namely techno-overload/-invasion/-insecurity, and hair cortisol/DHEA(S) ratio, in such a way that the association between these TCs and hair cortisol/DHEA(S) ratio was positive and significant when JA was high, but not significant when JA was low. Thus, a high degree of autonomy at work appeared to aggravate the negative consequences of (at least some) technology-related risk factors.

We believe that our study makes at least two valuable contributions to the field. First, to the best of our knowledge, this is the first study to investigate the association between TCs and hair cortisol/DHEA(S) ratio as a possible biomarker of work-related stress among SWs. By showing that perceptions of techno-overload/-invasion/-insecurity — especially when coupled with high job autonomy — are positively associated with hair cortisol/DHEA(S) ratio when working remotely, this research suggests that under certain circumstances TCs may lead to a dysregulation of the HPA axis over time (i.e., low DHEA(S) levels are unable to offset the negative effects of high cortisol levels; Goulter et al., 2019; Kimonis et al., 2019). In doing so, we believe that our study contributes to the field by elucidating one physiological mechanism (among others; see O'Connor et al., 2021) potentially involved in the association between TCs and stress-related health impairment in SWs (Huo et al., 2017; Nastjuk et al., 2023), a population of workers who are particularly at risk due to the extensive use of ICT to perform work-related tasks and communicate with colleagues/supervisors (Eurofound, 2020; Singh et al., 2022). Notably, our findings were robust as we controlled for the effects of sex and age, two factors associated with hair concentrations of both cortisol and DHEA(S) (e.g., Qiao et al., 2017; Stalder et al., 2017), but we encourage researchers to further investigate the possible, substantive role of sex/age differences in technostress (e.g., diversity in coping strategies; Nimrod, 2022).

The discussion of our findings would benefit from a wider contextualization in the light of previous research that, although in its infancy, is likely to provide useful insights. In a longitudinal study among workers from different organizational contexts, Falco et al. (2023) found that workload — as the amount of work to be done in a given time or the complexity of job tasks (De Carlo et al., 2019) — was positively associated with hair cortisol/DHEA(S) ratio in SWs. Although not focused on technostress, this research suggests that SWs may have difficulty in managing their workload effectively (e.g., due to information overload or disrupted workflow), which may lead to a dysregulation of the HPA axis over time, as reflected by an elevated cortisol/DHEA(S) ratio in hair. In a more recent research Kaltenegger et al. (2024) found that technology-related job demands in the form of work interruptions, multitasking, and information overload were negatively associated with hair cortisol concentration but not associated with C-reactive protein — a biomarker of chronic low-grade inflammation — in a sample of healthcare workers (Rohleder, 2014). While these findings provide an initial examination of the physiological mechanisms involved in the association between technostressors and health impairment, the study by Kaltenegger et al. (2024) also highlights that the effects of prolonged/chronic exposure to technostressors on the HPA axis and chronic low-grade inflammation — two key biological mechanisms linking stress and disease (Kaltenegger et al., 2021) — have been largely overlooked to date. We believe that our study contributes to this emerging line of research by showing an association between well-established TCs and hair cortisol/DHEA(S) ratio — especially when job autonomy is elevated — which has been proposed to be more informative as a stress biomarker than the absolute concentrations of either cortisol or DHEA(S) (Maninger et al., 2009; Whitham et al., 2020). Clearly, more research is needed to further investigate the association between TCs and hair cortisol/DHEA(S) ratio in different working populations and using longitudinal data.

Our study makes a second contribution by exploring the role of JA — a well-established job resource — in technostress, a topic that has not been extensively explored in the literature (Karimikia et al., 2021). The reversed effect of autonomy in the relationship between some TCs and hair cortisol/DHEA(S) ratio was unexpected, as JA plays a central, beneficial role in several theoretical models of work-related stress and motivation. For example, according to the Job Demand-Control model (Karasek, 1979) job autonomy, as one key aspect of decision latitude, may buffer the potential negative effects of high demands on psychophysical health (Van der Doef & Maes, 1998), while the Job Characteristics theory (Hackman & Oldham, 1976) states that jobs should contain sufficient amounts of resources — including autonomy — as they promote motivation and performance. These theoretical assumptions are also incorporated in the JD-R theory, according to which job resources, including JA, may help in dealing with job demands and reduce their negative health outcomes (e.g., job burnout), but they also promote motivation (e.g., work engagement) through the satisfaction of basic human needs such as the need for autonomy (i.e., Self-Determination theory; Deci et al., 2017). More recently, however, a more nuanced perspective has emerged, with job resources having either favorable or unfavorable effects, depending on their level, the context in which a particular resource occurs, but also on personal factors (van Veldhoven et al., 2020).

In terms of resource levels, the Vitamin model (Warr, 1994) recognizes that the beneficial effect of a job resource may increase to a certain level, after which further increases in the resource may have no additional effect (e.g., salary, income) or may even have a detrimental effect, such as in the case of JA. Notably, the study participants were white-collar and middle/top managers, who were likely to have had jobs characterized by high levels of autonomy even before taking advantage of SW (Sewell & Taskin, 2015). When working remotely, these workers may have further increased their levels of JA to the point where this leads to a lack of clarity and difficult decision making (Dettmers & Bredehöft, 2020), with individuals feeling overburdened by the pervasiveness of technology-related demands (Karimikia et al., 2021), a phenomenon known as "too much of a good thing" (van Veldhoven et al., 2020). In line with this reasoning, it should be noted that participants in our study reported relatively high JA scores (M = 4.13, SD = 1.14 on a six-point response scale).

