International Journal of Stress Management

Intra-Syndrome Dynamics of Burnout: Cross-Lagged Relations Among Core Components

Leoni van der Vaart, Leon T. De Beer, Hans De Witte, and Wilmar B. Schaufeli

Online First Publication, December 8, 2025. https://dx.doi.org/10.1037/str0000382

AMERICAN PSYCHOLOGICAL ASSOCIATION

International Journal of Stress Management

ISSN: 1072-5245

https://doi.org/10.1037/str0000382

Intra-Syndrome Dynamics of Burnout: Cross-Lagged Relations Among Core Components

Leoni van der Vaart[1, 2], Leon T. De Beer[1, 3, 4], Hans De Witte[2, 5], and Wilmar B. Schaufeli[5, 6]

[1] Department of Psychology, Norwegian University of Science and Technology
[2] Optentia Research Unit, Faculty of Humanities, North-West University
[3] WorkWell Research Unit, Faculty of Economic and Management Science, North-West University
[4] Unit of Occupational Medicine, Institute of Environmental Medicine, Karolinska Institutet
[5] Research Unit Occupational and Organizational Psychology and Professional Learning, Faculty of Psychology and Educational Sciences, KU Leuven
[6] Department of Psychology, Utrecht University

Given the increasing number of employees reporting burnout complaints and the negative outcomes associated with these complaints, both researchers and practitioners are interested in understanding how burnout develops over time. Despite previous efforts to elucidate burnout's internal dynamics, our knowledge remains limited. By leveraging several theoretical models and previous empirical studies, we proposed six competing hypotheses to examine how the intra-syndrome dynamics of burnout may evolve over time. Using cross-lagged panel models and data from 1,035 Belgian employees collected at three different time points, we evaluated these potential pathways. Our results provide initial support for a dynamic in which intra-syndrome burnout begins with exhaustion, impairing emotional functions and more consistently affecting cognitive functions. However, only cognitive impairment then adds to more mental distancing. Contrary to previous theoretical assumptions, we found limited evidence that mental distancing contributes to maintaining a cycle of exhaustion and impairment. We discuss the theoretical contributions of our findings and their practical implications for early detection of struggling employees and tailored intervention strategies.

Keywords: burnout, Burnout Assessment Tool, longitudinal, exhaustion, work stress

Supplemental materials: https://doi.org/10.1037/str0000382.supp

Work-related stress has harmful consequences that result in substantial labor market costs due to increased sickness absence and unemployment, underscoring the need for effective prevention and intervention strategies (Pedersen et al., 2024). Applying the burnout paradigm within an organizational context can help occupational health practitioners to address work-related stress and its consequences (see De Beer & Schaufeli, 2025). Burnout is a work-induced state of exhaustion that can be characterized by significant fatigue, impaired cognitive and emotional regulation, and mental distancing (Schaufeli, De Witte, & Desart, 2020), adversely affecting employees and their workplaces (De Beer, Christensen, et al., 2024; De Beer et al., 2022; Salvagioni et al., 2017). However, the question arises whether these burnout components compound one another further across time. For example, does initial exhaustion only contribute to more exhaustion over time, or does it also explain variation in the other components over time. These findings could reveal important considerations surrounding the sequence of burnout's intra-syndrome development. In this study, we do not define 'stages' as fixed clinical phases but rather refer to the temporal ordering of symptoms; how one component of burnout may predict subsequent changes in another, thus reflecting a developmental progression rather than a categorical sequence within the syndrome.

Previous research employing this definition of burnout provides extensive psychometric support for this conceptualization but limited evidence for the sequential dynamics of burnout through its components. In general, longitudinal studies predominantly underscore the overall rank-order stability (or consistency) of burnout (see Harju et al., 2022; Maunz & Glaser, 2024) or its individual dimensions over time (see Sørengaard & Saksvik-Lehouillier, 2022; Spagnoli et al., 2021), rather than the progression from one stage to another. For

Jesse Michel served as action editor.

Leon T. De Beer https://orcid.org/0000-0001-6900-2192

Leoni van der Vaart and Leon T. De Beer are joint first authors of the article. The data supporting the findings of this study are available from Leon T. De Beer upon reasonable request. The authors acknowledge that these data have not been used in other peer-reviewed publications, nor any publications that are currently under review at any other publisher. Our initial findings were presented at the 21st European Association of Work and Organizational Psychology conference in Poland (2023) under the title: "Investigating the causal dynamics between the core components of the Burnout Assessment Tool with longitudinal mediation models." This was only an oral presentation and included no proceedings. The authors report that there are no personal or financial competing interests to declare. This work was supported by the Internal Funding of KU Leuven C3 Grant (C32/15/003), awarded to Hans De Witte. The authors thank Chiel Buseyne and Jana Wouters for their roles in the collection of the data of Wave 1, and Steffie Desart and Kelly Smet for their roles in the collection of the data at Waves 2 and 3.

Correspondence concerning this article should be addressed to Leon T. De Beer, Department of Psychology, Norwegian University of Science and Technology, Dragvoll Campus, Edvard Bulls veg 1, Trondheim 7491, Norway. Email: leondb@gmail.com

instance, individuals exhibiting high burnout levels initially tend to report similar levels after 6 months (Harju et al., 2022), and experiencing significant exhaustion initially maintains high exhaustion levels 2 months later (Spagnoli et al., 2021). While these findings highlight the temporal persistence of burnout and its facets, they offer little insight into how different components of burnout may interrelate over time or the mechanism order of burnout's progression. Furthermore, prior research (e.g., Golembiewski et al., 1986; Lee & Ashforth, 1993; Leiter & Maslach, 1988; Schaufeli et al., 2011; Taris et al., 2005) studied the dynamics of burnout by employing alternative conceptualizations of the concept also faced limitations: their operationalization of burnout was suboptimal, and their findings were inconclusive. Recent debates have underscored the importance of adopting a process-oriented perspective on burnout (Baillien & Taris, 2025), emphasizing a gradual unfolding rather than an abrupt appearance (Leiter & Maslach, 2024; Taris et al., 2005). Specifically, Baillien and Taris (2025) highlighted the need to better understand how burnout's components interact over time, calling for more longitudinal approaches to clarify which components are most central at different stages of the burnout process.

The Burnout Assessment Tool (BAT) introduced a theoretical model focusing on the internal dynamics of burnout through four components. This model suggests a dynamic process where exhaustion occurs alongside cognitive and emotional impairment (as types of exhaustion), leading to mental distancing. This distancing is then expected to initiate a feedback loop, perpetuating a negative cycle that further deteriorates cognitive and emotional regulation (Schaufeli, De Witte, & Desart, 2020). The challenge is that this model and competing alternatives have yet to be tested against real-world longitudinal data, limiting their validity, applicability to everyday settings, and utility in identifying, preventing, and treating burnout. This lack of empirical testing has implications for theoretical development and practical application.

Therefore, this study aimed to address the limitations of previous longitudinal research on the causal relationships between intra-syndrome burnout components by evaluating a series of models that depict its development across individuals. Specifically, we compared the model proposed by Schaufeli, De Witte, and Desart (2020) with five alternative models to identify the most accurate representation of the causal mechanisms driving the dynamic process of burnout. Our definition of burnout remains based on the theoretical foundation of Schaufeli and Taris (2005), which incorporates energetic as well as motivational aspects and also the cognitive and emotional deficits (impairment)—which were often overlooked in previous conceptualizations or measurements of burnout (Deligkaris et al., 2014; Desart & De Witte, 2019)—allowing for a more nuanced understanding of the syndrome and its development.

By achieving its objectives, the present study enriches our knowledge about burnout in several key areas: it (a) investigates whether there is an internal dynamic between burnout symptoms over time, (b) provides insight into the sequence in which symptoms may arise, and (c) investigates whether mental distancing is a dysfunctional coping strategy that worsens the burnout cycle. Practically, this research offers guidance on recognizing early symptoms of burnout and its progression, facilitating both timely detection and targeted intervention. This targeted approach may not only aid in more effective management of burnout but also inform the development of workplace interventions and therapeutic practices to halt its progression.

Theory and Hypotheses

The Conceptualization of Burnout

Burnout was initially conceptualized as a syndrome with only three dimensions: emotional exhaustion, depersonalization, and diminished personal accomplishment (Maslach & Jackson, 1981). The Maslach Burnout Inventory (MBI), the most utilized assessment, reflects this tripartite definition (Maslach & Jackson, 1986). Over time, as our understanding and measurement of the concept has evolved, 'depersonalization' was renamed and worked into 'cynicism', and 'personal accomplishment' became 'professional efficacy' to better suit various jobs (Schaufeli et al., 1996). Exhaustion and cynicism were recognized as the core elements of burnout, indicating a lack of energy and motivation, respectively, whereas professional efficacy can be considered more of a separate factor or an outcome of burnout (De Beer & Bianchi, 2019; Schaufeli & Taris, 2005). Recent research (see Schaufeli, De Witte, & Desart, 2020; Schaufeli, Desart, & De Witte, 2020) has focused on refining the understanding and measurement of burnout in response to criticisms of its conceptualization (Bianchi & Schonfeld, 2025; Schaufeli & Taris, 2005) and measurement (De Beer & Bianchi, 2019; De Beer, van der Vaart, et al., 2024), as well as the clinical usefulness of existing burnout measures (De Beer, van der Vaart, et al., 2024; Schaufeli, Desart, & De Witte, 2020).

