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Revisiting the Stressor–Burnout Relationship: Evidence for Reverse Causation and Conditional Change

Lucas A. Maunz[1], Leon T. De Beer[2, 3], Bernad Batinic[4], Christian Seubert[1], and Jürgen Glaser[1]
[1] Department of Psychology, University of Innsbruck
[2] Department of Psychology, Norwegian University of Science and Technology
[3] WorkWell Research Unit, North-West University
[4] Department of Work, Organizational, and Media Psychology, Johannes Kepler University Linz

The assumption that work stressors cause burnout is central to many occupational health theories. In this study, we addressed three limitations in prior research: (a) the limited understanding of how within-person increases in work stressors drive increases in burnout (the stressor hypothesis), including the consideration of whether the reverse effect (the strain hypothesis) offers greater predictive value; (b) the limited research on varying long-term time lags in the development of burnout; and (c) the limited evaluation of the effects of multiple work stressors. We applied random-intercept cross-lagged panel models with different time lags to analyze data from 2,131 German-speaking employees, collected across five time points over 24 months. Our findings showed stronger support for the strain hypothesis, suggesting that an increase in burnout over 6 months results in a subsequent increase in work stressors. This finding remained consistent across three types of stressors (i.e., work overload, social stressors, and organizational stressors) and when accounting for additional longer term time lags. We found limited evidence for the stressor hypothesis, particularly when disregarding stable between-person differences. However, cross-level moderation analyses showed that work stressors resulted in increased burnout for individuals who experience chronically lower levels of job resources (i.e., job autonomy and social support) or higher levels of work stressors. Our findings challenge the unconditional applicability of the stressor effect. They emphasize the theoretical importance of considering reverse causation, the timing of effects, and a clearer distinction between within-person changes and between-person differences to advance the understanding of burnout development processes.

Keywords: burnout, work stressors, job demands, job resources, temporal dynamics

Theories in occupational *Health Psychology* have long attributed the development of burnout to work-related factors (Freudenberger, 1974). In particular, *work stressors*, aspects of work that need considerable mental or physical effort, are commonly seen as the primary cause of burnout (World Health Organization, 2019). This *stressor hypothesis* has been adopted in a similar way by many theories, such as the job demand-control model (Karasek, 1979), the transactional model of stress (Lazarus & Folkman, 1984), the effort-reward imbalance model (Siegrist, 1996), and the job demands-resources (JDR) theory (Bakker, Demerouti, & Sanz-Vergel, 2023). However, researchers have recently started to doubt the causal relationship predicted by the stressor hypothesis (Bianchi & Schonfeld, 2025a). An alternative causal effect has been proposed, offering a different explanation for the commonly observed association between work stressors and burnout. The *strain hypothesis* posits that burnout impairs employees' ability to perform their tasks effectively, which in turn results in an actual or perceived increase in work-related stressors (Guthier et al., 2020). Meta-analyses have shown that empirical

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Lucas A. Maunz https://orcid.org/0000-0001-9289-6876
Leon T. De Beer https://orcid.org/0000-0001-6900-2192
Bernad Batinic https://orcid.org/0000-0002-8873-6308
Christian Seubert https://orcid.org/0000-0002-9519-8659
Jürgen Glaser https://orcid.org/0000-0002-6935-1779
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Correspondence concerning this article should be addressed to Lucas A. Maunz, Department of Psychology, University of Innsbruck, Innrain 52, 6020 Innsbruck, Austria. Email: lucas.maunz@uibk.ac.at

evidence for the strain hypothesis appears stronger than for the stressor hypothesis (Guthier et al., 2020; Lesener et al., 2019). These findings cast doubt on the causal origin of burnout stemming from work stressors—or at least suggest that both directions of causality are plausible.

However, three limitations hinder the understanding of the stressor–burnout relationship. *First*, current knowledge mainly stems from studies that lack insight into the within-person change process or neglect reverse causation, as predicted by the strain hypothesis. This gap is significant because theories on the emergence of burnout typically rely on the logic of within-person changes. For instance, previous literature suggested that employees who face continuous exposure to stressful or hindering job demands (hereafter referred to as work stressors) are expected to experience a decline in psychological health, ultimately leading to burnout over time (Bakker & Demerouti, 2024; Bakker & de Vries, 2021). These predictions suggest that an increase in the frequency or severity of work stressors causes the onset of burnout in the individual. An effective approach to empirically capture such change processes relies on longitudinal data (Demerouti et al., 2021) focusing on within-person effects (Curran & Bauer, 2011), ideally while ruling out alternative explanations, including reverse causation (Zyphur et al., 2020). While several longitudinal studies have examined direct and reverse effects between burnout and work stressors (e.g., Ângelo & Chambel, 2015; De Lange et al., 2004; Harju et al., 2022), their approach confounds within-person change with stable between-person differences, thus limiting conclusions about causality (see Lucas, 2023). In other words, prior studies may not adequately show how extended changes in a person's stressors lead to increases in their burnout over the long term. Although research on such within-person changes in burnout research is gaining traction (Abdo et al., 2025; Frick et al., 2024; Maunz & Glaser, 2024; Toth-Kiraly et al., 2024), the stressor and strain hypotheses have largely been overlooked in this emerging literature.

Second and relatedly, the timing of burnout development remains unclear (Bakker & de Vries, 2021; Demerouti et al., 2021). Burnout-related health impairment processes are commonly expected to emerge over a longer period of time (Bakker & Demerouti, 2024). Based on this assumption and the high stability of burnout over multiple years (Schaufeli et al., 2011), previous literature has recommended that burnout-related health impairment should be studied over a duration from 6 months to 2 years (De Lange et al., 2004; Dormann & Zapf, 2002; Drouin-Rousseau et al., 2024; Dunford et al., 2012; Sianoja et al., 2018). For example, Dunford et al. (2012) suggested that the emergence of burnout should be measured in 6-month intervals over 2 years because this period captures more enduring changes, avoiding irrelevant daily, weekly, or seasonal fluctuations (see also Che Mat et al., 2025; de Lange et al., 2003; Drouin-Rousseau et al., 2024; Leiter, 1996). Previous studies have found support for the stressor–burnout relationship over this 2-year time frame (e.g., De Lange et al., 2004; Dormann & Zapf, 2002). However, the analysis approach of these studies paid little attention to within-person changes, which limits their ability to capture how burnout unfolds over time (Voelkle et al., 2018). Understanding these temporal dynamics is crucial for formulating larger scale policy recommendations and designing effective interventions (Hamaker, 2023; Pearl, 2018).

Third, the understanding of the stressor–burnout relationship is limited by conceptual limitations of stressors and burnout. Much of the insight into the antecedents of burnout relies on a limited set of work stressors and proxy variables to measure burnout. By considering only selected work stressors, predominantly workload and role conflict (Guthier et al., 2020), previous literature may have neglected other causal stressor variables and thus failed to provide a comprehensive assessment of the relationship between stressors and burnout. Furthermore, studies have frequently relied on exhaustion to capture burnout, which may not yield valid conclusions about burnout as a whole, given that burnout comprises multiple components (Demerouti & Bakker, 2025). Therefore, recent studies showing that time pressure increased emotional exhaustion over 8 weeks (Peter et al., 2025) may not allow insight into how work stressors lead to burnout. Until recently, the reliance on proxy measures for burnout was a significant methodological limitation in studies seeking to explore the long-term development of burnout (De Beer et al., 2024; Schaufeli, 2021). This limitation has given rise to recent calls for a more systematic investigation of the causes of burnout (Bianchi & Schonfeld, 2025b; Demerouti & Bakker, 2025).

In addressing these limitations, our study offers several contributions to the burnout literature. By employing the random intercept cross-lagged panel model (RI-CLPM) to analyze within-person changes (Hamaker, 2023; Hamaker et al., 2015), we address a key limitation of previous studies that confounded within- and between-person levels or neglected reverse causation. This approach is crucial for evaluating psychological theory, which is typically formulated at the within-individual level. Our focus on within-person effects aligns with calls in epidemiology to move beyond statistical association toward identifying causal effects, especially when more rigorous experimental research is challenging (Schwartz et al., 2016). Overall, the study of within-person changes contributes to the literature by reexamining long-standing assumptions about how burnout develops over time. These insights are important not only for understanding the etiology of burnout but also for developing effective interventions and policy recommendations (Pearl, 2018; Schwartz et al., 2016).

We evaluate previously suggested plausible time frames of the burnout-related health impairment process, considering changes over 6 (Dunford et al., 2012), 12 (De Lange et al., 2004; Maricuțoiu et al., 2017), 18, and 24 months (Dormann & Zapf, 2002). This evaluation makes an empirical contribution by allowing us to gain a deeper insight into the temporal change processes (Asendorpf, 2021; de Lange et al., 2003). Particularly, this study contributed to stress research by evaluating when previously proposed long-term changes may occur. Investigating such temporal dynamics is essential for identifying causal relationships (see Aguinis & Bakker, 2021) and addresses the call to "carefully consider optimal time lags and statistical analysis to better capture the dynamic nature of the stressor–burnout relationship" (Che Mat et al., 2025, p. 1). Furthermore, we conduct additional analyses to examine how stable between-person differences in work stressors and job resources moderate time-lagged within-person changes. These analyses aim to identify boundary conditions of the stressor–burnout relationship and advance theory by highlighting the temporal dynamics of burnout.

Finally, we offer insights into the stressor–burnout relationship by examining three relevant work stressors, considering their *combined* and *individual* influence on burnout. Drawing from a multilevel categorization of employee resources (Nielsen et al., 2017), we suggest that work stressors reside at different levels of the organization: the task, the group, and leader, and the organizational level. Our analysis focuses on prominent work stressors within these categories that have been previously linked to employee burnout and ill-being: *work overload* (Cordes & Dougherty, 1993; Guthier et al., 2020); *social* *stressors* from colleagues, managers, and clients (Dormann & Zapf, 2002, 2004); and *organizational stressors* (Crawford et al., 2010; Mazzola & Disselhorst, 2019; Nixon et al., 2011; Spector & Jex, 1998). Moreover, unlike previous literature that often focused narrowly on exhaustion, we enhance the understanding of the work stressor–burnout relationship by utilizing a robust and validated measurement tool of burnout (De Beer et al., 2020; Schaufeli et al., 2020, 2023). We further strengthen the validity of our findings by drawing on a large, highly generalizable sample of the German and Austrian working populations (in terms of age, sex, weekly working hours, and income; Bundesanstalt Statistik Österreich, Statistik Austria, 2023; Statistisches Bundesamt, Destatis, 2023). Therefore, by reexamining whether and under what conditions work stressors lead to burnout, we aim to enhance the understanding of the causes of burnout and offer practical insights to guide future interventions.