Next, employees may not necessarily benefit from traditional job resources such as JA in the context of remote working. For example, SWs with greater JA may face particular problems in using technology due to their idiosyncratic work schedules or ways of using ICT that may not be shared by colleagues or supervisors (Karimikia et al., 2021). This specificity of working patterns may hinder, rather than enhance, their ability to manage technostress effectively. Similarly, while a high degree of autonomy may allow smart workers to benefit in the short term from some of the advantages of ICT, such as professional flexibility and control over interactions, it also intensifies expectations of one's availability and reduces the ability to disconnect from work in the long run (i.e., "autonomy paradox"; Mazmanian et al., 2013). It is also possible that job autonomy may cause longer work hours, less breaks, and work with lower ergonomic standards compared to work in the office or lab. A longitudinal study found ergonomics after change into home offices to be worse compared to ergonomics onsite at baseline (Aegerter et al., 2021). Finally, previous research has shown that personal characteristics, such as locus of control or self-efficacy, may influence the potential buffering effect of JA (Meier et al., 2008). Hence, personal characteristics, such as locus of control or self-efficacy — that is, personal resources (Schaufeli & Taris, 2014) — are needed to be able to use JA effectively. When these personal resources are low, at best JA does not provide any advantage; at worst, JA may even become a stressor, turning from a resource to a demand (Meier et al., 2008). This emphasizes the importance of context-specific personal resources in technostress, including for example technology self-efficacy, which refers to an individual's subjective perception about one's ability to use technology in the accomplishment of a work task (Tarafdar et al., 2015). In summary, the finding that JA exacerbates the association between TCs and stress biomarkers is counterintuitive and warrants further exploration in future research.

This reasoning does not imply, of course, that JA should no longer be regarded as a valuable resource when working remotely. In the future, it might be useful to pay more attention to new forms of JA aimed at integrating the modern work organization based on teamwork and interdependence (e.g., tied autonomy; Väänänen & Toivanen, 2018), the specific needs of remote workers (e.g., a self-paced, self-determined use of new technologies; Fleischer & Wanckel, 2023), as well as the need for support from colleagues and supervisors (e.g., to reduce social and professional isolation; Sewell & Taskin, 2015). Additionally, further investigation is necessary into the role of personal resources, such as technology self-efficacy (Tarafdar et al., 2015). At a more general level, research into the benefits and potential harms of job resources in the context of technostress and SW for different individuals and situations would be valuable at multiple levels (van Veldhoven et al., 2020). From a theoretical standpoint, this will facilitate a deeper understanding of the complex nature and function of job resources in the context of remote work, where ICT plays a pivotal role. From a practical perspective, understanding why, when, and for whom resources may have positive or negative effects can assist practitioners in designing high-quality work, both in terms of technology and psychosocial aspects.

Limitations and Future Research

The results should be interpreted while considering some limitations. First, the cross-sectional design of this research precluded conclusions about the direction of the observed relationships. Although our hypotheses are consistent with the health impairment process of the JD-R theory, it is important to note that reversed causal and reciprocal effects may also be possible (Bakker et al., 2023). For instance, employees who already experience strain — as reflected by higher cortisol/DHEA(S) ratio — may also perceive higher levels of technology-related demands (e.g., due to their diminished coping resources, in terms of psycho-physical energies). Next, in this study we investigated work experience and well-being among SWs of a metalworking company, which leads to two considerations. On the one hand, the participants came from a single organization, were relatively young, and the gender distribution was rather unbalanced. This, coupled with the relatively limited sample size, may limit the generalizability of the findings to the general working population. On the other hand, it is important to note that SW is not always a binary phenomenon, as employees may vary in the degree to which they work remotely (Golden & Gajendran, 2019). Therefore, further research is necessary to explore whether and how the extent of remote working may affect technostress and well-being. Future studies could also consider the potential impact of past experience with SW on employees' well-being. For example, recent research showed that supervisors who did no home-office before COVID-19 were more stressed during COVID-19 than supervisors with prior experience in home-office work (Galliker et al., 2024). Finally, to explore possible differences in the associations between constructs across work arrangements, further studies should test a potential three-way interaction between ICT stressors, ICT control, and remote working. It is important to note that the study lacked statistical power to detect significant three-way interactions due to the limited sample size.