Despite the development of several other instruments [e.g., the Copenhagen Burnout Inventory (Kristensen et al., 2005), the Oldenburg Burnout Inventory (Halbesleben & Demerouti, 2005), and the Shirom-Melamed Burnout Measure (Shirom & Melamed, 2006)], none have successfully addressed all concerns raised (Desart & De Witte, 2019; Schaufeli, Desart, & De Witte, 2020). Consequently, four core dimensions were constituted to more accurately represent burnout based on what we know currently from deductive and inductive approaches (see Schaufeli, Desart, & De Witte, 2020): exhaustion, cognitive impairment, emotional impairment, and mental distance. Exhaustion encompasses both physical and mental fatigue. Cognitive and emotional impairment describes workers' difficulties in managing their cognitive functions and feelings. Mental distance reflects psychological disengagement from work and interpersonal relationships. Exhaustion and impairment reflect the inability to exert effort, while mental distance indicates withdrawal and an unwillingness to do so (Schaufeli, De Witte, & Desart, 2020; Schaufeli, Desart, & De Witte, 2020).

While earlier burnout models emphasized exhaustion and mental distancing (or cynicism) as the central components of burnout (Maslach & Jackson, 1981; Schaufeli & Taris, 2005), the BAT reconceptualizes burnout to include cognitive and emotional impairment as core elements of the syndrome rather than downstream outcomes. This reconceptualization stems from clinical and empirical evidence that difficulties in regulating thoughts and emotions are not merely consequences of burnout but key symptoms that co-occur and interact with exhaustion and distancing. Importantly, these impairments reflect the inability to exert effort (akin to exhaustion), while mental distance reflects withdrawal and an unwillingness to do so. As such, all four components are assessed simultaneously and contribute to a unified burnout syndrome (Schaufeli, Desart, & De Witte, 2020). Our study builds on this framework to explore the temporal unfolding of these component symptoms.

Research endorses the theoretical and empirical advantages of the four- (i.e., BAT) over the three-dimensional (i.e., MBI) conceptualization of burnout (Maunz & Glaser, 2024). This model not only maintains the essence of burnout (namely, inability and withdrawal) but also aligns with its clinical presentations—cognitive and emotional impairment (Schaufeli, Desart, & De Witte, 2020). Moreover, the BAT also allows for a total score that mirrors the concept of burnout as a syndrome (De Beer, Schaufeli, et al., 2024; Schaufeli et al., 2023), demonstrates invariance across countries (De Beer et al., 2020), and exhibits adequate convergent and discriminant validity (e.g., De Beer et al., 2025).

The Internal Dynamics of Burnout Across Individuals

Occupational health practitioners and clinicians utilize the BAT to detect individuals at risk for burnout via burnout complaints, relying on specific cut-off scores for identification (Schaufeli et al., 2023). However, given that burnout evolves with increasing job demands or stressors rather than suddenly appearing (Harju et al., 2022), we expect the core components to display predictive coupling over time, reflecting intra-syndrome dynamics. This sequential development of symptoms, rather than a one-off occurrence, has been supported by several studies using the three-dimensional model of MBI-defined burnout (Golembiewski et al., 1986; Lee & Ashforth, 1993; Leiter & Maslach, 1988; Taris et al., 2005).

What needs clarification in the literature is how these symptoms unfold over time. Several models have been proposed. However, the four-dimensional models still need to be tested, and the results from the three-dimensional model were inconclusive (see Taris et al., 2005 for an overview). With this in mind, we explored several plausible models that investigate the intra-syndrome dynamics of BAT-assessed burnout with its four components. Each model is derived from established theory—primarily conservation of resources (COR) theory (Hobfoll, 1989), the transactional model of stress and coping (Lazarus & Folkman, 1984), and classic stage frameworks of the three-dimensional burnout (e.g., Lee & Ashforth, 1993).

Schaufeli, De Witte, and Desart (2020) proposed a process model of burnout that integrates the COR (Hobfoll, 1989) theory (and its work-specific counterpart, the job demands-resources theory; Bakker & Demerouti, 2024) with the transactional model of stress and coping (Lazarus & Folkman, 1984). According to COR theory's primacy of loss (Hobfoll et al., 2018), burnout begins with exhaustion, as this symptom directly results from sustained exposure to chronic cognitive and emotional demands and represents a salient and impactful loss of energetic resources. Concurrently with this exhaustion, individuals experience significant emotional and cognitive impairments, characterized by a diminished capacity to regulate emotions and thoughts and a subjective sense of losing control. Similarly, the transactional model views exhaustion as arising from stressors perceived to exceed one's coping resources, causing cognitive and emotional dysfunction. As resource depletion progresses, a loss spiral occurs, characterized by progressively reduced capability to regulate thoughts and emotions and a subjective feeling of losing control. To protect their remaining resources (or energy), individuals mentally distance themselves from demanding work tasks and interpersonal interactions (Schaufeli, De Witte, & Desart, 2020). However, this is considered a maladaptive coping strategy per the transactional model (Lazarus & Folkman, 1984). This reasoning aligns with earlier burnout stage models proposed and tested by Lee and Ashforth (1993) and Leiter and Maslach (1988), both of which depict emotional exhaustion as the initial symptom that triggers subsequent cynicism (i.e., mental distancing) and reduced personal accomplishment. Other studies also provided empirical support for this sequential progression of burnout symptoms (e.g., Houkes et al., 2011; Rogala et al., 2016; Toppinen-Tanner et al., 2002).

Following this logic, Schaufeli, De Witte, and Desart (2020) suggested that exhaustion directly impairs the ability to regulate cognitive and emotional processes. As extreme tiredness intensifies this impairment, individuals are increasingly likely to resort to mental distancing as a protective response. Therefore, we hypothesized that:

> *Hypothesis 1:* Exhaustion and cognitive and emotional impairment result in increased mental distancing among employees at subsequent time points.

Alternatively, mental distancing might not directly result from exhaustion and cognitive–emotional impairment simultaneously but rather follow a sequential pathway. Drawing on COR's resource investment principle (Hobfoll, 1989; Hobfoll et al., 2018), individuals experiencing exhaustion must expend remaining cognitive and emotional resources to manage chronic stressors. Over time, however, these resources become increasingly depleted (i.e., a loss cycle), impairing cognitive clarity and emotional regulation capabilities. According to the transactional model (Lazarus & Folkman, 1984), this impairment is perceived as overwhelming and further erodes confidence in one's ability to cope effectively. Consequently, employees may adopt mental distancing as a coping mechanism, attempting to protect against further resource loss. This implies a mediation model where cognitive and emotional impairments transmit the effect of exhaustion onto mental distancing. Therefore, we hypothesized that:

> *Hypothesis 2:* Exhaustion leads to cognitive and emotional impairment, which then leads to mental distancing among employees over time.

In contrast, we also considered a competing model like that of Golembiewski et al. (1986). Reversing the conventional burnout sequence, the first phase is mental distancing, where individuals adopt a detached stance toward chronic work stress as a protective strategy to conserve limited resources (or energy) and avoid emotional and cognitive overload (i.e., the desperation principle in COR). Initially intended to offer protection, this distancing inadvertently damages professional relationships and impairs job performance, triggering negative feedback and increased stress (Golembiewski et al., 1986; Maslach et al., 2001). As the protective effect of distancing erodes under the weight of accumulated stress and isolation (i.e., resource depletion), the individual's ability to cope diminishes, leading to severe exhaustion and emotional and cognitive impairment. Therefore, rather than being in the initial phase of burnout, exhaustion and cognitive–emotional impairment emerge because of prolonged reliance on mental distancing as an ineffective (self-defeating) coping mechanism against workplace stress (i.e., resource loss cycle). Albeit for the three-dimensional conceptualization of burnout, some studies provided empirical support for cynicism/depersonalization (akin to mental distancing) as the primary trigger for the burnout process (Houkes et al., 2011; Padmanabhanunni & Pretorius, 2024). Therefore, we hypothesized that:

Hypothesis 3: Mental distancing at an earlier time point predicts increased exhaustion and cognitive and emotional impairment among employees at subsequent time points.