Theoretical Background and Hypotheses

The Burnout Concept

Previous research commonly relies on the burnout definition as a multidimensional concept consisting of emotional exhaustion, depersonalization, and reduced personal accomplishment (Maslach et al., 2001). However, this conceptualization has sparked considerable discussion due to its methodological shortcomings (Bianchi, Swingler, & Schonfeld, 2024; De Beer et al., 2024; Schaufeli & Taris, 2005; Wheeler et al., 2011). For example, the most prominent measurement tool of this conceptualization, the Maslach Burnout Inventory (Maslach et al., 2016), has shown limited practicability as a composite score (De Beer et al., 2024). According to the MBI conceptualization, burnout is defined as a syndrome, composed of a set of co-occurring components. However, the MBI's manual explicitly discourages using a composite burnout score, contradicting a valid understanding of burnout as a syndrome (Bianchi, Swingler, & Schonfeld, 2024). Furthermore, although clinical burnout is often associated with emotional and cognitive impairment (Deligkaris et al., 2014; see also Kulikowski, 2021), the MBI overlooks these aspects as part of the burnout concept. These oversights have raised concerns about the validity and practicality of the MBI conceptualization for research and clinical purposes (Schaufeli et al., 2020, 2023).

To address these concerns, Schaufeli et al. (2020) presented an updated conceptualization and measurement model of burnout. Aiming to retain the core meaning of the concept, burnout was defined as a work-related state characterized by severe exhaustion, impaired emotional and cognitive functions, and a sense of mental distancing (Schaufeli et al., 2020). *Exhaustion* refers to a severe form of fatigue, including low levels of energy on both physical and mental levels. *Mental distance* describes psychological withdrawal from the job, often regarded as a dysfunctional coping strategy for managing exhaustion. *Emotional impairment* and *cognitive impairment* reflect employees' diminished capacity to regulate their emotional and cognitive processes, respectively. Despite the relative novelty of this conceptualization, it has already shown convergent validity with other burnout measurement tools, discriminant validity from related concepts (e.g., depression, boredom, workaholism), and predictive validity for several theoretical assumptions, including those from the JDR theory (De Beer et al., 2022; De Beer et al., 2025; Schaufeli et al., 2019).

Work Stressors as a Cause of Burnout: The Stressor Hypothesis

The stressor hypothesis, which assumes that work stressors cause burnout, dates to the original proposal of the concept of burnout. Freudenberger (1974) suggested that employees who experience high levels of pressure from work, such as working too much or too intensely, are prone to burning out. Recent literature has voiced the concern that this initial assumption was not based on a robust pattern in empirical data or a systematic theoretical foundation (Bianchi & Schonfeld, 2025a) but rather derived from anecdotal evidence and unchallenged impressions (Bianchi & Schonfeld, 2024). While the role of work stressors as the predominant cause of burnout remains a topic of ongoing debate (Bianchi, Lindsäter, et al., 2024; Demerouti & Bakker, 2025; De Witte & Schaufeli, 2025), contemporary theories in occupational health have widely adopted this perspective. For example, JDR theory (Bakker, Demerouti, & Sanz-Vergel, 2023; Bakker & de Vries, 2021) suggests that frequent and severe job demands lead to increased effort, ultimately causing exhaustion and health problems, including burnout (Bakker, Demerouti, & Sanz-Vergel, 2023; Bakker & de Vries, 2021). Importantly, the theory predicts that work stressors will have a *unique* impact on health outcomes (Bakker & Demerouti, 2024), indicating that an increased long-term exposure to work stressors leads to an increase in burnout.

More specifically, a recent theoretical model of burnout emergence suggested that job demands and short-term exhaustion can escalate into more severe and enduring burnout through an accumulation process (Bakker & de Vries, 2021). Over the short term, job demands systematically increase through maladaptive regulation strategies for managing job strain. Over the long term, these short-term increases in job demands and exhaustion accumulate and lead to a more enduring change in burnout. Thus, the model suggests that slowly increasing levels of job demands instigate a burnout change process. The model depicts this change process as a long-term process that changes the individual in a more lasting way.

The assumption that work stressors cause strain and burnout seems to be well-established, which is evident from the conclusion of many meta-analytic studies (Mazzola & Disselhorst, 2019; Nahrgang et al., 2011; Nixon et al., 2011; Pindek et al., 2019). However, methodological limitations in original studies have recently led to the conclusion that the causes of burnout are not as well understood as previously thought (Demerouti & Bakker, 2025). Moreover, recent meta-analyses have shown limited effectiveness of work-focused interventions for burnout, concluding that the root causes of burnout remain poorly understood (Dreison et al., 2018; Haslam et al., 2024; cf. Panagioti et al., 2017). In an ideal scenario, studies would use randomized controlled trials varying the level of work stressors to gain insight into the etiology of burnout. However, designing such an experiment would be impractical, unethical, and likely not yield insights into causal effects (see Schwartz et al., 2016). Findings from intervention studies may also provide limited insights into the development of burnout because the intervention effect (e.g., providing social support) is often fundamentally different from the causal effect (e.g., increasing social conflicts; see Schwartz et al., 2016). Therefore, a useful, although not perfect, way to gain insight into the causal process is through observational within-person designs using longitudinal data (see Rohrer & Murayama, 2023). Such analysis allows insight into the theoretical assumption that a person's burnout increases uniquely in response to a prolonged increase in work stressors. As such analyses are currently scarce in the literature, revisiting the stressor–burnout hypothesis appears warranted.

The Timing of the Stressor–Burnout Relationship

A central challenge in studying the development of burnout lies in determining the appropriate study period (Che Mat et al., 2025). If the time lag between measurements exceeds the duration of the causal process, the effect may have already dissipated, causing researchers to miss the process entirely (Aguinis & Bakker, 2021). If a measurement time lag is shorter than the causal process, the effect of the causal variable might be equally missed or underspecified (Aguinis & Bakker, 2021; e.g., De Lange et al., 2004). Studying the causes of burnout is particularly challenging due to its assumed prolonged emergence. The duration of the effect makes it difficult to pinpoint when the cause translates into a lasting effect on the individual. Some researchers have argued that such enduring changes are best captured by research designs that aim to uncover why individuals are different from each other (Orth et al., 2021). Others, however, emphasize that focusing on investigating the causes of long-term changes is useful, but requires an extension of the study period (Hamaker, 2023).

The consideration of such temporal aspects is crucial for identifying valid relationships. Causal relationships inherently involve the consideration of time because they are based on the idea that the independent variable occurs before the dependent variable (Granger, 1980). Taking time into account is also essential, as phenomena can differ conceptually depending on their stability (Aguinis & Bakker, 2021). For instance, burnout is expected to be highly stable (Schaufeli et al., 2011), suggesting that observing its daily fluctuations over a workweek may not yield meaningful insights into its etiology. Instead, such short-term changes may capture a normal strain response, from which employees can easily recover (Meijman & Mulder, 1998; Sonnentag et al., 2017). Therefore, we suggest, when aiming to understand the etiology of a more enduring phenomenon, such as burnout, it is necessary to choose an appropriate longer term time lag to observe meaningful change and minimize the contribution of more irrelevant fluctuations that occur at shorter timescales (for an overview of this discussion, see Hamaker, 2023).

To date, occupational health theories are unclear in their prediction of when burnout will emerge. Nevertheless, there seems to be some consensus that work stressors cause burnout "over a longer period of time" (Bakker & Demerouti, 2024). Additionally, most studies suggest that longer time lags are more suitable for capturing the development of burnout. For example, after evaluating time lags over 1, 2, and 3 years, De Lange et al. (2004) found the strongest effect of job demands on mental health (i.e., depression, emotional exhaustion, job satisfaction) after 1 year. Dormann and Zapf (2002) evaluated the relationship between social stressors and mental health (i.e., irritation and depressive symptoms) and found that a time lag of 2 years was best suited to capture the effect. Additionally, Dunford et al. (2012) studied the effect of career transition on burnout and found that emotional exhaustion and depersonalization increased up to approximately 1 year after the job change and then leveled off by the second year. Overall, longitudinal studies reviewed in previous meta-analyses on work stressors and burnout most frequently relied on time lags of 12, 24, and 6 months (Guthier et al., 2020; Mäkikangas et al., 2016). These findings collectively support the view that burnout develops gradually and that sufficient time is necessary to observe its onset.

Therefore, to determine the study period and select appropriate time lags, we relied on prior theoretical accounts that emphasized burnout's high stability and the need to avoid insignificant short-term fluctuations as well as existing empirical evidence. Based on these considerations, we investigate changes in burnout over a 2-year period, using 6-month measurement intervals, while also considering alternative, plausible longer term intervals (Lüdtke & Robitzsch, 2022).

Types of Stressors in the Stressor–Burnout Relationship

Work stressors may arise from various organizational levels and have an impact on burnout. Recently, the idea that work characteristics emerge from different levels within the organization has become more prominent (Bakker, Demerouti, & Sanz-Vergel, 2023; Gillet et al., 2024). For example, to better capture the multilevel nature of work, Nielsen et al. (2017) proposed a multilevel classification of job resources. They showed that each type of resource played an incremental role in promoting employees' health, attitudes, and behaviors. We suggest that work stressors similarly stem from or reside at different levels within the organization.

At the task level, each employee may encounter unique work tasks that result in a high workload, leading to job strain. Prior research has consistently linked workload to burnout (for meta-analyses, see Alarcon, 2011; Guthier et al., 2020; Lee & Ashforth, 1996). This association is often explained by the additional effort required to manage an increased workload, resulting in strain that can gradually become more enduring over time (Guthier et al., 2020). In support of this assumption, recent longitudinal studies showed that workload was associated with higher levels of burnout after 6 months (Harju et al., 2022) and that time pressure was associated with an increase in emotional exhaustion over 8 weeks (Peter et al., 2025). Furthermore, recent studies using latent profile analysis indicated that workload was associated with an increased probability of group membership in the burned-out profile at two distinct points over an 8-month period (Drouin-Rousseau et al., 2024). While some conflicting within-person evidence on longer term links between time pressure and emotional exhaustion exists (Maas et al., 2021), previous studies largely suggest that a prolonged increase in workload contributes to the development of burnout.