Practical Implications

Finally, despite the aforementioned limitations, we believe that our study has several practical implications. First, by identifying TCs associated with a biomarker of stress, our study will help managers and practitioners to recognize different ways in which technology-related stressors may lead to negative health outcomes (Mishra & Rašticová, 2024), especially when working remotely (De Carlo et al., 2022). For example, addressing techno-overload (e.g., technology-mediated interruptions and increased workload due to information overload/security requirements), techno-invasion (e.g., expectations of 24/7 availability and blurred boundaries between work and private life), and techno-insecurity (e.g., individuals' fear of being replaced by technology or someone with stronger technological skills) may contribute to reduce negative technology-related outcomes while increasing employee well-being and motivation (Hakanen et al., 2021). Additionally, drawing on the JD-R theory, a good balance between job demands and resources is essential to prevent negative outcomes. However, employees do not necessarily benefit from elevated JA when working remotely, as high individual task autonomy may conflict with intense socio-temporal interdependence with team members, resulting in increased organizational disorientation and work fragmentation (Väänänen et al., 2020). In this perspective, interventions should be aimed at promoting tied autonomy, where high levels of individual freedom to make decisions and plan one's work are balanced by high levels of connectivity and temporal interdependence (Väänänen et al., 2020). Examples are shared and mutually agreed silent times in workplaces and specific days of the week for teleworking or meetings. In addition, interventions could be aimed at promoting an organizational culture that is attentive to the problems of over-connectivity. In this regard, training and information activities could promote the right to disconnect, also in line with Italian Legislative Decree 81/2017.

Conclusion

The widespread use of ICT in personal and professional settings suggests an increasing prevalence of technology-related outcomes over time, which may be positive (e.g., efficiency and innovation) or negative (e.g., technostress; Tarafdar et al., 2007, 2019). Research suggests that technology-related risk factors such as TCs — if not managed appropriately — can lead to health problems and reduced job satisfaction, while also hindering organizational effectiveness (Karimikia et al., 2021). By showing an association between TCs and hair cortisol/DHEA(S) ratio, our study sheds light on a physiological mechanism — dysregulation of the HPA axis — potentially linking (techno)stress and disease (Kaltenegger et al., 2024). While further research is certainly needed, our study also contributes to the identification of possible biomarkers of technostress that could be useful to identify and support particularly vulnerable workers, including SWs (Kasemy et al., 2022), with potential positive consequences for both workers and organizations.

References

Aegerter, A. M., Deforth, M., Johnston, V., Sjøgaard, G., Volken, T., Luomajoki, H., Dratva, J., Dressel, H., Distler, O., Elfering, A., & Melloh, M. (2021). No evidence for an effect of working from home on neck pain and neck disability among Swiss office workers: Short-term impact of COVID-19. *European Spine Journal*, *30*(6), 1699-1707. https://doi.org/10.1007/s00586-021-06829-w

Abell, J. G., Stalder, T., Ferrie, J. E., Shipley, M. J., Kirschbaum, C., Kivimäki, M., & Kumari, M. (2016). Assessing cortisol from hair samples in a large observational cohort: The Whitehall II study. *Psychoneuroendocrinology*, *73*, 148-156. https://doi.org/10.1016/j.psyneuen.2016.07.214

Ahmed, T., Qassem, M., & Kyriacou, P. A. (2023). Measuring stress: A review of the current cortisol and dehydroepiandrosterone (DHEA) measurement techniques and considerations for the future of mental health monitoring. *Stress*, *26*(1), 29-42. https://doi.org/10.1080/10253890.2022.2164187

Allen, T. D., Golden, T. D., & Shockley, K. M. (2015). How effective is telecommuting? Assessing the status of our scientific findings. *Psychological Science in the Public Interest*, *16*(2), 40-68. https://doi.org/10.1177/1529100615593273

Andreassen, C. S., Nielsen, M. B., Pallesen, S., & Gjerstad, J. (2017). The relationship between psychosocial work variables and workaholism: Findings from a nationally representative survey. *International Journal of Stress Management*, *26*(1), 1-10. https://doi.org/10.1037/str0000073

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly*, *35*(4), 831-858. https://doi.org/10.2307/41409963

Bakker, A. B. (2015). Towards a multilevel approach of employee well-being. *European Journal of Work and Organizational Psychology*, *24*(6), 839-843. https://doi.org/10.1080/1359432X.2015.1071423

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*, *22*(3), 309-328. https://doi.org/10.1108/02683940710733115

Bakker, A. B., & Demerouti, E. (2017). Job demands-resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, *22*(3), 273-285. https://doi.org/10.1037/ocp0000056

Bakker, A. B., Demerouti, E., & Euwema, M. C. (2005). Job resources buffer the impact of job demands on burnout. *Journal of Occupational Health Psychology*, *10*(2), 170-180. https://doi.org/10.1037/1076-8998.10.2.170

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands–resources theory: Ten years later. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 25-53. https://doi.org/10.1146/annurev-orgpsych-120920-053933

Barrett, A. K. (2018). Technological appropriations as workarounds: Integrating electronic health records and adaptive structuration theory research. *Information Technology & People*, *31*(2), 368-387. https://doi.org/10.1108/ITP-01-2016-0023

Bellingrath, S., Weigl, T., & Kudielka, B. M. (2008). Cortisol dysregulation in school teachers in relation to burnout, vital exhaustion, and effort-reward-imbalance. *Biological Psychology*, *78*(1), 104-113. https://doi.org/10.1016/j.biopsycho.2008.01.006