Alternatively, the burnout sequence may unfold in a slightly different manner. According to COR theory's desperation principle (Hobfoll et al., 2018), mental distancing, initially adopted as a coping strategy, could progressively compromise an individual's cognitive and emotional functioning. As employees disengage from their work, they experience reduced social support, fewer constructive interactions, and deteriorating job performance. This cumulative impairment in cognitive–emotional resources exacerbates their sense of stress and inability to cope (i.e., loss spiral), ultimately manifesting in severe exhaustion. Thus, cognitive and emotional impairment may serve as a mediating mechanism through which initial mental distancing eventually leads to exhaustion. Therefore, we hypothesized that:

Hypothesis 4: Mental distancing at an earlier time point results in cognitive and emotional impairment later, subsequently causing exhaustion among employees at a later time point.

While this mediation model emphasizes the directional pathway from distancing to later exhaustion, it is also important to consider that these processes may not unfold linearly. Rather, they may interact recursively, reinforcing one another over time through a cycle of mutually amplifying effects.

According to COR theory (particularly the corollary of resource loss cycles; Hobfoll et al., 2018), initial exhaustion and cognitive–emotional impairment may trigger a self-reinforcing process in which attempts to conserve resources (e.g., mental distancing) ultimately backfire. Withdrawal or emotion-focused coping strategies (like mental distancing) may offer short-term relief but fail to address underlying demands, thereby exacerbating stress over time. As distancing increases, social and performance resources may diminish (i.e., loss of resource caravans), compounding emotional strain and reinforcing perceptions of helplessness. In other words, the cycle begins with exhaustion, and emotional and cognitive impairments that lead to mental distancing. This distancing further exacerbates exhaustion, and emotional and cognitive impairments, creating a self-perpetuating cycle (Schaufeli, De Witte, & Desart, 2020). This model is consistent with the framework proposed and empirically supported by Taris et al. (2005), which is rooted in the MBI conceptualization of burnout. In their view, depersonalization is a mechanism that traps employees in a negative feedback loop of burnout. Therefore, we hypothesized that:

Hypothesis 5: Exhaustion and cognitive and emotional impairment at an earlier time point trigger mental distance at subsequent time points; conversely, mental distance at an earlier time point also results in exhaustion and cognitive and emotional impairment among employees at subsequent time points.

Finally, it is plausible that the two classic components of burnout, namely exhaustion (a loss of energy) and mental distancing (a loss of motivation; Schaufeli & Taris, 2005), jointly erode employees' capacity for effective cognitive and emotional regulation. According to COR theory's resource' caravan principle', individuals draw on interconnected personal and contextual resources to function effectively. When energy and motivational resources are depleted, the broader caravan weakens, leaving individuals vulnerable to further losses (Hobfoll et al., 2018). In line with the resource loss cycle corollary (Hobfoll et al., 2018), this reduction in regulatory capacity may then amplify both exhaustion and distancing over time, creating a cyclical dynamic. The transactional model (Lazarus & Folkman, 1984) also suggests impaired regulation undermines coping appraisal, triggering further maladaptive responses. This model thus conceptualizes cognitive and emotional impairment as both an outcome of and a contributor to worsening burnout states, closing the feedback loop. Therefore, we hypothesized that:

Hypothesis 6: Exhaustion and mental distancing at an earlier point trigger cognitive and emotional impairments at a subsequent time point, which in turn lead to increased levels of exhaustion and mental distancing among employees later.

Taken together, these six hypotheses (models) reflect diverse but theoretically grounded perspectives on how burnout's components may evolve over time. While each model offers a plausible sequence, supported to varying degrees by existing evidence, the lack of direct empirical testing using the four-dimensional BAT framework leaves the internal dynamics of burnout largely unresolved. By comparing alternative longitudinal pathways grounded in COR theory (Hobfoll, 1989; Hobfoll et al., 2018), the transactional model of coping (Lazarus & Folkman, 1984), and classic burnout stage models, this study acknowledges the complexity and multiplicity of burnout development. Rather than assuming a single developmental path, we adopt an open, comparative approach to determine which sequence (or temporal configuration) most accurately represents how burnout component symptoms may unfold across time.

While external stressors undoubtedly initiate and moderate burnout trajectories, our focus in this study was on understanding the syndrome's internal architecture. More specifically, how components develop self-perpetuating dynamics and predict each other over time. This approach directly responds to current process-oriented perspectives that specifically call for better understanding of how burnout's components interact over time and which components are most central at different stages. This complements etiological models by isolating the symptom-to-symptom pathways within the syndrome itself, as called for in recent process-oriented perspectives (Baillien & Taris, 2025). By investigating these intra-syndrome pathways, we provide important and useful groundwork for future studies that can then examine how external stressors initiate and/or moderate these internal processes.

Method

Participants and Procedure

This study was approved by the Social and Societal Ethics Committee of KU Leuven (reference number: G-2016062027). To test our hypotheses, we used longitudinal data collected at three time points with 6-month intervals (March 2018, September 2018, and March 2019) in Belgium. For this study, we chose 6-month intervals for practical reasons but also because time window could show the coevolution and the long-term effects of the intra-syndrome components more clearly. In the literature, observational designs with 6-month follow-ups have captured the ebb and flow of

employee well-being, demonstrating changes in burnout and its effects on functioning within that timeframe (e.g., Che Mat et al., 2025; de Vries & Bakker, 2022; Travis et al., 2016). Participants were invited to complete an anonymous online survey through two avenues: email invitations disseminated via workplace and professional networks, and a publicly available link shared on social media. The study targeted a broad audience of workers, regardless of their current well-being status. Participants' emails were collected and used for the follow-up measures. Initially, 964 Flemish-speaking full- and part-time employees participated at Time 1 (T1), 649 at Time 2 (T2), and 481 at Time 3 (T3; see Table 1). At the initial time point, the participants had an average age of 40.43 years with 17.78 years of work experience. Across every measurement wave, the valid percentages for gender were consistent but predominantly female: roughly 70%–74% of respondents with known gender identified as female, whereas males accounted for the remaining 26%–30%. However, many participants chose not to disclose their gender. Overall, the sample's heterogeneity is evidenced by a broad range of education levels, sectors, and occupational roles.

For the dropout analysis, see Supplemental Figure S1, Supplemental Tables S1 and S2 located in the Supplemental Materials which is available online (see De Beer, 2025). Worth mentioning is that unit increases in cognitive impairment scores at T2 significantly predict an increased likelihood of dropout at T3 (52% increase in odds).

Measures

Burnout was measured using the 12-item version of the Burnout Assessment Tool (Hadžibajramović et al., 2022). The following instruction was given: "The following statements are related to your work situation and how you experience this situation. Please state how often each statement applies to you." Each of the four components has three indicators. Sample items included "At work, I feel mentally exhausted" (exhaustion), "When I'm working, I have trouble concentrating" (cognitive impairment), "At work, I feel unable to control my emotions" (emotional impairment), and "I'm cynical about what my work means to others" (mental distance). Items were rated on a 5-point scale, ranging from 1 = *never* to 5 = *always*. Therefore, we used a general frequency instruction without a fixed retrospective window, capturing typical symptom levels rather than time-anchored experiences.

Analytic Strategy

We analyzed the data using Mplus 8.11 (Muthén & Muthén, 2024). We used all available data, rather than restricting analyses to only matched participants with complete data. To handle missing data appropriately, we employed the full information maximum likelihood method (see the Supplemental Materials for dropout analyses). The measurement and structural models were specified

Table 1
Characteristics of the Participants

Characteristic	Time 1 (*n*%)	Time 2 (*n*%)	Time 3 (*n*%)
Age (years)	40.43 ± 10.52	40.85 ± 10.78	41.45 ± 10.60
Work experience (years)	17.78 ± 10.73	18.06 ± 10.90	18.60 ± 10.85
Gender			
Male (count)	191 (18.5%)	151 (14.6%)	115 (11.1%)
Female (count)	574 (55.5%)	362 (35.0%)	272 (26.3%)
Missing (count)	263 (25.4%)	522 (50.4%)	648 (62.6%)
Male (valid %)	25.6%	29.4%	29.7%
Female (valid %)	74.4%	70.6%	70.3%
Education			
Primary education	3 (0.3%)	1 (0.1%)	1 (0.1%)
Lower secondary education	24 (2.3%)	10 (1.0%)	14 (1.4%)
Higher secondary education	122 (11.8%)	80 (7.7%)	50 (4.8%)
Nonuniversity higher education	449 (43.3%)	322 (31.1%)	230 (22.2%)
University higher education	345 (33.3%)	224 (21.6%)	179 (17.3%)
PhD	21 (2.0%)	12 (1.2%)	7 (0.7%)
Missing	71 (6.9%)	386 (37.3%)	554 (53.5%)
Sector			
Private	588 (56.8%)	390 (37.7%)	280 (27.1%)
Government	307 (29.7%)	219 (21.2%)	171 (16.5%)
Self-employed and independent	69 (6.7%)	40 (3.9%)	30 (2.9%)
Missing	71 (6.9%)	386 (37.3%)	554 (53.5%)
Occupation			
Unskilled worker	14 (1.4%)	8 (0.8%)	8 (0.8%)
Skilled worker	13 (1.3%)	10 (1.0%)	8 (0.8%)
Executive or administrative assistant	140 (13.5%)	92 (8.9%)	66 (6.4%)
Mid-level white-collar or white-collar supervisor	403 (38.9%)	287 (27.7%)	212 (20.5%)
Senior, lower, or middle management	238 (23.0%)	157 (15.2%)	121 (11.7%)
Higher management or board	87 (8.4%)	55 (5.3%)	36 (3.5%)
Missing	140 (13.5%)	426 (41.2%)	584 (56.4%)