At the social level, taxing interactions and interpersonal conflicts with clients, colleagues, or managers may exert significant strain on employees. These interactions may hinder employees' goal attainment and lead to emotional distress, ultimately affecting their overall well-being and job performance (Ito & Brotheridge, 2012; Maslach & Jackson, 1986). If social stressors persist over time, they are expected to contribute to the development of burnout, as employees are left emotionally depleted and unable to recover (Maslach & Leiter, 2016; Sonnentag, 2018). The emotional labor literature similarly suggested that work requiring high levels of emotion regulation in social interactions drains mental resources, increases strain, and leads to burnout (e.g., Dormann & Zapf, 2004; for an overview, see Hülsheger & Schewe, 2011). For example, previous longitudinal studies found that social stressors were associated with higher levels of irritation, particularly after longer term exposure of 2 years (Dormann & Zapf, 2002), and workplace bullying was associated with higher levels of depressive symptoms and sleep problems over a 6-year period (Törnroos et al., 2020).

At the organizational level, personnel changes and shortages, uncertain information, and restructuring may systematically impede employees from completing their tasks and lead to strain (Crawford et al., 2010; Mazzola & Disselhorst, 2019; Nixon et al., 2011; Spector & Jex, 1998). Employees perceive these organizational stressors as constraints, barriers, or roadblocks that require additional effort and hinder task progress (Crawford et al., 2010). For example, dysfunctional organizational rules and practices may act as obstacles (DeHart-Davis, 2009; DeHart-Davis & Pandey, 2005), which evoke strong negative emotions, like frustration and anger (Hattke et al., 2020), making frequent exposure more likely to cause strain and burnout (Harju et al., 2022). In support of this assumption, Harju et al. (2022) showed that red-tape was positively related to higher levels of burnout after 6 months.

Recent literature suggested that work characteristics at higher organizational levels can influence those at lower levels (Bakker, Demerouti, & Sanz-Vergel, 2023) and similar effects may apply to work stressors. For example, organizational stressors, such as job insecurity, may increase an individual's workload (Giunchi et al., 2016). Conversely, bottom-up effects may occur, such that a high workload increases the likelihood of social conflicts or social conflicts, in turn, contribute to greater job insecurity (Garrido Vásquez et al., 2019). These dynamics suggest that stressors across organizational levels collectively contribute to burnout, underscoring the importance of examining multiple key stressors simultaneously to better understand burnout development. Drawing from the stressor hypothesis and previous findings, we propose the following hypothesis.

> *Hypothesis 1*: An increase in work stressors (i.e., work overload, social stressors, organizational stressors) over 6 months will lead to a subsequent increase in burnout.

Burnout as a Cause of Work Stressors: The Strain Hypothesis

Although the strain hypothesis is less established, previous literature has suggested several theoretical explanations for this effect. De Lange et al. (2004) argued that chronically exhausted employees evaluate their work environment more negatively. This assumption about a changed perception is echoed in the depression literature, where depression is commonly associated with more negative cognition and pessimism (Abramson et al., 1989; Teasdale, 1983). A similar effect may occur for burned-out employees. In support of this argument, an eye-tracking study showed that burnout was linked to longer attention to negative stimuli and shorter attention to positive stimuli (Bianchi & Laurent, 2015).

Another fundamental mechanism is that burned-out employees struggle to perform their work effectively, which in turn *creates stressors* (Spector et al., 2000). Burned-out employees often show a diminished ability to regulate their emotional states and struggle with cognitive processes (Schaufeli et al., 2020). This reduced emotional capacity likely hampers employees' interactions with clients, colleagues, and supervisors, making these interactions more stressful and increasing the risk of conflict. Similarly, reduced mental capacity, coupled with severe exhaustion and mental distance from work, may create substantial challenges in completing tasks efficiently. This combination of cognitive and emotional impairment may lead to the accumulation of unfinished tasks and thus increase work overload and interpersonal conflicts with supervisors and colleagues.

Garst et al. (2000) argued that employees who experience high levels of strain seek out tasks that are supposed to reduce their strain. This so-called refugee hypothesis was originally proposed to suggest that burnout leads to lower levels of work stressors. However, seeking out supposedly easier tasks might harm employees in the long run because such tasks are often boring or offer no possibilities for growth and learning, which could act as yet another stressor (Glaser et al., 2015; Harju et al., 2022; Kubicek et al., 2022).

Finally, the drift hypothesis assumes that burned-out employees proactively seek out easier tasks (see Guthier et al., 2020). However, being proactive might be an unrealistic expectation from an employee who is chronically exhausted—especially given that proactive behavior requires mental resources (Bolino et al., 2010). It might be more reasonable to assume that employees experiencing burnout are highly exhausted, displaying lower levels of initiative and performance while also procrastinating on tasks they should be doing (Steel, 2007). These constraints may not only create more stressors but also lead to being reassigned to less desirable roles or more boring tasks (i.e., shift assumption; Ettner & Grzywacz, 2001; Frese, 1982; Guthier et al., 2020; Zapf et al., 1996). For instance, when an individual experiences increased burnout, they may not only encounter greater stigmatization (Favre et al., 2023) but also face a heightened risk of being laid off (Olesen et al., 2013). These effects align with the drift hypothesis, which posits that burnout can lead to elevated levels of organizational stressors, such as workplace rumors, job insecurity, and personnel shortages.

The strain effect caused by burnout likely takes considerable time to unfold. Sherif and Hovland (1961) suggested that individuals tend to evaluate new information in the context of their existing attitudes. If the difference between the two positions is small, recipients perceive new information as congruent with their prior attitudes, leading to a gradual shift toward the new perspective. Following this logic, small increases in burnout may gradually lead individuals to develop more negative attitudes toward their work. This process suggests that the strain effect takes time to unfold. Additionally, the refugee and drift assumptions may also occur over the long term, as it may take significant time for supervisors to reassign roles, and for employees to secure a new job. Drawing from these assumptions, we propose the following hypothesis.

> *Hypothesis 2*: An increase in burnout over 6 months will lead to a subsequent within-person increase in work stressors (i.e., work overload, social stressors, organizational stressors).

Which Direction of the Effect Is More Plausible?

Despite the prevailing focus on the stressor hypothesis in occupational health psychology, we suggest that the strain hypothesis may exert a stronger causal effect based on theoretical and empirical reasons. First, the strain effects of burnout are likely to be less dependent on individual and situational factors than the stressor effects. For instance, previous literature has argued that the development of psychological health issues depends on an individual's recovery (Meijman & Mulder, 1998), coping mechanisms (Britt et al., 2016), and personal as well as job resources (Bakker & de Vries, 2021). In contrast, once burnout levels are elevated, burnout may unconditionally affect how employees think, feel, and behave, thereby more directly and actively contributing to the development or amplification of stressors. Furthermore, as previously noted, burnout may impair emotional regulation and cognitive functioning (Schaufeli et al., 2020), foster negative interpretations of the environment (Bianchi & Laurent, 2015; De Lange et al., 2004), decrease engagement and meaning (Brauchli et al., 2013; Maunz & Glaser, 2024), and initiate unfavorable structural workplace changes (Ettner & Grzywacz, 2001; Frese, 1982; Guthier et al., 2020; Zapf et al., 1996). Therefore, burnout may not only lead to increases in a single stressor but facilitate a conglomerate of stressors that may mutually influence each other.

Second, strain-related processes are likely to be more stable and pervasive than stressor effects. Research on stressor–strain relationships consistently suggests that high job demands need to accumulate over time to result in increased burnout (Bakker & Demerouti, 2024; Bakker & de Vries, 2021). However, such stressors may fluctuate substantially over time, which potentially gives employees periods of relief. For instance, weekends and vacations may temporarily relieve stressors and its impact on strain (Fritz & Sonnentag, 2005; Grant et al., 2025; Hilbert et al., 2025). In contrast, once burnout sets in, its negative consequences are more lasting and stable, as evidenced by the high stability of burnout (Schaufeli et al., 2011). This asymmetry in stability and reactivity may explain why burnout has stronger downstream effects on perceived and actual stressors than the other way around.

Finally, empirical evidence appears to favor the strain hypothesis (Guthier et al., 2020; Lesener et al., 2019). In a systematic review and meta-analysis, Guthier et al. (2020) examined the relationship between work stressors (e.g., workload, time pressure, role conflict) and burnout across 48 longitudinal studies. They considered reciprocal effects while accounting for variations in time intervals and sources of bias. Guthier et al. found a modest, yet likely inflated, link between work stressors and emotional exhaustion. However, their results revealed a substantially larger estimate for the strain effect and nonsignificant results for the effect of work stressors on depersonalization or cynicism. Similar findings were reported by Lesener et al. (2019), whose meta-analysis of 74 studies showed that the longitudinal strain effect was stronger than the stressor effect. However, it is important to note that the primary studies included in these meta-analyses did not isolate within-person changes. Instead, they confounded between-person and within-person variance (Lucas, 2023), potentially further inflating estimates of the stressor effect (see Orth et al., 2024).

Taken together, these considerations suggest that the causal effect from burnout to work stressors may be stronger and more consequential than currently assumed. We provide an evaluation of the relative strength of the stressor versus strain hypothesis, which may help to gain a better causal understanding of the burnout development process. Based on our rationale for more unconditional and enduring effects of the strain effect and previous meta-analytical findings (Guthier et al., 2020; Lesener et al., 2019), we predict that the strain hypothesis is "causally dominant" (Altinisik et al., 2021; Sukpan & Kuiper, 2024).

> *Hypothesis 3*: The effect of burnout on subsequent work stressors has greater predictive strength, or is causally dominant, over the effect of work stressors on burnout.

Method

Sample and Procedure

The data were collected by a German polling firm through an online panel. We aimed to recruit at least 1,000 participants from Germany and Austria at T1. Participants were recruited to create a balanced sample by nationality, gender, and age, reflecting the working populations of Germany and Austria. The data were gathered from German-speaking full- and part-time employees in December 2018 (T1, $n = 2{,}131$) June 2019 (T2, $n = 1{,}197$), December 2019 (T3, $n = 916$), June 2020 (T4, $n = 856$), and December 2020 (T5, $n = 595$). Participants from the first wave were invited to each subsequent wave. Details on participant dropout analyses and previous data use are available in the additional online material (https://osf.io/v4jfh/files).

At T1, the sample was 49.3% female (50.7% male) and on average 42.4 years old (SD = 13.3), worked 15.75 years in their current job (SD = 15.24), and worked 35.84 hr per week (SD = 9.42). The participants worked in a variety of professional fields, the most prominent being health and social services (13.5%), business services (10.6%), retail (10.5%), public administration (9.9%), production (9.2%), and education (8.1%). The participants worked in Germany (50.2%), Austria (49.4%), or an unspecified country (0.4%). Regarding their highest education, 32.1% reported a university degree, 27.5% an apprenticeship diploma, 23.7% a high-school diploma (i.e., Matura or Abitur), 13.8% some form of secondary school education, and 2.8% reported compulsory school education. First- or second-generation immigrants made up 8.4% of the sample. The sample showed a high degree of generalizability to the German and Austrian populations at the first measurement time point, in terms of age, sex, weekly working hours, and income (Bundesanstalt Statistik Österreich, Statistik Austria, 2023; Statistisches Bundesamt, Destatis, 2023).