Binz, T. M., Rietschel, L., Streit, F., Hofmann, M., Gehrke, J., Herdener, M., Quednow, B. B., Martin, N. G., Rietschel, M., Kraemer, T., & Baumgartner, M. R. (2018). Endogenous cortisol in keratinized matrices: Systematic determination of baseline cortisol levels in hair and the influence of sex, age and hair color. *Forensic Science International*, *284*, 33-38. https://doi.org/10.1016/j.forsciint.2017.12.032

Bošković, A. (2021). Employee autonomy and engagement in the digital age: The moderating role of remote working. *Ekonomski Horizonti*, *23*(3), 231-246. https://doi.org/10.5937/ekonhor2103241B

Cianci, J., Weibel, D., & Elfering, A. (2024). Measuring work demands and resources of digitalization: The ICT resources and stressors scale. *Swiss Psychology Open*, *4*(1), 1-26. https://doi.org/10.5334/spo.59

Clausen, T., Pedersen, L. R. M., Andersen, M. F., Theorell, T., & Madsen, I. E. H. (2022). Job autonomy and psychological well-being: A linear or a non-linear association? *European Journal of Work and Organizational Psychology*, *31*(3), 395-405. https://doi.org/10.1080/1359432X.2021.1972973

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159. https://doi.org/10.1037/0033-2909.112.1.155

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. Erlbaum.

Cox, B. E., McIntosh, K., Reason, R. D., & Terenzini, P. T. (2014). Working with missing data in higher education research: A primer and real-world example. *The Review of Higher Education*, *37*(3), 377-402. https://doi.org/10.1353/rhe.2014.0026

Davenport, M. D., Tiefenbacher, S., Lutz, C. K., Novak, M. A., & Meyer, J. S. (2006). Analysis of endogenous cortisol concentrations in the hair of rhesus macaques. *General and Comparative Endocrinology*, *147*(3), 255-261. https://doi.org/10.1016/j.ygcen.2006.01.005

Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. *Journal of Business and Psychology*, *29*(1), 1-19. https://doi.org/10.1007/s10869-013-9308-7

De Carlo, A., Girardi, D., Dal Corso, L., Arcucci, E., & Falco, A. (2022). Out of sight, out of mind? A longitudinal investigation of smart working and burnout in the context of the job demands-resources model during the COVID-19 pandemic. *Sustainability*, *14*(12), Article 12. https://doi.org/10.3390/su14127121

De Carlo, A., Girardi, D., Falco, A., Dal Corso, L., & Di Sipio, A. (2019). When does work interfere with teachers' private life? An application of the job demands-resources model. *Frontiers in Psychology*, *10*, Article 1121. https://doi.org/10.3389/fpsyg.2019.01121

De Carlo, N. A., Falco, A., & Capozza, D. (2008). *Test di valutazione del rischio stress lavoro-correlato nella prospettiva del benessere organizzativo, Qu-Bo [Test for the assessment of work-related stress risk in the organizational well-being perspective, Qu-Bo]*. FrancoAngeli. https://doi.org/10.3280/TEST4000_2

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*(1), 19-43. https://doi.org/10.1146/annurev-orgpsych-032516-113108

Delfino, G. F., & van der Kolk, B. (2021). Remote working, management control changes and employee responses during the COVID-19 crisis. *Accounting, Auditing & Accountability Journal*, *34*(6), 1376-1387. https://doi.org/10.1108/AAAJ-06-2020-4657

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology*, *86*(3), 499-512. https://doi.org/10.1037/0021-9010.86.3.499

Dettenborn, L., Tietze, A., Kirschbaum, C., & Stalder, T. (2012). The assessment of cortisol in human hair: Associations with sociodemographic variables and potential confounders. *Stress*, *15*(6), 578-588. https://doi.org/10.3109/10253890.2012.654479

Dettmers, J., & Bredehöft, F. (2020). The ambivalence of job autonomy and the role of job design demands. *Scandinavian Journal of Work and Organizational Psychology*, *5*(1), Article 1. https://doi.org/10.16993/sjwop.81

Dutheil, F., de Saint Vincent, S., Pereira, B., Schmidt, J., Moustafa, F., Charkhabi, M., Bouillon-Minois, J.-B., & Clinchamps, M. (2021). DHEA as a biomarker of stress: A systematic review and meta-analysis. *Frontiers in Psychiatry*, *12*. https://doi.org/10.3389/fpsyt.2021.688367

Eisenbeiss, L., Binz, T. M., Baumgartner, M. R., Kraemer, T., & Steuer, A. E. (2020). Towards best practice in hair metabolomic studies: Systematic investigation on the impact of hair length and color. *Metabolites*, *10*(10), Article 10. https://doi.org/10.3390/metabo10100381

Eurofound. (2020). *Telework and ICT-based mobile work: Flexible working in the digital age* (TJ-04-20-008-EN-N). Publications Office of the European Union. https://doi.org/10.2806/337167

European Agency for Safety and Health at Work, Caprile, M., Arasanz, J., & Sanz, P. (2021). *Telework and health risks in the context of the COVID-19 pandemic: Evidence from the field and policy implications*. Publications Office of the European Union. https://doi.org/10.2802/84372

Falco, A., Girardi, D., Elfering, A., Peric, T., Pividori, I., & Dal Corso, L. (2023). Is smart working beneficial for workers' wellbeing? A longitudinal investigation of smart working, workload, and hair cortisol/dehydroepiandrosterone sulfate during the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, *20*(13), Article 13. https://doi.org/10.3390/ijerph20136220

Feller, S., Vigl, M., Bergmann, M. M., Boeing, H., Kirschbaum, C., & Stalder, T. (2014). Predictors of hair cortisol concentrations in older adults. *Psychoneuroendocrinology*, *39*, 132-140. https://doi.org/10.1016/j.psyneuen.2013.10.007

Finney, S. J., & DiStefano, C. (2013). Nonnormal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (2nd ed., pp. 439-492). IAP Information Age Publishing.