Note. Total unique participants: $n = 1{,}035$. Dropout across waves leads to increasing missing data over time, and a limited number of participants only entered the study at later waves. Table reports all available data per time point, not limited to completers. Values in parentheses are percentages. Unless stated otherwise, percentages are calculated against the total unique cohort ($n = 1{,}035$) at each time point. 'Valid %' rows use the number of nonmissing responses at that time point as the denominator. Age and work experience are mean ±standard deviations.

according to our hypotheses. The data set was used in a wide format (not multigroup), and we specified the measurement models with correlated residuals (uniquenesses) of each factor's item indicators in sequence over time. Model fit was judged based on the following criteria: comparative fit index (CFI; >.90), Tucker–Lewis index (TLI; >.90), root-mean-square error of approximation (RMSEA; <.08), and standardized root-mean-square residual (SRMR; <.08; Wang & Wang, 2020).

Measurement invariance was assessed with increasingly constrained longitudinal models testing for configural (equal factor structures), weak (factor loading patterns), strong (equal intercepts), and strict (equal residuals) invariance (Cheung & Rensvold, 2002). We considered a type of invariance as supported when ΔCFI did not deteriorate by .01 or more and ΔRMSEA did not increase by .015 or more between models (Chen, 2007; Cheung & Rensvold, 2002).

After establishing measurement invariance, our approach included testing a series of structural models in line with the stated hypotheses in this study. We deliberately focused on isolating how components influence each other within the syndrome architecture, without conditioning on specific time-varying stressors. This approach allowed us to identify any dynamics that characterizes intra-syndrome burnout development, providing foundational evidence for how the syndrome unfolds once initiated. Relationships were specified within (as correlations) and across waves (longitudinally with structural paths). First, we tested a baseline cross-lagged panel model (CLPM; Model 0) with only autoregressive paths (i.e., the stability model). This model formed the basis of all subsequent models. Second (see Table 2), we added paths from exhaustion (T1/T2), cognitive (T1/T2), and emotional (T1/T2) impairment to mental distance (T2/T3; Model 1). Third, we added paths from exhaustion (T1) to cognitive (T2) and emotional impairment (T2). We also specified paths from cognitive (T2) and emotional impairment (T2) to mental distance (T3; Model 2). Fourth, we tested a model that was the opposite of Model 2. In Model 3, we specified paths from mental distance (T1/T2) to exhaustion (T2/T3) and cognitive and emotional (T2/T3) impairment. Model 4 was the opposite of Model 2 and contained paths from mental distance (T1) to cognitive and emotional (T2) impairment and from cognitive and emotional (T2) impairment to exhaustion (T3). Finally, we tested two CLPMs like Models 1 and 2 but added reverse causation paths. In Model 5, the additional paths went from mental distance (T1/T2) to exhaustion and cognitive (T2/T3) and emotional impairment (T2/T3; Model 5). In Model 6, the additional paths went from mental distance (T1) to cognitive (T2) and emotional impairment (T2) to exhaustion (T3; Model 6).

When the models fit equally well, we opted for a more parsimonious model. Given that model complexity influences fit indices, we also considered the sample-size-adjusted Bayesian information criterion (SSABIC), with a reduction in the SSABIC-value of 2–6 indicating positive evidence in favor of the model, 6–10 indicating strong evidence, and more than 10 indicating very strong evidence favoring the model with a lower value (Wang & Wang, 2020). We also calculated a heuristic Bayes factor to further interpret the difference between the two best-fitting models. This Bayes factor can be interpreted similarly to an approximate evidence ratio established by calculating the difference between the SSABIC values, divided by two and then transformed using the exponential function (see Kass & Raftery, 1995). This provided a pragmatic gauge of relative model fit, though it should not be considered a formal Bayes factor in the strict sense.

Furthermore, we performed proper mediation tests as the variables were separated in time with prior levels of the variables controlled for. Specifically, we tested all the indirect effects for each proposed model by bootstrapping the data 10,000 times. Here, we focused on the standardized estimate of the indirect effect, including the associated 95% lower and upper confidence intervals (CIs), with both the lower and upper intervals of the indirect estimate having to retain the same sign to be considered a meaningful indirect effect (Hayes, 2022).

Results

Correlation Matrix and Omega Coefficients

The correlations between factors are reported from the full invariance model ($\chi^2(562) = 1{,}134.233$; CFI = .967; TLI = .962; RMSEA = .031 [.029, .034]), along with McDonald's omega coefficients and presented in Table 3. All BAT subscales had acceptable reliability at all time points, with coefficients ranging from .797 to .890. The factors showed strong intercorrelations (as expected for a syndrome), indicating a close relationship between exhaustion, mental distance, cognitive impairment, and emotional impairment at each time point. Exhaustion tended to have the strongest correlations with other factors at each time point, followed by mental distance, with emotional impairment having somewhat stronger correlations than cognitive impairment in most cases. Across the different time points, there were strong correlations, particularly those concerning the same factors, indicating stability over time. Beyond the strong correlations over time, the patterns suggested that exhaustion and mental distance have consistently strong relationships with each other and with emotional impairment over time. Cognitive impairment showed relatively weaker correlations but maintains consistent relationships, particularly with emotional impairment. These patterns highlight the interrelated nature of these burnout complaints, suggesting that changes in one factor are likely to be accompanied by changes in others.

Longitudinal Invariance of the Measurement Model Over Time

As can be seen from Table 4, full measurement (strict) invariance was found over time. This indicates that the factor structure (configural), loading patterns (weak), item intercepts (strong) and item uniquenesses (strict) could be considered equivalent over time. Scalar and strict invariance allows for meaningful comparisons of means over time (see Supplemental Figure S2).

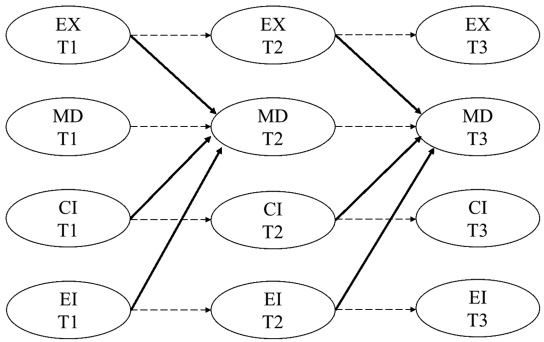
Hypothesized Model Results

We tested six competing structural models, each corresponding to a distinct theoretical hypothesis. All models fulfilled the established cutoff criteria and exhibited overlapping confidence intervals for their RMSEA 90% confidence interval values, demonstrating both adequate and similar fit to the data (see Table 5). However, when comparing the models based on their BIC and SSABIC values, Model 2 (representing Hypothesis 2) emerged as the best choice, showing very strong (ΔBIC = −25.41) and strong evidence (ΔSSABIC = −6.36) in its favor when compared to the next best choice (i.e., Model 6). Additionally, the heuristic Bayes factor we calculated showed an approximate evidence ratio indicating that Model 2 was 24 times more likely compared to Model 6, given these data.