Measures

Burnout was measured with the Burnout Assessment Tool (Schaufeli et al., 2020). The measure captures burnout with four dimensions. Exhaustion (e.g., "At work, I feel physically exhausted") was measured with eight items. The dimensions, mental distance (e.g., "I struggle to find any enthusiasm for my work"), cognitive impairment (e.g., "At work, I have trouble staying focused"), and emotional impairment (e.g., "At work, I feel unable to control my emotions") were measured with five items each. The items were anchored on a scale ranging from 1 (*never*) to 5 (*always*). The measurement tool demonstrated reliability and validity in multiple previous studies (e.g., De Beer et al., 2020; Villacura-Herrera et al., 2025) and showed good reliability in this study (ω ranged from 0.87 to 0.88).

Work overload, social stressors, and organizational stressors were each measured using three items from the respective scales of the German Screening for Work and Task Analysis (Glaser et al., 2020). The anchors of the scale of work overload (e.g., "I often have to hurry and still cannot complete my work"), social stressors (e.g., "In this unit, cooperation among coworkers is often burdensome"), and organizational stressors (e.g., "In this unit, I am often confronted with ambiguous information or rumors") ranged from 1 (*not at all*) to 5 (*to a very great extent*). The three items of social stressors capture stressors from colleagues, supervisors, and clients. The three items of organizational stressors capture personnel shortages, ambiguous information, and organizational changes. The scales were validated for German-speaking employees with data from 58 samples (Glaser et al., 2020). They showed good reliability in multiple occupational settings (e.g., Herrmann & Glaser, 2021) and showed good reliability in this study (ω ranged from 0.66 to 0.71).

Job autonomy was measured with the three items of the German Screening for Work and Task Analysis (Glaser et al., 2020). The items (e.g., "I can determine for myself how to do my work") were measured on a scale ranging from 1 (*not at all*) to 5 (*to a very great extent*). To capture employees' stable level of job autonomy over the study period, we manually created a person-mean score for each participant, capturing the individual's average level of job autonomy. The scale showed good reliability in this study (ω ranged from 0.89 to 0.91).

Social support at work was measured with the frequently used Social Support at Work Scale (Frese, 1989) consisting of a dimension for social support from colleagues (three items, e.g., "How much can you rely on your colleagues when things get difficult at work?") and a dimension for social support from supervisors (three items; e.g., "How much can you rely on your supervisor when things get difficult at work?"). The items were measured on a scale ranging from 1 (*not at all*) to 4 (*fully*). To capture employees' stable level of social support over the study period, we manually created a person-mean score for each participant, capturing the individual's average level of social support. The scale showed reliability in this study (ω ranged from 0.74 to 0.85).

Analysis Approach

We evaluated the convergent and discriminant validity of our measures with confirmatory factor analysis at each time point and the reliability of constructs with the ω coefficients for first-order (ω) and higher order (ω_{ho}) constructs (Cheung et al., 2024; Raykov & Zinbarg, 2011). We relied on a robust maximum likelihood estimation method in confirmatory factor analysis models to obtain model fit parameters, accounting for inflation caused by nonnormality (Heck & Reid, 2023; Savalei, 2018). We evaluated the measurement time invariance of constructs. Based on configural models, we subsequently constrained factor loadings (i.e., metric invariance), intercepts (i.e., scalar invariance), and residual variances (i.e., strict invariance) to be equal across measurement points (Brown, 2015). We evaluated measurement time invariance in models with first-order constructs and higher order constructs. After a good model fit was established, we extracted factor scores of constructs to test our hypotheses.

We evaluated our hypotheses about cross-lagged effects with the RI-CLPM (Hamaker et al., 2015). The RI-CLPM decomposes constructs into within-person and between-person components. Cross-lagged effects in the RI-CLPM reflect associations between wave-specific components that deviate from the stable component of that variable. Our analysis approach facilitates the interpretation of how changes in one variable result in subsequent increases or decreases in another variable.

In simpler terms, between-person effects help to answer the question: "Do employees who *generally* experience more work stressors compared with others tend to report higher levels of burnout?" In contrast, within-person effects address questions such as: "When an employee faces greater work stressors compared to their average work stressors, does their burnout increase *compared to their usual level*?" Thus, between-person analyses help to understand how people differ, while within-person analyses explore how an individual changes based on their varying levels of a predictor. Importantly, previous longitudinal research that did not consider within-person and between-person components, for example, by relying on the traditional cross-lagged panel model, may not be able to answer either of these questions, as their level of analysis conflates within-person changes with between-person differences (Lucas, 2023).

Before evaluating our hypotheses, we subsequently imposed increasing path constraints on autoregressive and cross-lagged paths in the RI-CLPM to evaluate whether the lagged effects are time-invariant (Hamaker et al., 2015; Mulder & Hamaker, 2021; B. Muthén & Asparouhov, 2024). This approach was previously recommended because it improves precision and power, enhances model convergence for complex longitudinal analyses, and simplifies results by reducing between-interval variability (Orth et al., 2021). Orth et al. (2021) noted that exceptions to this recommendation include study designs involving experimental treatments or major transitions during specific intervals. During our study period, after T3, the onset of the COVID-19 pandemic occurred. Therefore, we compared models without path constraints over the last two waves to rule out that major transitions during these intervals influence our interpretation. We selected the best-fitting model based on log-likelihood, Bayesian information criterion (BIC), and root-mean-square error of approximation, with preference given to models exhibiting lower BIC values (Preacher & Yaremych, 2023).

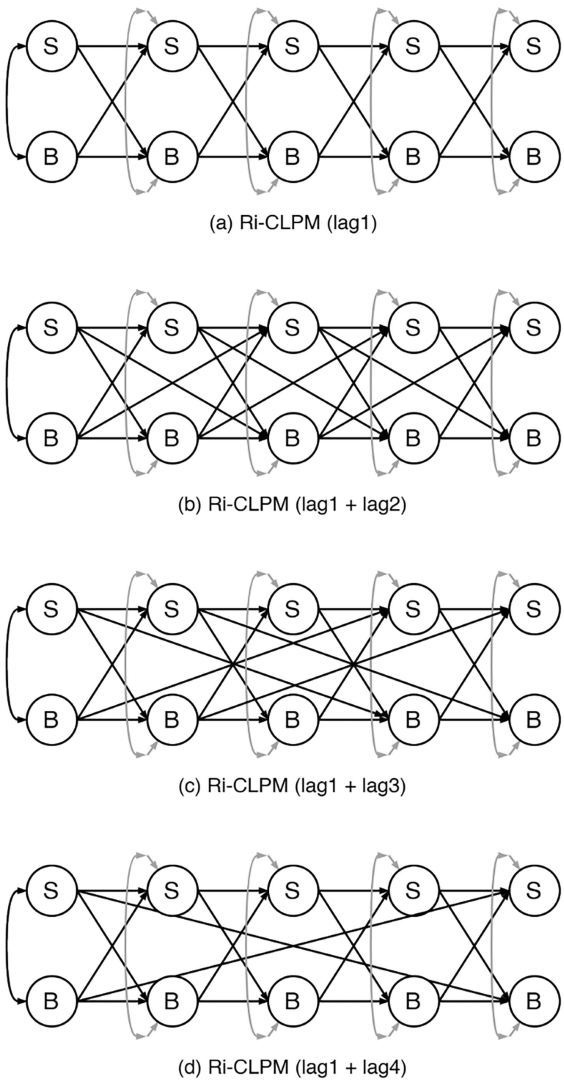
In addition to evaluating changes over 6 months, we evaluated changes over 12 months (lag2), 18 months (lag3), and 24 months (lag4) to gain a deeper insight into the potentially longer term temporal dynamics and reduce potential misinterpretation (Asendorpf, 2021; Lüdtke & Robitzsch, 2022). These cross-lagged models were previously proposed in a similar configuration (Lüdtke & Robitzsch, 2022). Figure 1 visualizes our tested models. To account for missing data, we estimated the models using the full information maximum likelihood estimator (Newman, 2014). To examine the causal dominance of the strain hypothesis, we evaluated which cross-lagged path has greater predictive strength (Sukpan & Kuiper, 2024). We made use of the procedure outlined by Sukpan and Kuiper (2024), relying on the generalized order-restricted information criterion approximation (GORICA; Altinisik et al., 2021), which allows us to examine inequality-constrained hypotheses in the RI-CLPM.

Finally, we conducted additional analyses concerning whether between-person differences in job autonomy, social support, and work stressors moderate the lagged within-person effect of work stressors on burnout. We used an approach that is analogous to a cross-level moderation in more traditional multilevel modeling, adopted for the RI-CLPM by Ozkok et al. (2022). In short, we manually created a person-mean job autonomy and social support variable for each participant and centered these variables at the grand mean. In the RI-CLPM, we then created a latent interaction term among each within-person component of work stressors and the moderating between-person variable. In terms of the moderation of between-person differences in work stressors, we used the between-person intercept component of work stressors and created a latent interaction term with the respective within-person component. These interaction terms were used as predictors of the subsequent within-person burnout component.

As is typical in multilevel approaches, we constrained autoregressive, cross-lagged, and interaction effects to be invariant over time. Thus, the interaction effect reflects the average interaction effect at all time points; the autoregressive and cross-lagged effects reflect the average effect across all individuals when the between-person interacting variables are mean-centered (Ozkok et al., 2022).

Figure 1

Visualization of Tested Random Intercept Cross-Lagged Panel Models



Note. To improve clarity, residuals and their correlation are displayed in gray and observed indicators and intercept factors are omitted. RI-CLPM = random intercept cross-lagged panel model; S = work stressor; B = burnout.

As recommended, we performed the analysis using the Bayes estimator (Ozkok et al., 2022), treating the mean score of constructs as observed variables.

Analysis code, output of analyses, missing data analysis, a full correlation table including means and standard deviation over all time points, results of supplementary analyses, and research materials are available in the additional online material at https://osf.io/v4jfh/files. The data set is available upon request. All analyses and data management, except for the moderation analysis, which was performed in Mplus 8.11 (L. Muthén & Muthén, 2025), were conducted using the R statistical programming language (R Core Team, 2023) with the lavaan (Rosseel, 2020), restriktor (Vanbrabant & Kuiper, 2024), and semTools (Jorgensen et al., 2022) packages.