Fischer, T., & Riedl, R. (2017). Technostress research: A nurturing ground for measurement pluralism? *Communications of the Association for Information Systems*, *40*(1), 375-401. https://doi.org/10.17705/1CAIS.04017

Fleischer, J., & Wanckel, C. (2023). Job satisfaction and the digital transformation of the public sector: The mediating role of job autonomy. *Review of Public Personnel Administration*, *44*(3), 431-452. https://doi.org/10.1177/0734371X221148403

Galliker, S., Igic, I., Semmer, N. K., & Elfering, A. (2024). Stress at work and well-being before and during the COVID-19 pandemic: A 1-year longitudinal study in Switzerland. *Journal of Occupational and Environmental Medicine*, *66*(1), 56-70. https://doi.org/10.1097/JOM.0000000000002995

Geurts, S. A. E., & Sonnentag, S. (2006). Recovery as an explanatory mechanism in the relation between acute stress reactions and chronic health impairment. *Scandinavian Journal of Work, Environment & Health*, *32*(6), 482-492. https://doi.org/10.5271/sjweh.1053

Golden, T. D., & Gajendran, R. S. (2019). Unpacking the role of a telecommuter's job in their performance: Examining job complexity, problem solving, interdependence, and social support. *Journal of Business and Psychology*, *34*(1), 55-69. https://doi.org/10.1007/s10869-018-9530-4

Goulter, N., Kimonis, E. R., Denson, T. F., & Begg, D. P. (2019). Female primary and secondary psychopathic variants show distinct endocrine and psychophysiological profiles. *Psychoneuroendocrinology*, *104*, 7-17. https://doi.org/10.1016/j.psyneuen.2019.02.011

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance*, *16*(2), 250-279. https://doi.org/10.1016/0030-5073(76)90016-7

Hakanen, J. J., Bakker, A. B., & Turunen, J. (2021). The relative importance of various job resources for work engagement: A concurrent and follow-up dominance analysis. *BRQ Business Research Quarterly*, *27*(3), 227-243. https://doi.org/10.1177/23409444211012419

Herr, R. M., Almer, C., Loerbroks, A., Barrech, A., Elfantel, I., Siegrist, J., Gündel, H., Angerer, P., & Li, J. (2018). Associations of work stress with hair cortisol concentrations – initial findings from a prospective study. *Psychoneuroendocrinology*, *89*, 134-137. https://doi.org/10.1016/j.psyneuen.2018.01.011

Huo, R., Zeng, B., Zeng, L., Cheng, K., Li, B., Luo, Y., Wang, H., Zhou, C., Fang, L., Li, W., Niu, R., Wei, H., & Xie, P. (2017). Microbiota modulate anxiety-like behavior and endocrine abnormalities in hypothalamic-pituitary-adrenal axis. *Frontiers in Cellular and Infection Microbiology*, *7*. https://doi.org/10.3389/fcimb.2017.00489

Ibar, C., Fortuna, F., Gonzalez, D., Jamardo, J., Jacobsen, D., Pugliese, L., Giraudo, L., Ceres, V., Mendoza, C., Repetto, E. M., Reboredo, G., Iglesias, S., Azzara, S., Berg, G., Zopatti, D., & Fabre, B. (2021). Evaluation of stress, burnout and hair cortisol levels in health workers at a University Hospital during COVID-19 pandemic. *Psychoneuroendocrinology*, *128*, Article 105213. https://doi.org/10.1016/j.psyneuen.2021.105213

Ilies, R., Aw, S. S. Y., & Pluut, H. (2015). Intraindividual models of employee well-being: What have we learned and where do we go from here? *European Journal of Work and Organizational Psychology*, *24*(6), 827-838. https://doi.org/10.1080/1359432X.2015.1071422

Jamal, M. T., Anwar, I., & Khan, N. A. (2021). Voluntary part-time and mandatory full-time telecommuting: A comparative longitudinal analysis of the impact of managerial, work and individual characteristics on job performance. *International Journal of Manpower*, *43*(6), 1316-1337. https://doi.org/10.1108/IJM-05-2021-0281

Joint Research Centre of the European Commission. (2020). *Telework in the EU before and after the COVID-19: Where we were, where we head to* (JRC1209452). Joint Research Centre of the European Commission. https://joint-research-centre.ec.europa.eu/system/files/2021-06/jrc120945_policy_brief_-_covid_and_telework_final.pdf