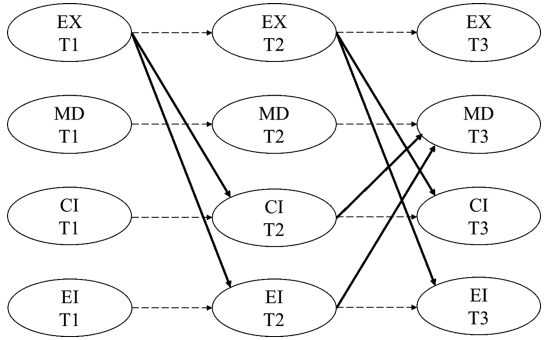
Table 2

Conceptual Representation of the Hypotheses Expressed as Models

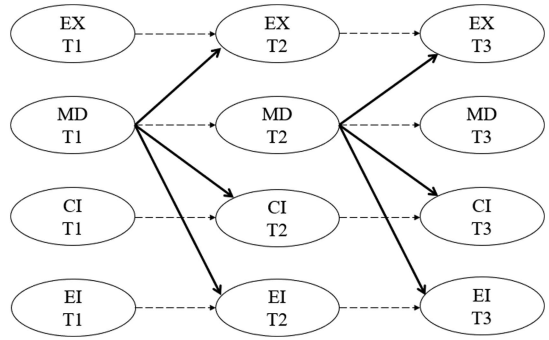
Hypothesis 1, *Model 1 (M1)*



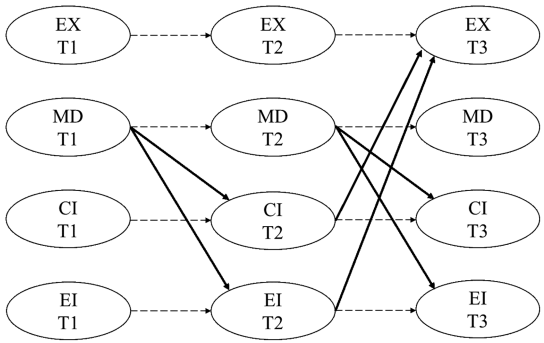
Hypothesis 2, *Model 2 (M2)*



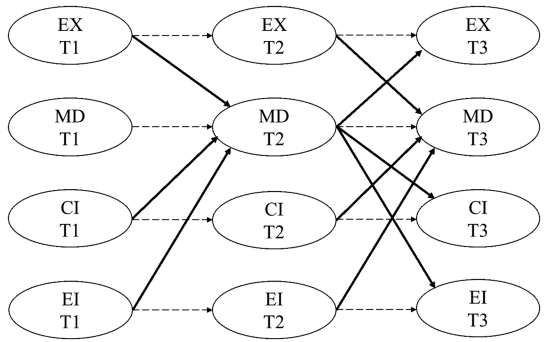
Hypothesis 3, *Model 3 (M3)*



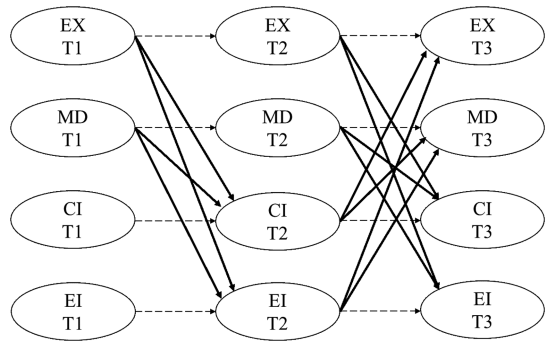
Hypothesis 4, *Model 4 (M4)*



Hypothesis 5, *Model 5 (M5)*



Hypothesis 6, *Model 6 (M6)*



Note. The thin dashed arrows are control paths; the bolded arrows are the hypothesized paths across time; the factors are correlated, but these are not included for simplicity. EX = exhaustion; MD = mental distance; CI = cognitive impairment; EI = emotional impairment.

Table 3
Correlations and Omega Coefficients

Factor	1	2	3	4	5	6	7	8	9	10	11	12
1. EX_T1	**.841**											
2. MD_T1	.772	**.866**										
3. CI_T1	.710	.674	**.797**									
4. EI_T1	.726	.657	.598	**.890**								
5. EX_T2	.745	.582	.564	.594	**.840**							
6. MD_T2	.628	.742	.539	.500	.808	**.852**						
7. CI_T2	.556	.495	.693	.405	.711	.626	**.807**					
8. EI_T2	.658	.522	.483	.735	.787	.745	.589	**.874**				
9. EX_T3	.752	.563	.536	.564	.800	.644	.586	.631	**.830**			
10. MD_T3	.539	.658	.460	.472	.618	.715	.499	.551	.796	**.863**		
11. CI_T3	.512	.418	.602	.431	.545	.461	.676	.494	.688	.654	**.808**	
12. EI_T3	.533	.484	.415	.648	.595	.557	.386	.712	.753	.726	.570	**.878**

Note. Omega coefficients on the diagonal in bold text. EX = exhaustion; MD = mental distance; CI = cognitive impairment; EI = emotional impairment; T1 = Time 1; T2 = Time 2; T3 = Time 3.

Figure 1 illustrates Model 2, and the remaining models are illustrated in the Supplemental Figures S3–S8. The Supplemental Materials also include standardized beta coefficients for all direct and indirect paths specified in the various models (see Supplemental Tables S3–S15). Figure 1 shows that over time, exhaustion (T1) resulted in both cognitive ($\beta = .275$, $p < .001$) and emotional ($\beta = .386$, $p < .001$) impairment at T2. While cognitive impairment (T2) led to mental distance (T3; $\beta = .126$, $p < .001$), emotional impairment (T2) did not significantly contribute to mental distance (T3; $\beta = .07$, $p = .180$). All significant direct relationships could be described as having large effect sizes (see Orth et al., 2024). The data also showed that the dimensions of burnout, particularly exhaustion and mental distance, demonstrated more stability over time. In partial support of Hypothesis 2, and contrary to Hypotheses 1 and 3–6, the results suggest that burnout initiates with exhaustion, which then leads to impairment of both cognitive and emotional functions. However, then only cognitive impairment results in mental distancing according to the data.

Additional evidence for this sequence is provided by the indirect effect, which shows that exhaustion (T1) affects mental distance (T3) via cognitive impairment as mediator (T2; $\beta = .035$, 95% CI [.010, .076]) over time. In other words, evidence supports the notion that cognitive impairment mediates the relationship between exhaustion and mental distancing over time. In contrast, the mediation path through emotional impairment was not significant ($\beta = .027$, 95% CI [−.012, .072]).

It is important to note, however, that not all directional effects were consistent across the waves. For example, although exhaustion (T2) significantly predicted cognitive impairment (T3; $\beta = .140$, $p = .017$), its relationship with emotional impairment (T3) was marginally nonsignificant ($\beta = .117$, $p = .069$; 95% CI [−.007, .247]). This indicates that while the T1 → T2 paths support the hypothesized sequence, the T2 → T3 paths show a decline in strength or significance for some components. Therefore, while the sequence represented in Model 2 provides the best-fitting temporal configuration among those tested, it should be interpreted as a dominant—but not uniformly stable—pattern.

The results also indicated that exhaustion at T2 mediates the relationship between exhaustion at T1 and exhaustion at T3 ($\beta = .687$, 95% CI [.601, .760]). This mediation pattern was also consistent across other stability paths of the burnout components: cognitive impairment ($\beta = .308$, 95% CI [.208, .415]), emotional impairment ($\beta = .298$, 95% CI [.210, .392]), and mental distance ($\beta = .475$, 95% CI [.374, .571]).

Discussion

This study explored the intra-syndrome dynamics of burnout following the updated conceptualization of Schaufeli, Desart, and De Witte (2020). Our findings indicate that burnout develops progressively and originates from exhaustion. This initial exhaustion leads to cognitive and emotional impairment, with cognitive impairment subsequently resulting in further mental distancing from work and interpersonal interactions, whereas emotional impairment does not lead to eventual mental distancing and appears only to be a consequence of initial exhaustion. This makes sense as a primary manifestation of burnout has previously been described as emotional exhaustion (Maslach et al., 2001). Furthermore, we found limited evidence that mental distancing contributes to a feedback loop that

Table 4
Longitudinal Measurement Invariance of the Measurement Model

Model	χ^2	*df*	CFI	TLI	RMSEA [90% CI]	CM	$\Delta\chi^2$	ΔCFI	ΔTLI	ΔRMSEA
1. Configural	1,011.17	506	.970	.963	.031 [.028, .034]					
2. Weak	1,036.17	522	.970	.964	.031 [.028, .034]	1	+25.00*	.000	+.001	.000
3. Strong	1,067.75	538	.969	.964	.031 [.028, .034]	2	+31.58*	−.001	.000	.000
4. Strict	1,134.23	562	.967	.962	.031 [.029, .034]	3	+66.48*	−.002	−.002	.000

Note. χ^2 = chi-square; *df* = degrees of freedom; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; CI = confidence interval; CM = comparison model.
* $p < .01$.