Results

Confirmatory Factor Analysis and Measurement Time Invariance

Table 1 presents the means, standard deviations, intraclass correlation coefficients 1, correlation coefficients, and ω statistics. intraclass correlation coefficients 1 coefficients ranged from .62 (organizational stressors) to .76 (burnout), justifying multilevel analyses with sufficient variance at the within-person level (Gabriel et al., 2019). This result suggests that 76% of the variance in burnout is between-person, while 24% is within-person, indicating that although most differences in burnout are stable across individuals, there are meaningful changes over 6-month intervals.

Table 2 shows the fit indices of the confirmatory factor analysis. We tested a model that included burnout as a higher order factor, incorporating its subdimensions and respective items. We tested the proposed work stressor model with a higher order work stressor factor, incorporating three items for work overload, social stressors, and organizational stressors. In addition, we evaluated a model that also included three items each for job autonomy, social support of colleagues, and social support of supervisors. The constructs of social support from colleagues and supervisors formed a higher order social support construct. Finally, we tested a full-measurement model that included all constructs, including the higher order constructs of burnout, work stressors, and social support, and the first-order construct of job autonomy. As shown in Table 2, the tested models showed acceptable model fit and the correlation between higher order constructs was below the threshold of .75, suggesting convergent and discriminant validity (Cheung et al., 2024). As shown in Table 3, the minor changes in model fit indicated at least scalar measurement time invariance of constructs.

Cross-Lagged Effects Between Burnout and Work Stressors

We evaluated whether lagged regression coefficients between work stressors and burnout are time-invariant in a series of lag1 cross-lagged panel models with increasing path constraints in an iterative approach (e.g., Mulder & Hamaker, 2021). We tested (M1) the RI-CLPM with no invariance constraints, (M2) with invariant autoregressive effects of work stressors, (M3) with invariant paths for all autoregressive effects, (M4) with invariant autoregressive effects of stressors and invariant paths of stressors on burnout, (M5) with invariant autoregressive effects of stressors and invariant cross-lagged paths, and (M6) with invariant autoregressive and cross-lagged paths. Finally, we evaluated whether the onset of the COVID-19 pandemic systematically disrupted the invariance of lagged effects by not imposing path constraints for the effects over the last two waves (M7). As shown in Table 4, Model 6 (M6) demonstrated the best fit to the data, as indicated by the lowest BIC values, supporting the assumption that the lagged regression coefficients are time invariant. In the next step, we used M6 to evaluate the hypotheses.

The results of Model 6 are presented in Table 5. The autoregressive paths between work stressors ($\beta = .17–.19$, $p < .001$) and burnout ($\beta = .28–.35$, all $p < .001$) were significant, suggesting meaningful carryovers from one occasion to the next. We found no

Table 1
Means, Standard Deviations, ICC1s, Internal Consistencies, and Correlations Among the Study Variables

Variable	M_b	SD_b	ICC1	1	2	3	4	5	6	7	8	9	10	11
1. Burnout	2.05	0.67	0.76	(.87)	.90	.88	.86	.87	.56	.43	.59	.37	−.32	−.38
2. Exhaustion	2.36	0.79	0.74	.80	(.92)	.71	.72	.70	.59	.51	.56	.38	−.26	−.35
3. Mental distance	2.01	0.85	0.72	.79	.54	(.90)	.64	.69	.44	.29	.53	.30	−.36	−.41
4. Cog. imp.	2.02	0.71	0.71	.74	.47	.41	(.92)	.66	.45	.36	.45	.30	−.23	−.24
5. Emo. imp.	1.80	0.73	0.66	.80	.51	.50	.50	(.91)	.48	.36	.53	.31	−.23	−.31
6. Work stressors	2.77	0.73	0.70	.35	.33	.27	.23	.27	(.65)	.81	.81	.83	−.23	−.37
7. Work overload	2.87	0.98	0.67	.26	.29	.16	.18	.19	.74	(.88)	.48	.47	−.13	−.23
8. Social stressors	2.37	0.78	0.64	.32	.27	.29	.20	.25	.71	.31	(.73)	.58	−.29	−.49
9. Org. stressors	3.06	0.90	0.62	.21	.18	.16	.14	.17	.75	.30	.34	(.78)	−.16	−.22
10. Job autonomy	3.69	0.91	0.69	−.15	−.10	−.16	−.10	−.11	−.09	−.07	−.10	−.04**	(.90)	.27
11. Social support	2.90	0.63	0.66	−.29	−.23	−.29	−.15	−.22	−.27	−.16	−.30	−.16	.17	(.79)

Note. Correlations below the diagonal are within-person correlations (N = 5,699) and above the diagonal are between-person correlations (N = 2,131). Average ω coefficients over all waves are presented in parentheses. A correlation table considering all individual time points is available as additional online material (https://osf.io/v4jfh/files). ICC = intraclass correlation coefficients; cog. imp. = cognitive impairment; emo. imp. = emotional impairment; org. stressors = organizational stressors; M_b = between-person mean; SD_b = between-person standard deviation.
** p < .01.

support for the stressor hypothesis in Model 6. All paths from work stressors to burnout were nonsignificant. Instead, we found support for the strain hypothesis. Burnout was associated with a subsequent increase in work stressors (β = .12–.14, all p = .002). The between-person correlation between work stressors and burnout was high (β = .85, p < .001), suggesting that people who generally experience high levels of burnout also experience high levels of work stressors in general.

To gain additional insight into the temporal dynamics of the reciprocal effects, we tested cross-lagged effects over 12 months (M8–M13), 18 months (M14), and 24 months (M15). These models showed a worse fit compared with Model 6 (see Table 4). Furthermore, the results provided no evidence for the effects of burnout on work stressors at 12, 18, or 24 months, nor the effects of work stressors on burnout at these intervals. We further substantiate these temporal effects through a continuous-time modeling approach (Voelkle & Muthén), available in the additional online material (https://osf.io/v4jfh/files). The results of this approach confirm our finding that the effects are strongest after 6 months and provide further support for the strain hypothesis, but not the stressor hypothesis.

Finally, a model accounting for the disruption of the COVID-19 pandemic (M7) showed consistent support for the strain effect but not the stressor effect. Thus, this model showed the same pattern of results during the onset of the pandemic as it did at previous time points. The results of these models are presented in more detail in the additional online material (https://osf.io/v4jfh/files).

Table 2
Model Fit Indices of Confirmatory Factor Analysis

Model	χ^2	df	CFI	RMSEA	SRMR
Burnout T1	1,730.21	226	0.94	0.06	0.04
Burnout T2	1,219.25	226	0.94	0.07	0.05
Burnout T3	931.81	226	0.94	0.07	0.05
Burnout T4	866.53	226	0.94	0.07	0.05
Burnout T5	795.28	226	0.93	0.07	0.05
Work stressors T1	157.20	24	0.98	0.06	0.04
Work stressors T2	94.48	24	0.98	0.05	0.03
Work stressors T3	86.89	24	0.98	0.06	0.04
Work stressors T4	88.65	24	0.97	0.06	0.04
Work stressors T5	63.91	24	0.98	0.06	0.04
Job resources T1	107.27	24	0.99	0.04	0.02
Job resources T2	79.28	24	0.99	0.05	0.02
Job resources T3	93.58	24	0.99	0.06	0.02
Job resources T4	60.95	24	0.99	0.05	0.02
Job resources T5	55.58	24	0.99	0.05	0.02
Full model T1	3,998.14	764	0.93	0.05	0.05
Full model T2	2,708.29	764	0.93	0.05	0.06
Full model T3	2,275.37	764	0.93	0.05	0.06
Full model T4	2,146.75	764	0.93	0.05	0.06
Full model T5	1,890.47	764	0.93	0.05	0.06

Note. Robust variants of model fit statistics are reported. CFI = comparative fit index; RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual.

Pattern of Effects for the Types of Stressors

To gain deeper insight into the stressor–burnout relationship, we evaluated three additional models, one each for the relationship between burnout and work overload, social stressors, and organizational stressors. We fitted these models with time-invariant autoregressive and cross-lagged effects. Figure 2 shows the within-person slopes of these models. The figure shows a similar pattern of effects across all three stressors. The stressor effect was consistently not supported, while the strain effect was supported. Specifically, burnout was associated with an increase in work overload (β = .07–.11, all p = .003), social stressors (β = .12–.15, all p = .003), and organizational stressors (β = .08–.12, all p = .003). In contrast, we found no support for significant effects of work overload (β = .00, all p = .981), social stressors (β = .01, all p = .311), and organizational stressors (β = −.03 to −.04, all p = .242) on burnout.

Causal Dominance Analysis

We evaluated the informative hypothesis that the strain effect is causally dominant over the stressor hypothesis. We evaluated the predictive strength of cross-lagged paths for both higher order and first-order components of work stressors. Table 6 shows that the strain hypothesis received more support than the stressor hypothesis across all

Table 3
Measurement Time Invariance Tests

Model	χ^2	*df*	RMSEA	BIC	Comp	$\Delta\chi^2$	Δdf
Higher order constructs							
C1: Configural	15,490.06	3,820	0.05	511,366.86			
C2: Metric	15,663.87	3,968	0.05	510,260.76	**C2**, C1	163.13 *ns*	148
C3: Scalar	15,809.71	4,080	0.05	509,438.02	**C3**, C2	131.82 *ns*	112
C4: Strict	16,416.82	4,244	0.05	508,626.84	C4, **C3**	398.23***	164
First-order constructs							
C5: Configural	13,568.51	3,670	0.05	510,742.52			
C6: Metric	13,693.34	3,794	0.05	509,794.99	**C6**, C5	120.19 *ns*	124
C7: Scalar	13,840.38	3,918	0.05	508,869.67	**C7**, C6	147.15 *ns*	124
C8: Strict	14,448.81	4,082	0.05	508,059.82	C8, **C7**	398.66***	164

Note. Bold represents the favorable model based on a comparison test. Models C1–C4 include burnout and work stressors as higher order factors. Models C5–C8 include the first-order constructs: work overload, social stressors, organizational stressors, exhaustion, mental distance, emotional impairment, cognitive impairment, job autonomy, social support from colleagues, and social support from supervisors. Robust variants of chi-square, *df*, and RMSEA are reported. Results of the robust chi-square difference test are reported. The test is based on standard chi-square and *df* coefficients (Satorra & Bentler, 2010). RMSEA = root-mean-square error of approximation; BIC = Bayesian information criterion; Comp = compared models; *ns* = not significant.
*** $p < .001$.

models. The GORICA weight ratios indicated that the strain hypothesis has 4.09 times more support than the stressor hypothesis in the model with a higher order work stressor factor, 82.5 times more support in the work overload model, 24.63 times more support in the social stressor model, and 6.57 times more support in the organizational stressor model.