Juster, R.-P., McEwen, B. S., & Lupien, S. J. (2010). Allostatic load biomarkers of chronic stress and impact on health and cognition. *Neuroscience & Biobehavioral Reviews*, *35*(1), 2-16. https://doi.org/10.1016/j.neubiorev.2009.10.002

Kaltenegger, H. C., Becker, L., Rohleder, N., Nowak, D., & Weigl, M. (2021). Associations of working conditions and chronic low-grade inflammation among employees: A systematic review and meta-analysis. *Scandinavian Journal of Work, Environment & Health*, *47*(8), 565-581. https://doi.org/10.5271/sjweh.3982

Kaltenegger, H. C., Marques, M. D., Becker, L., Rohleder, N., Nowak, D., Wright, B. J., & Weigl, M. (2024). Prospective associations of technostress at work, burnout symptoms, hair cortisol, and chronic low-grade inflammation. *Brain, Behavior, and Immunity*, *117*, 320-329. https://doi.org/10.1016/j.bbi.2024.01.222

Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative Science Quarterly*, *24*(2), 285-308. https://doi.org/10.2307/2392498

Karasek, R., Brisson, C., Kawakami, N., Houtman, I., Bongers, P., & Amick, B. (1998). The Job Content Questionnaire (JCQ): An instrument for internationally comparative assessments of psychosocial job characteristics. *Journal of Occupational Health Psychology*, *3*(4), 322-355. https://doi.org/10.1037/1076-8998.3.4.322

Karimikia, H., Singh, H., & Joseph, D. (2021). Negative outcomes of ICT use at work: Meta-analytic evidence and the role of job autonomy. *Internet Research*, *31*(1), 159-190. https://doi.org/10.1108/INTR-09-2019-0385

Kasemy, Z. A., Sharif, A. F., Barakat, A. M., Abdelmohsen, S. R., Hassan, N. H., Hegazy, N. N., Sharfeldin, A. Y., El-Ma'doul, A. S., Alsawy, K. A., Abo Shereda, H. M., & Abdelwanees, S. (2022). Technostress creators and outcomes among Egyptian medical staff and students: A multicenter cross-sectional study of remote working environment during COVID-19 pandemic. *Frontiers in Public Health*, *10*, Article 796321. https://doi.org/10.3389/fpubh.2022.796321

Kimonis, E. R., Fleming, G. E., Wilbur, R. R., Groer, M. W., & Granger, D. A. (2019). Dehydroepiandrosterone (DHEA) and its ratio to cortisol moderate associations between maltreatment and psychopathology in male juvenile offenders. *Psychoneuroendocrinology*, *101*, 263-271. https://doi.org/10.1016/j.psyneuen.2018.12.228

Kraus, S., Jones, P., Kailer, N., Weinmann, A., Chaparro-Banegas, N., & Roig-Tierno, N. (2021). Digital transformation: An overview of the current state of the art of research. *Sage Open*, *11*(3). https://doi.org/10.1177/21582440211047576

La Torre, G., Esposito, A., Sciarra, I., & Chiappetta, M. (2019). Definition, symptoms and risk of technostress: A systematic review. *International Archives of Occupational and Environmental Health*, *92*(1), 13-35. https://doi.org/10.1007/s00420-018-1352-1

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer.

Lennartsson, A.-K., Theorell, T., Kushnir, M. M., Bergquist, J., & Jonsdottir, I. H. (2013). Perceived stress at work is associated with attenuated DHEA-S response during acute psychosocial stress. *Psychoneuroendocrinology*, *38*(9), 1650-1657. https://doi.org/10.1016/j.psyneuen.2013.01.010

Maninger, N., Wolkowitz, O. M., Reus, V. I., Epel, E. S., & Mellon, S. H. (2009). Neurobiological and neuropsychiatric effects of dehydroepiandrosterone (DHEA) and DHEA sulfate (DHEAS). *Frontiers in Neuroendocrinology*, *30*(1), 65-91. https://doi.org/10.1016/j.yfrne.2008.11.002

Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, *52*(1), 397-422. https://doi.org/10.1146/annurev.psych.52.1.397

Mazmanian, M., Orlikowski, W. J., & Yates, J. (2013). The autonomy paradox: The implications of mobile email devices for knowledge professionals. *Organization Science*, *24*(5), 1337-1357.

McCrory, C., McLoughlin, S., Layte, R., NiCheallaigh, C., O'Halloran, A. M., Barros, H., Berkman, L. F., Bochud, M., M. Crimmins, E., T. Farrell, M., Fraga, S., Grundy, E., Kelly-Irving, M., Petrovic, D., Seeman, T., Stringhini, S., Vollenveider, P., & Kenny, R. A. (2023). Towards a consensus definition of allostatic load: A multi-cohort, multi-system, multi-biomarker individual participant data (IPD) meta-analysis. *Psychoneuroendocrinology*, *153*, Article 106117. https://doi.org/10.1016/j.psyneuen.2023.106117

McEwen, B. S. (1998). Protective and damaging effects of stress mediators. *New England Journal of Medicine*, *338*(3), 171-179. https://doi.org/10.1056/NEJM199801153380307

Meier, L. L., Semmer, N. K., Elfering, A., & Jacobshagen, N. (2008). The double meaning of control: Three-way interactions between internal resources, job control, and stressors at work. *Journal of Occupational Health Psychology*, *13*(3), 244-258. https://doi.org/10.1037/1076-8998.13.3.244