Table 5
Fit Statistics for the Competing Structural Models

Model	χ^2	*df*	CFI	TLI	RMSEA	90% CI	AIC	BIC	SSABIC	Rank
M0	1,937.54	608	.922	.919	.046	[.044, .048]	54,874.85	55,339.42	55,040.86	
M1	1,905.05	602	.924	.920	.046	[.043, .048]	54,854.36	55,348.58	55,030.97	6
M2	1,847.94	602	.927	.924	.045	[.042, .047]	54,797.25	55,291.47	54,973.85	1
M3	1,887.35	602	.925	.921	.045	[.043, .048]	54,836.66	55,330.88	55,013.26	3
M4	1,899.34	602	.924	.921	.046	[.043, [.048]	54,848.65	55,342.87	55,025.25	5
M5	1,887.02	599	.925	.921	.046	[.043, .048]	54,842.33	55,351.37	55,024.23	4
M6	1,831.69	596	.928	.924	.042	[.042, .047]	54,793.01	55,316.88	54,980.21	2

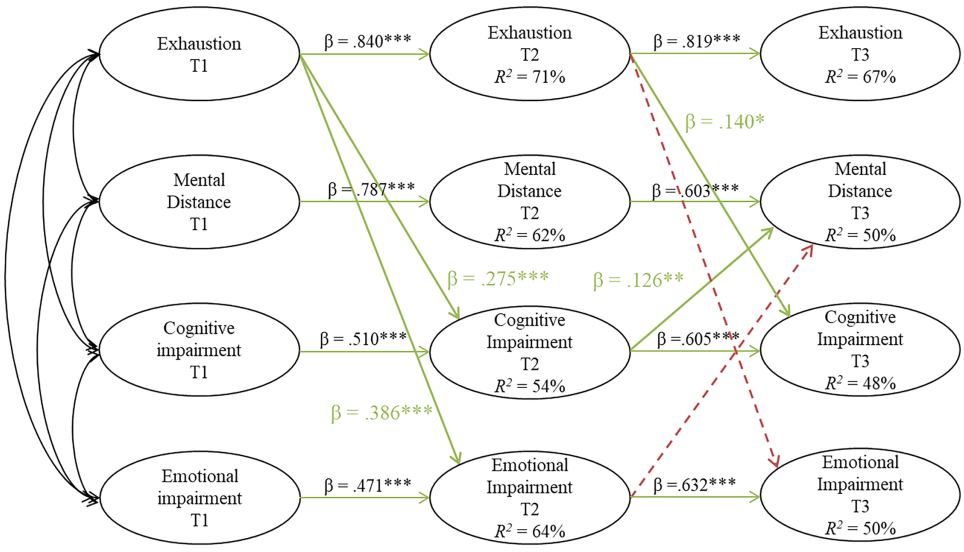
Note. M0 = stability; M1 = exhaustion + impairment → distance; M2 = exhaustion → impairment → distance; M3 = distance → exhaustion + impairment; M4 = distance → impairment → exhaustion; M5 = exhaustion + impairment ↔ distance; M6 = exhaustion + distance → impairment → exhaustion + distance; χ^2 = chi-square; *df* = degrees of freedom; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; CI = confidence interval; AIC = Akaike information criterion; BIC = Bayesian information criterion; SSABIC = sample-size adjusted Bayesian information criterion.

perpetuates the cycle of exhaustion and impairment. This pattern aligns closely with the primacy of resource loss (Hobfoll et al., 2018), where energetic depletion (exhaustion) initiates a loss spiral that undermines self-regulation. When key personal resources are eroded, individuals retreat to conserve what remains, a coping strategy that aligns with the transactional model (Lazarus & Folkman, 1984). The finding that cognitive, but not emotional, impairment predicts future mental distancing suggests that mental distancing may be a cognitively regulated coping mechanism (i.e., a motivated choice to withdraw), rather than an affect-driven reaction.

Theoretical Implications

This study makes four significant contributions to the literature on burnout. First, unlike previous longitudinal studies (see Harju et al., 2022; Maunz & Glaser, 2024), which treat burnout as a set of co-occurring symptoms with distinct causes and outcomes, this study demonstrates that these symptoms also follow an internal dynamic among themselves. Indeed, at each point in time, individuals experience certain levels of every symptom. However, in addition to each component's importance in its own future levels, other symptoms also play a role in forecasting additional changes across the broader symptom set. While earlier research (Golembiewski et al., 1986; Lee & Ashforth, 1993; Leiter & Maslach, 1988; Taris et al., 2005) has hinted at such dynamics, it did not fully capture the complexity of the syndrome. The updated conceptualization of burnout we used offers a more comprehensive perspective, encompassing not only the progression of exhaustion but also the associated cognitive and emotional impairments advocated by burnout researchers (Deligkaris et al., 2014; Schaufeli & Taris, 2005) and observed by practitioners who work with burnout more clinically (Schaufeli, Desart, & De Witte, 2020).

Figure 1
Structural Paths for the Selected Structural Model (Model 2)



Note. β = standardized beta coefficient; R^2 = variance explained in the dependent variable; green paths represent significant paths and dashed red paths represent nonsignificant results; all significant beta coefficients are reported. See the online article for the color version of this figure.
* $p < .05$. ** $p < .01$. *** $p < .001$.

The second key contribution emphasizes the critical role of cognitive and emotional impairment in burnout, which has been neglected in the most widely used conceptualization of burnout. We found that employees who experience exhaustion will struggle to manage future emotional processes and continue to struggle with cognitive processes over time, supporting qualitative accounts of cognitive and emotional incapacities resulting from exhaustion (Schaufeli, Desart, & De Witte, 2020). Importantly, our results demonstrate that cognitive impairment, because of exhaustion, specifically leads to mental distancing from work. This supports the idea that burnout begins with exhaustion (Lee & Ashforth, 1993; Leiter & Maslach, 1988), discounting earlier claims that mental distancing can be the initiator of the burnout process (e.g., Golembiewski et al., 1986). We extend previous research by illustrating the important mediating mechanism—cognitive impairment—through which exhaustion leads to mental distancing, a previously unclear link due to the inadequate conceptualization and measurement of burnout. This is theoretically consistent with COR's resource investment principle (Hobfoll et al., 2018), which holds that individuals must expend resources to manage ongoing demands. In doing so, they may gradually deplete their remaining self-regulatory capacity, leading to compromised cognitive functioning. Mental distancing can then be understood as a final cognitive act of conservation—an intentional strategy to avoid further depletion once one's capacity to cope is critically eroded.

While this pathway was the strongest and most theoretically coherent among the six tested models, we also acknowledge that not all hypothesized paths were statistically significant across time intervals. For instance, exhaustion significantly predicted emotional impairment at T2 but not at T3. Similarly, emotional impairment did not predict mental distancing at either interval. These inconsistencies suggest that although Model 2 reflects the best-fitting sequence, the process of burnout development may not unfold uniformly across time. Rather, it represents a dominant yet potentially context-sensitive pattern, subject to variation based on individual and situational factors.

An interesting finding connected to this was revealed in the dropout analysis, a one-unit increase in cognitive impairment at T2 increased the chances of being a dropout at T3 by 52%. A potential explanation is that completing questionnaires can be cognitively demanding, leading those with increased cognitive impairment to avoid them in order to conserve resources. This highlights the key role of cognitive impairment, which has been neglected (Deligkaris et al., 2014).

Our findings also contribute to understanding the impact of stress-related resource depletion. We showed that exhaustion leads to consistent cognitive dysfunction but also to emotional dysfunction (albeit initially). Presumably, this exhaustion is due to increasing stressors or an imbalance between stressors and (coping) resources (Bes et al., 2023; Demerouti et al., 2001; Hobfoll, 1989; Lazarus & Folkman, 1984). However, we found that only the resulting cognitive impairment triggered mental distancing as a potential defensive strategy for self-preservation. This may suggest that cognitive impairment and mental distance both operate at the cognitive level; for this reason, only cognitive impairment leads to mental distancing. In contrast, emotional impairment operates at an affective level and may prompt coping strategies, such as seeking social support or expressing emotions, which manage emotional states without requiring mental distancing. Future research should explore these different coping responses and investigate potential moderators (e.g., personality and personal resources) that may moderate the impact of emotional impairment on mental distancing. These moderators may also reduce the impact of emotional exhaustion on emotional impairment, explaining the nonsignificant effect over time. Another interesting insight is our mediation findings, which show that emotional impairment (T2) mediated between earlier exhaustion (T1) and later emotional impairment (T3). This indicates that by addressing exhaustion early, it may be possible to disrupt the pathway from initial exhaustion to later emotional impairment.

Our third contribution is the more nuanced evidence of the sequence of burnout development. We illustrated that mental distancing may not exacerbate the burnout cycle, as previously thought. Model 5, which specifically tested the feedback loop proposed by Schaufeli, De Witte, and Desart (2020), was not the best-fitting model for the data. Additionally, the second-ranked model, which proposed a reciprocal relationship, indicated that the paths from mental distancing to cognitive and emotional impairments were nonsignificant. This suggests that mental distancing may not necessarily increase impairment, especially when exhaustion is initially present. This finding challenges the traditional view of mental distancing as being a purely harmful coping strategy (Taris et al., 2005) and highlights the complexity of burnout dynamics. 'Mild' cynicism might be an effective coping strategy (e.g., dark humor or displaying 'detached concern' in helping professions), whereas 'strong' cynicism is counterproductive (e.g., depersonalizing people or social withdrawal). Recent research by De Beer et al. (2025) indicates that levels of mental distancing are similar between individuals diagnosed with depression and those experiencing burnout but are higher in those with job strain. These findings suggest that mental distancing may represent a final stage of burnout development, in line with Schaufeli and Taris (2005) who indicate burnout as both inability and withdrawal.