Additional Analyses

The Buffering Role of Job Resources in the Stressor–Burnout Relationship

While our study focuses on the unique effects of work stressors on burnout, an individual's level of job resources may serve as a crucial boundary condition for burnout development. Particularly, a supportive environment may help employees to manage organizational challenges and high workloads, while job autonomy may help employees to choose an approach that works best for them, mitigating the negative effects of work stressors. Accordingly, stressful work demands may not lead to increased burnout when employees have sufficient resources to manage these stressors (Bakker & de Vries, 2021).

Job autonomy and social support are two of the most studied job resources in occupational stress research (Guthier et al., 2020). The idea that they buffer against the effect of stressors on burnout is grounded in the influential job demand-control(-support) model (Johnson et al., 1989; Karasek, 1979; Karasek & Theorell, 1990). Accordingly, the likelihood of experiencing burnout is greatest when work involves high demands (i.e., work stressors), coupled with low levels of control and support. Broadening this perspective, the job demands resources theory posits that all job resources alleviate (i.e., moderate) the impact of job demands on strain, including burnout (Bakker, Demerouti, & Sanz-Vergel, 2023; Bakker & de Vries, 2021). Therefore, we conducted additional post hoc analyses investigating whether generally higher levels of social support and autonomy alleviate the impact of increased work stressors on subsequently increased burnout. In other words, we investigate whether the time-lagged within-person effect of stressors on burnout depends on between-person differences in stable job resources.

The results of the interaction effects are reported in Table 5. We found support for a cross-level interaction of job autonomy (see Figure 3, left panel). A higher average level of job autonomy buffered the within-person effect of work stressors on burnout ($b = –.10$, $p < .001$). The simple slope analysis showed that for individuals with low job autonomy compared with others, an increase in work stressors was associated with a subsequent increase in burnout ($b = .11$, $p < .001$). For individuals with average job autonomy levels, an increase in work stressors was not significantly associated with a subsequent change in burnout ($b = .01$, $p = .624$). For individuals with high job autonomy, an increase in work stressors was associated with a subsequent decrease in burnout ($b = –.09$, $p = .004$).

We found support for a cross-level interaction of social support at work (see Figure 3, middle panel). A higher average level of social support at work buffered the within-person effect of work stressors on subsequent burnout ($b = –.17$, $p < .001$). The simple slope analysis showed that for individuals with low social support compared to others, an increase in work stressors was associated with a subsequent increase in burnout ($b = .21$, $p < .001$). In contrast, for individuals with average ($b = .05$, $p = .204$) or high levels of social support ($b = –.09$, $p = .158$), an increase in work stressors was not significantly associated with a subsequent change in burnout.

We provide the results of interaction effects for each job resource in combination with each work stressor as additional online material (https://osf.io/v4jfh/files). These analyses provide support for the cross-level interaction effects: Work Overload × Job Autonomy, Work Overload × Social Support, Social Stressors × Job Autonomy, Social Stressors × Social Support, Organizational Stressors × Job Autonomy, and Organizational Stressors × Social Support.

Cross-Level Moderation Analysis of Work Stressors

According to Frese and Okonek (1984), the long-term effects of work stressors on burnout only appear after a certain threshold or breaking point is reached. Consistent with the idea of a threshold, we

Table 4
Model Fit Comparisons of Cross-Lagged Panel Models

Model	LogL	χ^2	*df*	BIC	RMSEA
lag1 models					
M1: Unconstrained	−4,999.69	60.01	21	10,336.61	0.05
M2: Invariant AR S → S	−5,003.25	67.13	24	10,320.74	0.05
M3: Invariant AR S → S and B → B	−5,010.10	80.84	27	10,311.45	0.05
M4: Invariant AR S → S Invariant LE S → B	−5,006.85	74.34	27	10,304.95	0.05
M5: Invariant AR S → S Invariant LE S → B and B → S	−5,022.53	105.70	30	10,313.32	0.06
M6: Invariant AR S → S and B → B Invariant LE S → B and B → S	−5,025.07	110.76	33	**10,295.39**	0.06
M7: Invariant paths until wave 3 Paths after t3 unconstrained	−5,005.27	71.17	25	10,317.11	0.05
lag1 + 2 models					
M8: Unconstrained	−4,997.59	55.80	15	10,378.39	0.07
M9: Invariant AR S → S	−5,000.39	61.41	18	10,361.01	0.06
M10: Invariant AR S → S and B → B	−5,003.47	67.57	21	10,344.17	0.06
M11: Invariant AR S → S and B → B Invariant LE S → B	−5,016.04	92.71	24	10,346.32	0.07
M12: Invariant AR S → S and B → B Invariant LE B → S	−5,017.00	94.64	26	10,332.92	0.06
M13: Invariant AR S → S and B → B Invariant LE S → B and B → S	−5,020.78	102.19	28	10,325.14	0.07
lag1 + 3 model					
M14: Invariant AR S → S and B → B Invariant LE S → B and B → S	−4,998.75	58.13	19	10,350.06	0.06
lag1 + 4 model					
M15: Invariant AR S → S and B → B Invariant LE S → B and B → S	−4,998.18	56.99	19	10,348.92	0.06

Note. Noteworthy values are presented in bold. The arrow indicates a path from a predictor to an outcome. LogL = log likelihood; BIC = Bayesian information criterion; RMSEA = root-mean-square error of approximation; AR = autoregressive; LE = lagged effect; S = work stressors; B = burnout.

examined in an additional post hoc analysis whether individuals with higher average work stressors (compared with others) are particularly susceptible to increases in work stressors leading to greater burnout.

The results of the interaction effects are reported in Table 5. The cross-level interaction of work stressors was supported (see Figure 3, right panel). A higher average level of work stressors compared with others amplified the within-person effect of work stressors on subsequent burnout ($b = .38$, $p < .001$). The simple slope analysis showed that for individuals with low work stressors compared to others, an increase in work stressors was not significantly associated with a subsequent increase in burnout ($b = .13$, $p = .204$). In contrast, for individuals with average ($b = .47$, $p < .001$) or high work stressors ($b = .83$, $p < .001$), an increase in work stressors was associated with a subsequent increase in burnout.

Discussion

This study examined reciprocal long-term within-person changes in the work stressor–burnout relationship. Our models indicate that an increase in work stressors over 6, 12, 18, and 24 months does not generally lead to a meaningful change in burnout. Instead, our findings show stronger support for the strain hypothesis, suggesting that an increase in burnout over 6 months results in a subsequent increase in work stressors. This finding was consistent across three types of stressors (see Figure 2). However, we found support for the stressor-effect when accounting for between-person differences in job resources and work stressor levels. These results indicate that the effect of work stressors on burnout depends on people's general levels of job autonomy and social support at work, with within-person stressor effects being stronger at lower levels of job resources. Our findings also suggest that the stressor-effect depends on people's general levels of work stressors with within-person stressor effects being stronger at higher average levels of work stressors. These findings have implications for theory and research on the dynamics of work stressors and burnout, causes of burnout, and boundary conditions of these effects.

Theoretical and Practical Implications

This study provided an evaluation of theoretical models that conceptualize burnout development as a long-term process (e.g., Bakker & de Vries, 2021). Consistent with previous literature, our findings showed that the model with 6-month lags demonstrated the best fit and the strongest effect sizes. However, we found limited support for work stressors leading to burnout over 6-, 12-, 18-, or 24-month intervals, when between-person moderators were not considered. Therefore, it seems that a prolonged increase in work stressors does not generally cause an increase in burnout. This finding challenges contemporary burnout theorizing, which suggests that health impairments develop uniquely through extended exposure to stressors in an accumulation process (Bakker & Demerouti, 2024; Bakker & de Vries, 2021; Meijman & Mulder, 1998). We investigated slower, longer term changes in stressors,

Table 5
Unstandardized Within-Person and Cross-Level Effects From the lag1 Random Intercept Cross-Lagged Panel Model (M6) and Interaction Models

Effect	*b*	Sig.	95% CI
Reciprocal lag1 model (M6)			
AR $B_t \rightarrow B_{t+1}$	0.29	***	[0.204; 0.379]
AR $S_t \rightarrow S_{t+1}$	0.17	***	[0.09; 0.254]
$S_t \rightarrow B_{t+1}$	0.01		[–0.075; 0.092]
$B_t \rightarrow S_{t+1}$	0.11	**	[0.04; 0.173]
Interaction model: job autonomy			
AR $B_t \rightarrow B_{t+1}$	1.02	***	[0.861; 1.109]
AR $S_t \rightarrow S_{t+1}$	0.93	***	[0.750; 1.025]
$S_t \rightarrow B_{t+1}$	0.01		[–0.046; 0.074]
$B_t \rightarrow S_{t+1}$	0.13	***	[0.044; 0.529]
Aut × $S_t \rightarrow B_{t+1}$	–0.10	***	[–0.139; –0.055]
Interaction model: social support			
AR $B_t \rightarrow B_{t+1}$	0.96	***	[0.520; 1.067]
AR $S_t \rightarrow S_{t+1}$	0.96	***	[0.719; 1.043]
$S_t \rightarrow B_{t+1}$	0.05		[–0.025; 0.235]
$B_t \rightarrow S_{t+1}$	0.11	**	[0.021; 0.504]
Sup × $S_t \rightarrow B_{t+1}$	–0.17	***	[–0.240; –0.109]
Interaction model: work stressors			
AR $B_t \rightarrow B_{t+1}$	0.54		[–0.012; 0.890]
AR $S_t \rightarrow S_{t+1}$	1.00	***	[0.809; 1.289]
$S_t \rightarrow B_{t+1}$	0.47	***	[0.172; 0.894]
$B_t \rightarrow S_{t+1}$	0.07		[–0.209; 0.302]
S × $S_t \rightarrow B_{t+1}$	0.38	***	[0.137; 0.647]

Note. Interactions are analogous to cross-level moderations. The arrow indicates a path from a predictor to an outcome. AR = autoregressive effect; B = Burnout; S = Work Stressor; t = time point; Aut = job autonomy; Sup = social support; 95% CI = 95% confidence interval of unstandardized effects; sig. = statistical significance; b = unstandardized coefficient.
** $p < .010$. *** $p < .001$.

aiming to capture instances where stressors have increased or accumulated, forming a more chronic component of work stress (Ford et al., 2014). Not finding support for the stressor effect over our study period may suggest that a linear accumulation of work stressors coinciding with increases in burnout is an unrealistic expectation of how burnout and enduring strain develop (see also Keller & Meier, 2024). Rather, it might be that employees can adapt to elevated stressor levels (Diener et al., 2006), particularly when the change is slow (Henderson et al., 2023; Suh et al., 1996). Furthermore, it might be that employees can cope with elevated stressor levels when they experience generally high levels of work resources and generally lower levels of work stressors, as suggested by our post hoc moderation results.