Mishra, P. K., & Rašticová, M. (2024). Role and status of biomarkers in technostress research: A systematic review. *Psychology Research and Behavior Management*, *17*, 1961-1972. https://doi.org/10.2147/PRBM.S446782

Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology*, *91*(6), 1321-1339. https://doi.org/10.1037/0021-9010.91.6.1321

Nastjuk, I., Trang, S., Grummeck-Braamt, J.-V., Adam, M. T. P., & Tarafdar, M. (2023). Integrating and synthesising technostress research: A meta-analysis on technostress creators, outcomes, and IS usage contexts. *European Journal of Information Systems*, *33*(3), 361-382. https://doi.org/10.1080/0960085X.2022.2154712

Nimrod, G. (2022). Technostress in a hostile world: Older internet users before and during the COVID-19 pandemic. *Aging & Mental Health*, *26*(3), 526-533. https://doi.org/10.1080/13607863.2020.1861213

Nixon, A. E., Mazzola, J. J., Bauer, J., Krueger, J. R., & Spector, P. E. (2011). Can work make you sick? A meta-analysis of the relationships between job stressors and physical symptoms. *Work & Stress*, *25*(1), 1-22. https://doi.org/10.1080/02678373.2011.569175

O'Connor, D. B., Thayer, J. F., & Vedhara, K. (2021). Stress and health: A review of psychobiological processes. *Annual Review of Psychology*, *72*(1), 663-688. https://doi.org/10.1146/annurev-psych-062520-122331

Pansini, M., Buonomo, I., De Vincenzi, C., Ferrara, B., & Benevene, P. (2023). Positioning technostress in the JD-R model perspective: A systematic literature review. *Healthcare*, *11*(3), Article 3. https://doi.org/10.3390/healthcare11030446

Peng, F.-J., Palazzi, P., Mezzache, S., Bourokba, N., Soeur, J., & Appenzeller, B. M. R. (2022). Profiling steroid and thyroid hormones with hair analysis in a cohort of women aged 25 to 45 years old. *European Journal of Endocrinology*, *186*(5), K9-K15. https://doi.org/10.1530/EJE-22-0081

Plan International & Bocconi University (2020). *Current and future challenges for gender equality in Italy: The gender digital divide*. Plan International.

Qiao, S., Li, X., Zilioli, S., Chen, Z., Deng, H., Pan, J., & Guo, W. (2017). Hair measurements of cortisol, DHEA, and DHEA to cortisol ratio as biomarkers of chronic stress among people living with HIV in China: Known-group validation. *PLOS ONE*, *12*(1), Aritcle e0169827. https://doi.org/10.1371/journal.pone.0169827

R Core Team. (2023). *R: A Language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Rademaker, T., Klingenberg, I., & Süß, S. (2023). Leadership and technostress: A systematic literature review. *Management Review Quarterly*. https://doi.org/10.1007/s11301-023-00385-x

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research*, *19*(4), 417-433. https://doi.org/10.1287/isre.1070.0165

Riedl, R. (2013). On the biology of technostress: Literature review and research agenda. *DATA BASE for Advances in Information Systems (ACM SIGMIS Database)*, *44*(1), 18-55. https://doi.org/10.1145/2436239.2436242

Rohleder, N. (2014). Stimulation of systemic low-grade inflammation by psychosocial stress. *Psychosomatic Medicine*, *76*(3), 181-189. https://doi.org/10.1097/PSY.0000000000000049

Schaafsma, F. G., Hulsegge, G., de Jong, M. A., Overvliet, J., van Rossum, E. F. C., & Nieuwenhuijsen, K. (2021). The potential of using hair cortisol to measure chronic stress in occupational healthcare: A scoping review. *Journal of Occupational Health*, *63*(1), Aritcle e12189. https://doi.org/10.1002/1348-9585.12189

Schaufeli, W. B., & Taris, T. W. (2014). A critical review of the job demands-resources model: Implications for improving work and health. In G. F. Bauer & O. Hämmig (Eds.), *Bridging Occupational, Organizational and Public Health: A Transdisciplinary Approach* (pp. 43-68). Springer. https://doi.org/10.1007/978-94-007-5640-3_4

Senarathne Tennakoon, K. L. U. (2021). Empowerment or enslavement: The impact of technology-driven work intrusions on work-life balance. *Canadian Journal of Administrative Sciences*, *38*(4), 414-429. https://doi.org/10.1002/cjas.1610

Sewell, G., & Taskin, L. (2015). Out of sight, out of mind in a new world of work? Autonomy, control, and spatiotemporal scaling in telework. *Organization Studies*, *36*(11), 1507-1529. https://doi.org/10.1177/0170840615593587

Singh, P., Bala, H., Dey, B. L., & Filieri, R. (2022). Enforced remote working: The impact of digital platform-induced stress and remote working experience on technology exhaustion and subjective wellbeing. *Journal of Business Research*, *151*, 269-286. https://doi.org/10.1016/j.jbusres.2022.07.002