Finally, our findings have significant implications for the diagnostic evaluation of burnout. Concerns regarding the lack of diagnostic criteria for burnout have been raised in the literature (e.g., Bianchi & Schonfeld, 2025). Developing such criteria would require several key steps, including a detailed description of progression (American Psychiatric Association, 2013; Robins & Guze, 1970). Our study advances burnout research by taking a first step in elucidating its internal dynamics and progression, offering insights that support timely intervention for burnout complaints and informs future discussions on potential diagnostic criteria.

Practical Implications

Understanding the sequence of burnout development is crucial for early symptom recognition and timely, targeted interventions, which can prevent more severe outcomes, such as cognitive and emotional impairment or mental distancing across the workforce. Since burnout is typically initiated with exhaustion, early detection measures are essential, such as regular assessments of employees' exhaustion levels using valid instruments (De Beer & Schaufeli, 2025). Preventive efforts should focus on identifying and mitigating factors contributing to exhaustion by fostering work–life balance, ensuring manageable workloads, offering flexible work arrangements, ensuring adequate workplace social support, and encouraging regular opportunities for recovery both during and after work. Once exhaustion is detected, intervention efforts should concentrate on managing fatigue (see Kelloway et al., 2023). A recent meta-analysis by Bes et al. (2023)

showed that interventions to reduce workload are particularly effective in lowering exhaustion levels. Effective workload interventions include increasing resources and reducing excessive demands to balance job stressors and support. Combined interventions, integrating both organizational and individual strategies, proved more effective than organizational interventions alone. Participatory approaches also reduced exhaustion by enhancing control and motivation.

Limitations and Directions for Future Research

Several limitations should be kept in mind when interpreting the results of this study. The first limitation revolves around the number and interval between time points. Burnout is typically studied over periods of 6 months to 1 year (Mäkikangas et al., 2016) and appears stable for up to 3 years (Hakanen & Schaufeli, 2012; Schaufeli et al., 2011), which makes it challenging to identify predictors. Therefore, it is recommended to have more data collection points and/or longer follow-up periods, ideally extending beyond 4 years (see Mäkikangas et al., 2011). Furthermore, cross-lagged parameters depend on the measurement interval and construct time scale. Our 6-month spacing fits burnout's stability, but shorter intervals might capture faster feedback for some pathways (e.g., impairment → exhaustion). Therefore, future work could also sample at shorter intervals or use continuous-time structural equation modeling to reexpress our dynamics at alternative lags. This temporal sampling issue is further complicated by the measurement approach itself. Because the BAT items use a general-frequency format (not time-anchored to a specific past-X-days window), they prioritize typical symptom levels over brief fluctuations immediately preceding a wave. Therefore, pairing BAT with time-anchored items or short measurement bursts could capture both near-term volatility and month-scale progression.

Second, our study's primary aim was to investigate how the components of burnout predict each other across individuals over time with a CLPM framework, which aligns with between-person analysis. This approach allowed us to identify general patterns and individual differences in burnout progression, thus providing valuable insights for organizational interventions. Although a within-person model could offer complementary insights, it would not fully capture the between-person variability central to our hypotheses. Future research should incorporate a within-person perspective to provide a more comprehensive understanding of burnout dynamics. However, even though Rohrer and Murayama (2023) hold that the distinction between CLPM and random intercept-CLPM can be informative, it does not play a decisive role in causal inference. The CLPM framework has its own set of limitations and has received criticism over the years (e.g., Lucas, 2023). Therefore, our findings should still be interpreted with the necessary caution and as a first step into the intra-syndrome dynamics of BAT-assessed burnout.

Third, adding additional waves of data (e.g., adding a fourth wave) would have been more optimal for testing the feedback loop for mental distance as an extension of our best-fitting model. As the sample was a general sample of employees in Belgium, it is also important to reflect on the contextual information (e.g., job types) that was not considered and how this may have affected the results. For example, how might the dynamics of burnout occur in a health care context? Perhaps the mediating mechanism in this context might be emotional impairment and not as much cognitive impairment, or both. Consequently, future research should consider the dynamics of burnout development in specific occupational contexts to determine whether our results can be replicated.

Fourth, the development of burnout may be shaped by contextual and individual-level moderators. While our current model focused on directional relationships among BAT components, it is possible that factors such as job demands and resources, work modality (e.g., remote or shift work), and individual characteristics (e.g., age, gender, or coping style) may influence both the strength and nature of the observed paths. For example, chronic sleep disruption in shift-based roles may disproportionately impair cognitive functioning, whereas socially isolating remote work conditions might accelerate mental distancing. Additionally, valid gender disclosure was predominantly female with many missing gender options making the actual sample composition uncertain. Future studies should test such moderators to explore how burnout develops across different occupational settings and demographic groups. Additionally, although our primary aim was to isolate the internal symptom dynamics of burnout, we did not control for the presence of ongoing work stressors or major life events during the 12-month period—factors that may have contributed to fluctuations in symptoms. External stressors can undoubtedly shape symptom trajectories but arbitrarily selecting stressors can also be counterproductive (e.g., Glymour et al., 2019; Schisterman et al., 2009). Future work explicitly designed for etiology should incorporate time-varying demands or events to provide a more comprehensive understanding of how internal burnout processes unfold under different external conditions. Examples of such events are proposed by Maslach and Leiter (2008): workload, control, reward, community, fairness, and values.

Finally, in some instances, the smaller cross-lagged effects may result from differential development trajectories within the sample. Building on Maslach and Leiter (2008) and others' (Mäkikangas et al., 2021) typologies, we recommend that future research take a person-centered approach to identify different subgroups (profiles) that could explain the intra-individual variety in the development of burnout. We also recommend the inclusion of antecedents (e.g., job demands and resources) to identify how they relate to these burnout components. For example, they may be directly related to exhaustion but indirectly related to impairment.

Conclusion

Guided by COR, the transactional model of stress and coping, and classic burnout progression frameworks, this study evaluated six competing models to improve our understanding of how burnout complaints may unfold over time. Among these, the model positing that exhaustion leads to emotional impairment and (consistent) cognitive impairment and that cognitive impairment leads to mental distancing, received the strongest empirical support. Importantly, cognitive impairment emerged as a key mechanism linking energetic depletion (exhaustion) to motivational withdrawal (mental distancing), aligning with the conceptualization of burnout as a self-regulatory failure driven by resource loss. However, our findings also revealed inconsistencies across time points. For instance, emotional impairment did not consistently contribute to mental distancing, and some lagged effects (e.g., from exhaustion to emotional impairment) weakened over time. These results suggest that while the sequence tested in Model 2 may reflect a dominant trajectory, burnout may not progress in a uniform or linear fashion across all individuals or contexts. Taken together this provides initial, yet theoretically

grounded support, for a processual view of burnout development. The models illustrate a dynamic interplay between exhaustion, impairment, and mental distancing—anchored in resource-based theories—but also underscore the need for further research to explore variability in these pathways across time, occupations, and individual characteristics.

References

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

Baillien, E., & Taris, T. (2025). Is burnout the toll of toil, or masked depression? Future directions in burnout research [Editorial]. *Work and Stress*, *39*(2), 111–115. https://doi.org/10.1080/02678373.2025.2492911

Bakker, A. B., & Demerouti, E. (2024). Job demands-resources theory: Frequently asked questions. *Journal of Occupational Health Psychology*, *29*(3), 188–200. https://doi.org/10.1037/ocp0000376

Bes, I., Shoman, Y., Al-Gobari, M., Rousson, V., & Guseva Canu, I. (2023). Organizational interventions and occupational burnout: A meta-analysis with focus on exhaustion. *International Archives of Occupational and Environmental Health*, *96*(9), 1211–1223. https://doi.org/10.1007/s00420-023-02009-z

Bianchi, R., & Schonfeld, I. S. (2025). Beliefs about burnout. *Work & Stress*, *39*(2), 116–134. https://doi.org/10.1080/02678373.2024.2364590

Che Mat, N., Idris, M. A., & Dormann, C. (2025). Exploring time lags between job stressors and burnout in cross-lagged panel and diary studies: A systematic literature review. *International Journal of Stress Management*. Advance online publication. https://doi.org/10.1037/str0000369

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

De Beer, L. T. (2025, October 7). *The intra-syndrome dynamics of burnout*. https://doi.org/10.17605/OSF.IO/YMAHS

De Beer, L. T., & Bianchi, R. (2019). Confirmatory factor analysis of the Maslach Burnout Inventory: A Bayesian structural equation modeling approach. *European Journal of Psychological Assessment*, *35*(2), 217–224. https://doi.org/10.1027/1015-5759/a000392

De Beer, L. T., Christensen, M., Sørengaard, T. A., Innstrand, S. T., & Schaufeli, W. B. (2024). The psychometric properties of the Burnout Assessment Tool in Norway: A thorough investigation into construct-relevant multidimensionality. *Scandinavian Journal of Psychology*, *65*(3), 479–489. https://doi.org/10.1111/sjop.12996