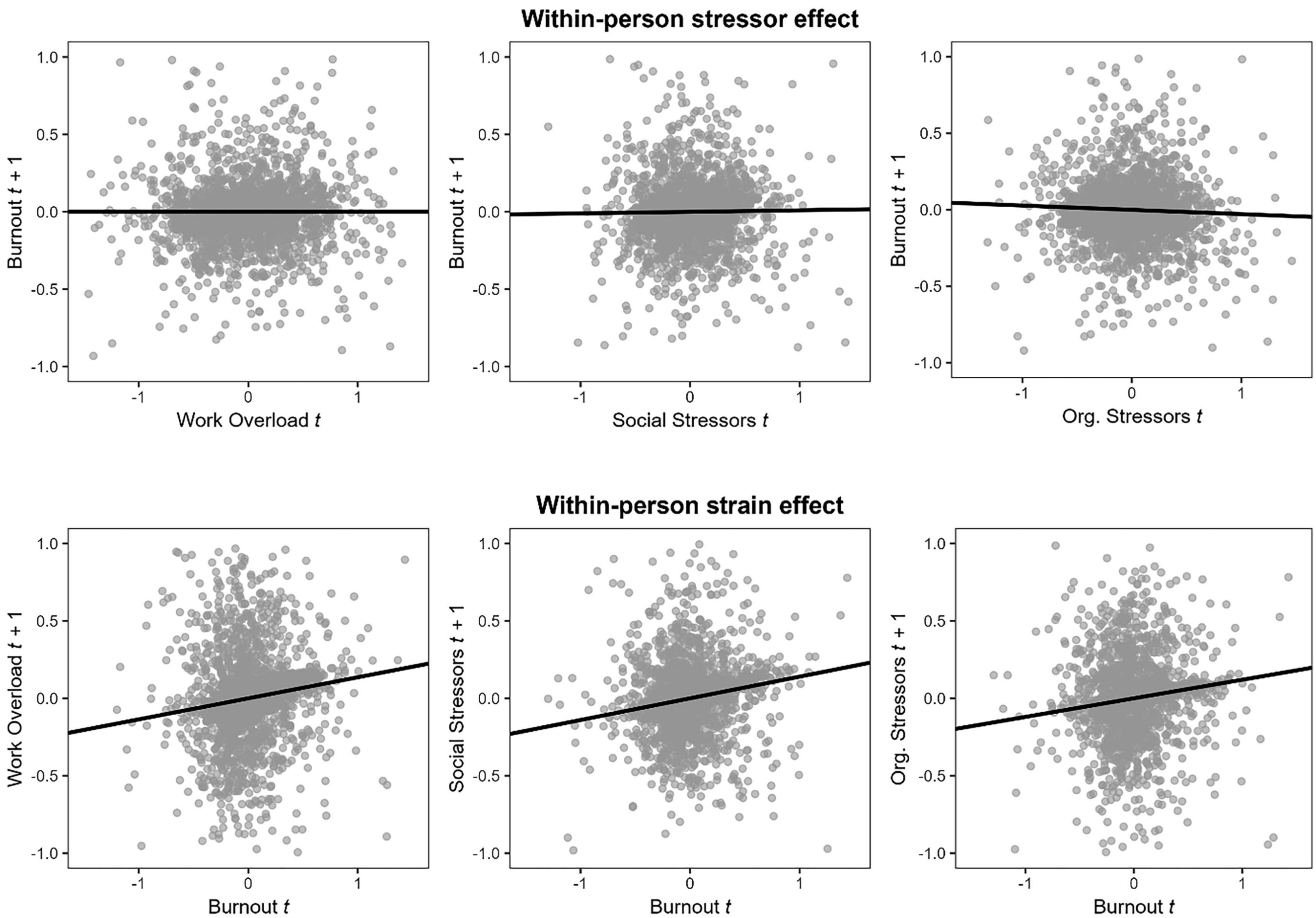
Our causal dominance analyses revealed that the strain effect was causally dominant over the stressor effect. This result suggests that burnout is more likely to increase subsequent work stressors than the reverse when disregarding between-person differences. The dominance of the strain effect aligns with findings from previous meta-analyses and emphasize the importance of considering the effects of burnout (Guthier et al., 2020; Lesener et al., 2019). Previous literature has already offered theoretical explanations for the strain effect. We suggest that the most plausible explanation is that burned-out employees have a reduced capacity to regulate emotional and cognitive processes (Schaufeli, 2021), which impairs social interactions and makes them more stressful. Additionally, burnout includes severe exhaustion and mental distance from work, potentially hindering employees from completing tasks and further increasing work stressors. We argued that strain effects outweigh stressor effects due to the conditional nature of the latter, an assumption that was supported by our post hoc moderation analyses, showing that stressor effects depend on stable resources and stressors. Overall, given the stronger evidence for the strain effect in our data and previous meta-analytic studies (Guthier et al., 2020; Lesener et al., 2019), we recommend adapting occupational health and stress theories to incorporate the strain hypothesis while carefully considering within-person changes and interpersonal differences.

Specifically, our findings suggest that increases in burnout may lead to enduring increases in the perception and potential creation of different forms of work stressors. This perspective not only adds to the list of the negative consequences of burnout but also indicates that burnout indirectly triggers further adverse outcomes by initiating more persistent changes in work stressors. Consequently, we recommend that burnout should be considered not only as an outcome in psychological health models, but also as a potential causal or moderating factor influencing negative individual or workplace outcomes (see Bakker, Xanthopoulou, & Demerouti, 2023). For instance, a recent iteration of the JDR theory depicted daily exhaustion as a dynamic antecedent in daily stressor–strain processes, influencing more general job demands, resources, and well-being (Bakker, Demerouti, & Sanz-Vergel, 2023). Building on this perspective, we suggest that burnout not only feeds back into daily experiences but also shapes the perception and experience of more enduring job demands, resources, and overall well-being. Therefore, we echo the recent call for a clearer focus on temporal processes (e.g., within-day, week, month, year) to untangle how short-term strain and more enduring burnout unfold over time (Che Mat et al., 2025). Such predictions seem necessary as not only concepts, but also their relationships, might be different based on temporal aspects (Aguinis & Bakker, 2021).

Our research contributes to the growing body of literature that employs within-person approaches to better understand the burnout phenomenon (Abdo et al., 2025; Frick et al., 2024; Maunz & Glaser, 2024; Toth-Kiraly et al., 2024). While burnout has often been conceptualized as a chronic, trait-like construct that primarily exists at the between-person level (Bakker & de Vries, 2021), our findings challenge this view. Specifically, we observed meaningful within-person variation in both burnout and work stressors over 6-month intervals across a 2-year period, as indicated by intraclass correlation coefficients values for both constructs. These results suggest that burnout and work stressors are not merely stable, trait-like characteristics, but malleable and dynamic components that can change over appropriately selected timeframes. As such, portraying burnout primarily as a stable, person-dependent characteristic may obscure key insights into how it develops and, importantly, how it can be mitigated. We have argued that a central challenge in studying the development of enduring changes in burnout lies in determining the appropriate study period. Our findings on different lag lengths underscore the importance of considering the temporal aspects of the burnout phenomenon in theoretical models and empirical research, even if these changes unfold slowly.

Our findings add to the recent discussion on the causes of burnout (Baillien & Taris, 2025; Bianchi, Lindsäter, et al., 2024; Bianchi & Schonfeld, 2025b; Demerouti & Bakker, 2025; De Witte & Schaufeli, 2025). We found that work stressors do play a role in

Figure 2
Within-Person Slopes for Three Different Lagged Stressor–Burnout Relationships



Note. Regression lines are derived from model-implied estimates of time-invariant, within-person effects of a predictor on a subsequent outcome. Visualized data points are estimated values for the latent variables in the models (i.e., factor scores). Org. = organizational; t = time point.

burnout development when certain boundary conditions are met. Particularly, an increase in work stressors may lead to an increase in burnout when the job resources of job autonomy and social support are generally low. These findings are in line with previous assumptions about the moderating role of job resources, as predicted by the JDR theory (Bakker, Demerouti, & Sanz-Vergel, 2023) and the job demand-control(-support) model (Johnson et al., 1989; Karasek, 1979). Notably, our support for these effects is in contrast to recent longitudinal studies that found no evidence for such moderations (Guthier et al., 2020; Kuhlmann & Süß, 2024; Maas et al., 2021). This discrepancy may stem from methodological limitations in previous studies. These limitations include neglecting cross-level moderation effects in long-term within-person changes, and, equally plausible, having insufficient statistical power to detect such effects (Arend & Schäfer, 2019). Therefore, our results offer an empirical contribution by showing support for the buffering role of job resources, which has predominantly relied on cross-sectional evidence (e.g., Bakker et al., 2005; de Jonge & Huter, 2021).

Furthermore, we found that higher average levels of job autonomy, when paired with an increase in work stressors, significantly *reduced* subsequent burnout. This effect was consistent across the types of stressors: work overload, social stressors, and organizational stressors, as shown in our additional online material (https://osf.io/v4jfh/files). These findings support the "active job" assumption, which posits that high demands paired with high control can have beneficial effects for employees (Karasek, 1979). Given that these moderation effects were consistent across different stressors and similar in magnitude, our results challenge the matching hypothesis (e.g., that social resources are particularly effective in buffering social stressors; de Jonge & Huter, 2021). Instead, our findings highlight the general benefits of enduring job resources, such as job autonomy and social support.