Solís, P., Lago-Urbano, R., & Real Castelao, S. (2023). Factors that impact the relationship between perceived organizational support and technostress in teachers. *Behavioral Sciences*, *13*(5), Article 5. https://doi.org/10.3390/bs13050364

Stalder, T., Steudte-Schmiedgen, S., Alexander, N., Klucken, T., Vater, A., Wichmann, S., Kirschbaum, C., & Miller, R. (2017). Stress-related and basic determinants of hair cortisol in humans: A meta-analysis. *Psychoneuroendocrinology*, *77*, 261-274. https://doi.org/10.1016/j.psyneuen.2016.12.017

Steptoe, A., Cropley, M., Griffith, J., & Kirschbaum, C. (2000). Job strain and anger expression predict early morning elevations in salivary cortisol. *Psychosomatic Medicine*, *62*(2), Aritcle 286. https://doi.org/10.1097/00006842-200003000-00022

Suh, A., & Lee, J. (2017). Understanding teleworkers' technostress and its influence on job satisfaction. *Internet Research*, *27*(1), 140-159. https://doi.org/10.1108/IntR-06-2015-0181

Tams, S., Ahuja, M., Thatcher, J., & Grover, V. (2020). Worker stress in the age of mobile technology: The combined effects of perceived interruption overload and worker control. *The Journal of Strategic Information Systems*, *29*(1), Aritcle 101595. https://doi.org/10.1016/j.jsis.2020.101595

Tarafdar, M., Cooper, C. L., & Stich, J.-F. (2019). The technostress trifecta – techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, *29*(1), 6-42. https://doi.org/10.1111/isj.12169

Tarafdar, M., Pullins, E. Bolman., & Ragu-Nathan, T. S. (2015). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal*, *25*(2), 103-132. https://doi.org/10.1111/isj.12042

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, *24*(1), 301-328. https://doi.org/10.2753/MIS0742-1222240109

Theorell, T., Engström, G., Hallinder, H., Lennartsson, A.-K., Kowalski, J., & Emami, A. (2021). The use of saliva steroids (cortisol and DHEA-s) as biomarkers of changing stress levels in people with dementia and their caregivers: A pilot study. *Science Progress*, *104*(2). https://doi.org/10.1177/00368504211019856

Väänänen, A., & Toivanen, M. (2018). The challenge of tied autonomy for traditional work stress models. *Work & Stress*, *32*(1), 1-5. https://doi.org/10.1080/02678373.2017.1415999

Väänänen, A., Toivanen, M., & Lallukka, T. (2020). Lost in autonomy – Temporal structures and their implications for employees' autonomy and well-being among knowledge workers. *Occupational Health Science*, *4*(1), 83-101. https://doi.org/10.1007/s41542-020-00058-1

Van der Doef, M., & Maes, S. (1998). The job demand-control(-support) model and physical health outcomes: A review of the strain and buffer hypotheses. *Psychology & Health*, *13*(5), 909-936. https://doi.org/10.1080/08870449808407440

van der Meij, L., Gubbels, N., Schaveling, J., Almela, M., & van Vugt, M. (2018). Hair cortisol and work stress: Importance of workload and stress model (JDCS or ERI). *Psychoneuroendocrinology*, *89*, 78-85. https://doi.org/10.1016/j.psyneuen.2017.12.020

van Veldhoven, M., Van den Broeck, A., Daniels, K., Bakker, A. B., Tavares, S. M., & Ogbonnaya, C. (2020). Challenging the universality of job resources: Why, when, and for whom are they beneficial? *Applied Psychology*, *69*(1), 5-29. https://doi.org/10.1111/apps.12211

Wang, B., Liu, Y., Qian, J., & Parker, S. K. (2021). Achieving effective remote working during the COVID-19 pandemic: A work design perspective. *Applied Psychology*, *70*(1), 16-59. https://doi.org/10.1111/apps.12290

Warr, P. (1994). A conceptual framework for the study of work and mental health. *Work & Stress*, *8*(2), 84-97. https://doi.org/10.1080/02678379408259982

Whitham, J. C., Bryant, J. L., & Miller, L. J. (2020). Beyond glucocorticoids: Integrating Dehydroepiandrosterone (DHEA) into animal welfare research. *Animals*, *10*(8), Article 8. https://doi.org/10.3390/ani10081381

Wright, K. D., Hickman, R., & Laudenslager, M. L. (2015). Hair cortisol analysis: A promising biomarker of HPA activation in older adults. *The Gerontologist*, *55*(Suppl_1), S140-S145. https://doi.org/10.1093/geront/gnu174

Zänkert, S., Bellingrath, S., Wüst, S., & Kudielka, B. M. (2019). HPA axis responses to psychological challenge linking stress and disease: What do we know on sources of intra- and interindividual variability? *Psychoneuroendocrinology*, *105*, 86-97. https://doi.org/10.1016/j.psyneuen.2018.10.027

Zhu, Z., Zhao, M., Wu, X., Shi, S., & Leung, W. K. S. (2023). The dualistic view of challenge-hindrance technostress in accounting information systems: Technological antecedents and coping responses. *International Journal of Information Management*, *73*, Aritcle 102681. https://doi.org/10.1016/j.ijinfomgt.2023.102681