Our findings indicate that an increase in stressors relative to an individual's baseline level may not, by itself, be sufficient to trigger increases in burnout. Instead, our results suggest that the *absolute* level of stressors, relative to others, is a critical factor in understanding the effect of within-person increases in stressors on burnout. Specifically, individuals who experienced higher average levels of work stressors (compared with others) appeared more vulnerable to burnout when subjected to further increases in stressors. Conversely, employees with consistently low stressor levels may be less impacted by such increases, as their overall level remains low in absolute terms. This interaction aligns with the idea

Table 6
Results of the Causal Dominance Analysis

Model and hypothesis	LogL	Penalty	GORICA	GORICA weight	Support
Higher order work stressor					
Strain hypothesis	10.32	3.50	−13.64	0.80	4.09×
Stressor hypothesis	8.91	3.50	−10.83	0.20	
Work overload					
Strain hypothesis	10.34	3.50	−13.67	0.99	82.50×
Stressor hypothesis	5.92	3.50	−4.85	0.01	
Social stressors					
Strain hypothesis	10.48	3.50	−13.95	0.96	24.63×
Stressor hypothesis	7.27	3.50	−7.55	0.04	
Organizational stressors					
Strain hypothesis	10.41	3.50	−13.81	0.87	6.57×
Stressor hypothesis	8.52	3.50	−10.05	0.13	

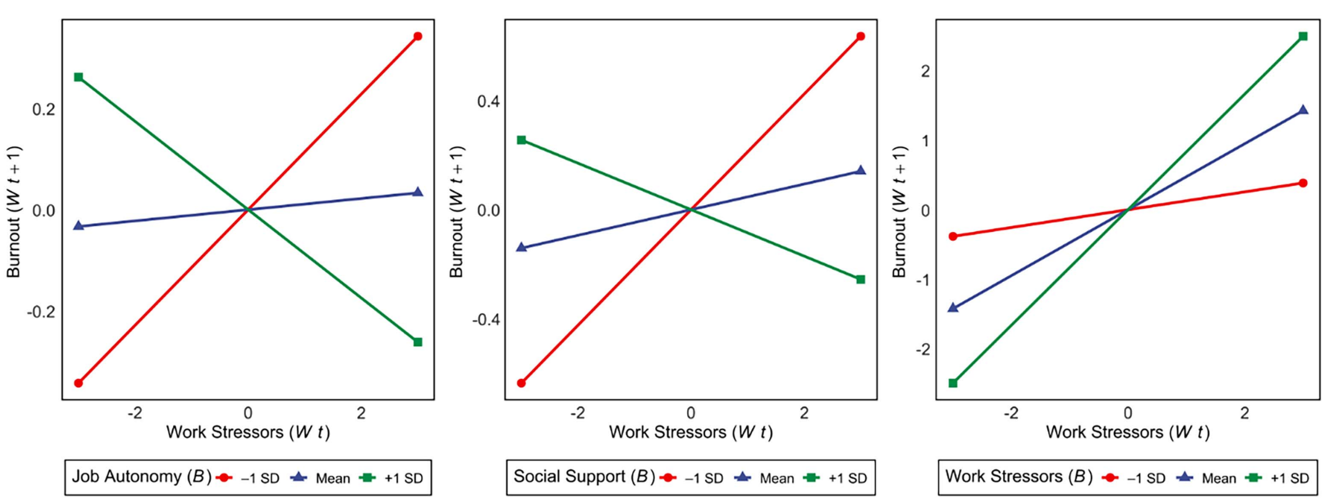
Note. Models are specified with time-invariant autoregressive and cross-lagged paths. LogL = log likelihood value; GORICA = generalized order-restricted information criterion approximation; support = supporting evidence of the hypothesis over the other.

of a threshold or breaking point, where health impairment emerges only after a certain threshold in stressors is surpassed (Frese & Okonek, 1984). Currently, theoretical accounts rarely consider the interplay of within-person changes with between-person differences in burnout development. Our findings highlight the need to consider both levels simultaneously to develop a more nuanced understanding of burnout trajectories (Demerouti & Bakker, 2025; De Witte & Schaufeli, 2025).

We shed light on the relationship between stressors and strain by investigating the individual and combined impact of multiple perceived work stressors on burnout. In contrast to previous studies, we have considered that stressors co-occur and potentially influence each other, which was supported by our correlational results. Furthermore, our analyses showed that the within-person effects of both combined and individual stressors show a similar pattern in their direct and reverse relationships with burnout. These findings emphasize the similar properties of stressful experiences. Previous literature has already considered that job resources exist in packs and emerge from common environmental and developmental conditions (Hobfoll et al., 2018). Like job resources, our findings may show that the experience of work stressors emerge from common environmental and developmental conditions and exist in packs. While it might be argued that combining work stressors into a combined factor loses information, the similar pattern of results in our study suggest that it is reasonable to consider a more abstract, higher order work stressor construct, as suggested by theory focusing more generally on job demands (e.g., Bakker, Demerouti, & Sanz-Vergel, 2023; Karasek, 1979).

Finally, our findings have practical implications. Based on our findings, we recommend that practitioners foster job autonomy and

Figure 3
Cross-Level Interactions of Job Autonomy (Left Panel), Social Support (Middle Panel), and Work Stressors (Right Panel) With Work Stressors on Subsequent Burnout



Note. Job autonomy: −1 *SD*: $b = .11, p < .001$; *M*: $b = .01, p = .624$; +1 *SD*: $b = -.09, p = .004$. Social support: −1 *SD*: $b = .21, p < .001$; *M*: $b = .05, p = .204$, +1 *SD*: $b = -.09, p = .158$. Work stressors: −1 *SD*: $b = .13, p = .204$; *M*: $b = .47, p < .001$; +1 *SD*: $b = .83, p < .001$. *W* = within-person; *B* = between-person; *t* = time point. See the online article for the color version of this figure.

social support, as these resources may buffer the negative health effects of temporal increases in work stressors. Additionally, practitioners should monitor employees with chronically high work stressors, as these employees may already be at their limit, and further increases could act as a tipping point, leading to psychological health impairment. Our between-person results suggest that employees who generally report high levels of stressors (compared to others) experience higher burnout on average. Therefore, screening employees for high levels of work stressors can help identify those at risk of burnout, regardless of the presence of a within-person effect on burnout (Lucas, 2023; Yarkoni & Westfall, 2017). Drawing from the strain hypothesis, these employees may already experience elevated levels of burnout and therefore are at risk of sickness absence or quitting. However, our findings suggest that lowering work stressors for a broad population over a 6- to 24-month period is insufficient to effectively decrease burnout. It therefore seems more promising to identify individually relevant factors for burnout development and tailor interventions specifically to employees at risk (see De Simone et al., 2021).

Limitations and Future Research

Our study did not consider the processes that may operate at shorter periods, as we focused on the theoretical assumption that burnout develops in response to work stressors over the long term (Bakker & de Vries, 2021). However, studies have shown that work demands can increase, and recovery can reduce strain in the short term (Headrick et al., 2023; Sonnentag et al., 2017), suggesting that aspects of long-term health impairment processes may begin with daily or weekly effects (Peter et al., 2025). Furthermore, effects between work stressors, exhaustion, and burnout might operate at different time scales. For example, work stressors may lead to short-term exhaustion and distress, ultimately leading to a cycle of distress and burnout when recovery is impaired. Future research should investigate how such short-term strain processes escalate into the development of more enduring burnout. To gain insights into these within-person dynamics, studies may use measurement bursts (Sliwinski, 2008) or continuous time approaches using varying short and long-term time lags (Chow et al., 2023; Voelkle et al., 2018).

We did not consider how overwhelming events or important nonwork factors may drive burnout (Haynie & Shepherd, 2011). For example, De Witte and Schaufeli (2025) discussed that work-related variables may initiate the development of burnout while subsequent nonwork factors, such as an impaired lack of recovery or work–home conflicts, mediate the relationship. Recent research has started to adopt an event-oriented perspective (Liu et al., 2023) to understand employee health and well-being (Bono et al., 2013). Particularly negative events at work, such as negative feedback, conflict, or harmful interactions with colleagues and supervisors, have shown adverse effects on employee health and well-being (Koopmann et al., 2016; Maunz et al., 2024). Such events may spark a conglomerate of work and nonwork-related mediating factors leading to burnout (De Witte & Schaufeli, 2025). Additionally, negative events outside of work may spill over to the work domain. For example, major life events have been shown to impair employees' ability to effectively utilize personal resources and lead to rumination (Bakker et al., 2019; Baranik et al., 2017), thereby potentially showing direct and moderating effects on burnout (Hakanen & Bakker, 2017). Although close attention to the temporal dynamics of these events is needed (e.g., Liu et al., 2023), the consideration of negative events could provide a valuable direction for examining the causal development of burnout.

We did not account for the possibility that chronically low personal resources may moderate employees' susceptibility to the within-person increase of burnout. Previous literature has identified several key personal resources, such as hope, resilience, self-efficacy, and optimism. Considering between-person differences in such personal resources may help to understand when increases in work stressors lead to increases in burnout (see Bakker & de Vries, 2021). Future research may investigate whether these personal resources show similar cross-level moderation effects as job resources in our study.

Our conclusions might be limited by our methodological approach, particularly the reliance on self-report data and the absence of experimental control, which may constrain causal inference. Although recent literature has noted that "within-persons data can be very helpful for causal inference" (Rohrer & Murayama, 2023, p. 4), experimental designs remain superior to self-report approaches for establishing causality. Ideally, randomized controlled trials would be necessary to validate our findings. We justified our approach by arguing that such experimental designs are challenging to implement, impractical in real-world settings, and potentially unethical when studying harmful outcomes (see Schwartz et al., 2016). Likewise, although self-reports are a valid method of assessing psychological states, we acknowledge that data from external sources, such as evaluations from medical specialists, may lead to more reliable conclusions.

A key limitation of our self-report approach to uncover causal effects is the potential omission of unobserved time-varying confounders (Rohrer & Murayama, 2023), such as nonwork-related factors that may influence burnout development (Bianchi & Schonfeld, 2025a). Therefore, future research simultaneously considering work-related stressors and nonwork-related causes may provide important insights into the relative strength of these causal processes (De Witte & Schaufeli, 2025). Finally, another potential confounding factor is that employees experiencing poor health may have dropped out during data collection. Our missing data analysis indicated that burnout is linked to lower participation rates, suggesting a healthy worker survivor bias (Buckley et al., 2015). This effect could limit our conclusions, as the remaining participants might be better adjusted to work stressors. To address this limitation, future research may usefully gather data on the factors leading to dropout (e.g., follow-up surveys).

Conclusion

The notion that work stressors are the primary cause of burnout is a core assumption in many theories of occupational health. Our findings offer a more nuanced perspective. In line with the strain hypothesis, we found that burnout had a stronger impact on the experience of subsequent work stressors than the reverse, particularly when moderating between-person differences were not considered. However, our findings also showed that work stressors do play a role in burnout development when certain boundary conditions are met. Specifically, work stressors did result in increased burnout for individuals who experience chronically lower levels of job resources or chronically higher levels of work stressors. We suggested theoretical modifications to address the timing of effects, reverse causation, and distinctions between within-person changes and between-person differences. Our findings open avenues for future research to integrate shorter and longer term processes to better understand the development of burnout.

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