De Beer, L. T., Hakanen, J. J., Schaufeli, W. B., De Witte, H., Glaser, J., Kaltiainen, J., Seubert, C., & Morin, A. J. S. (2025). The burnout-depression conundrum: Investigating construct-relevant multidimensionality across four countries and four patient samples. *Psychology & Health*, *40*(8), 1358–1385. https://doi.org/10.1080/08870446.2024.2321358

De Beer, L. T., & Schaufeli, W. B. (2025). Casting a wider net: On the utilitarian nature of burnout assessment in the workplace. *Evaluation & the Health Professions*, *48*(2), 238–241. https://doi.org/10.1177/01632787241259032

De Beer, L. T., Schaufeli, W. B., & Bakker, A. B. (2022). Investigating the validity of the short form Burnout Assessment Tool: A job demands-resources approach. *African Journal of Psychological Assessment*, *4*, Article a95. https://doi.org/10.4102/ajopa.v4i0.95

De Beer, L. T., Schaufeli, W. B., De Witte, H., Hakanen, J. J., Kaltiainen, J., Glaser, J., Seubert, C., Shimazu, A., Bosak, J., Procházka, J., Kajzar, A., & Christensen, M. (2024). Revisiting a global burnout score with the Burnout Assessment Tool (BAT) across nine country samples. *European Journal of Psychological Assessment*, Article 1015-5759/a000839. https://doi.org/10.1027/1015-5759/a000839

De Beer, L. T., Schaufeli, W. B., De Witte, H., Hakanen, J. J., Shimazu, A., Glaser, J., Seubert, C., Bosak, J., Sinval, J., & Rudnev, M. (2020). Measurement invariance of the Burnout Assessment Tool (BAT) across seven cross-national representative samples. *International Journal of Environmental Research and Public Health*, *17*(15), Article 5604. https://doi.org/10.3390/ijerph17155604

De Beer, L. T., van der Vaart, L., Escaffi-Schwarz, M., De Witte, H., & Schaufeli, W. B. (2024). Maslach Burnout Inventory—General survey: A systematic review and meta-analysis of measurement properties. *European Journal of Psychological Assessment*, *40*(5), 360–375. https://doi.org/10.1027/1015-5759/a000797

de Vries, J. D., & Bakker, A. B. (2022). The physical activity paradox: A longitudinal study of the implications for burnout. *International Archives of Occupational and Environmental Health*, *95*(5), 965–979. https://doi.org/10.1007/s00420-021-01759-y

Deligkaris, P., Panagopoulou, E., Montgomery, A. J., & Masoura, E. (2014). Job burnout and cognitive functioning: A systematic review. *Work & Stress*, *28*(2), 107–123.

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

Desart, S., & De Witte, H. (2019). Burnout 2.0—A new look at the conceptualisation of burnout. In T. Taris, M. Peeters, & H. De Witte (Eds.), *The fun and frustration of modern working life* (pp. 140–152). Pelckmans Pro.

Glymour, C., Zhang, K., & Spirtes, P. (2019). Review of causal discovery methods based on graphical models. *Frontiers in Genetics*, *10*, Article 524. https://doi.org/10.3389/fgene.2019.00524

Golembiewski, R. T., Munzenrider, R. F., & Stevenson, J. G. (1986). *Phases of burnout: Developments in concepts and applications*. Praeger.

Hadžibajramović, E., Schaufeli, W., & De Witte, H. (2022). Shortening of the Burnout Assessment Tool (BAT)-from 23 to 12 items using content and Rasch analysis. *BMC Public Health*, *22*(1), Article 560. https://doi.org/10.1186/s12889-022-12946-y

Hakanen, J. J., & Schaufeli, W. B. (2012). Do burnout and work engagement predict depressive symptoms and life satisfaction? A three-wave seven-year prospective study. *Journal of Affective Disorders*, *141*(2–3), 415–424. https://doi.org/10.1016/j.jad.2012.02.043

Halbesleben, J. R., & Demerouti, E. (2005). The construct validity of an alternative measure of burnout: Investigating the English translation of the Oldenburg Burnout Inventory. *Work & Stress*, *19*(3), 208–220. https://doi.org/10.1080/02678370500340728

Harju, L. K., Van Hootegem, A., & De Witte, H. (2022). Bored or burning out? Reciprocal effects between job stressors, boredom and burnout. *Journal of Vocational Behavior*, *139*, Article 103807. https://doi.org/10.1016/j.jvb.2022.103807

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). The Guilford Press.

Hobfoll, S. E. (1989). Conservation of resources. A new attempt at conceptualizing stress. *American Psychologist*, *44*(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Hobfoll, S. E., Halbesleben, J., Neveu, J.-P., & Westman, M. (2018). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual Review of Organizational Psychology and Organizational Behavior*, *5*(1), 103–128. https://doi.org/10.1146/annurev-orgpsych-032117-104640

Houkes, I., Winants, Y., Twellaar, M., & Verdonk, P. (2011). Development of burnout over time and the causal order of the three dimensions of burnout among male and female GPs. A three-wave panel study. *BMC Public Health*, *11*(1), Article 240. https://doi.org/10.1186/1471-2458-11-240

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*(430), 773–795. https://doi.org/10.1080/01621459.1995.10476572

Kelloway, E. K., Dimoff, J. K., & Gilbert, S. (2023). Mental health in the workplace. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 363–387. https://doi.org/10.1146/annurev-orgpsych-120920-050527

Kristensen, T. S., Borritz, M., Villadsen, E., & Christensen, K. B. (2005). The Copenhagen Burnout Inventory: A new tool for the assessment of burnout. *Work & Stress*, *19*(3), 192–207. https://doi.org/10.1080/02678370500297720

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

Lee, R. T., & Ashforth, B. E. (1993). A longitudinal study of burnout among supervisors and managers: Comparisons between the Leiter and Maslach (1988) and Golembiewski et al. (1986) models. *Organizational Behavior and Human Decision Processes*, *54*(3), 369–398. https://doi.org/10.1006/obhd.1993.1016

Leiter, M. P., & Maslach, C. (1988). The impact of interpersonal environment of burnout and organizational commitment. *Journal of Organizational Behavior*, *9*(4), 297–308. https://doi.org/10.1002/job.4030090402

Leiter, M. P., & Maslach, C. (2024). Job burnout. In L. E. Tetrick, G. G. Fisher, M. T. Ford, & J. C. Quick (Eds.), *Handbook of occupational health psychology* (3rd ed., pp. 291–307). American Psychological Association. https://doi.org/10.1037/0000331-015

Lucas, R. E. (2023). Why the cross-lagged panel model is almost never the right choice. *Advances in Methods and Practices in Psychological Science*, *6*(1), Article 25152459231158378. https://doi.org/10.1177/25152459231158378

Mäkikangas, A., Hyvönen, K., Leskinen, E., Kinnunen, U., & Feldt, T. (2011). A person-centered approach to investigating the development trajectories of job-related affective well-being: A 10-year follow-up. *Journal of Occupational and Organizational Psychology*, *84*(2), 327–346. https://doi.org/10.1111/j.2044-8325.2011.02025.x

Mäkikangas, A., Kinnunen, U., Feldt, T., & Schaufeli, W. (2016). The longitudinal development of employee wellbeing: A systematic review. *Work & Stress*, *30*(1), 46–70. https://doi.org/10.1080/02678373.2015.1126870

Mäkikangas, A., Leiter, M. P., Kinnunen, U., & Feldt, T. (2021). Profiling development of burnout over eight years: Relation with job demands and resources. *European Journal of Work and Organizational Psychology*, *30*(5), 720–731. https://doi.org/10.1080/1359432X.2020.1790651

Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. *Journal of Organizational Behavior*, *2*(2), 99–113. https://doi.org/10.1002/job.4030020205

Maslach, C., & Jackson, S. E. (1986). *Maslach Burnout Inventory* (2nd ed.). Consulting Psychologists Press.

Maslach, C., & Leiter, M. P. (2008). Early predictors of job burnout and engagement. *Journal of Applied Psychology*, *93*(3), 498–512. https://doi.org/10.1037/0021-9010.93.3.498

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

Maunz, L. A., & Glaser, J. (2024). Longitudinal dynamics of psychological need satisfaction, meaning in work, and burnout. *Journal of Vocational Behavior*, *150*, Article 103971. https://doi.org/10.1016/j.jvb.2024.103971

Muthén, L. K., & Muthén, B. O. (2024). *Mplus user's guide* (8th ed.). https://www.statmodel.com/download/usersguide/MplusUserGuideVer_8.pdf

Orth, U., Meier, L. L., Bühler, J. L., Dapp, L. C., Krauss, S., Messerli, D., & Robins, R. W. (2024). Effect size guidelines for cross-lagged effects. *Psychological Methods*, *29*(2), 421–433. https://doi.org/10.1037/met0000499

Padmanabhanunni, A., & Pretorius, T. B. (2024). Being cynical is bad for your wellbeing: A structural equation model of the relationship between cynicism and mental health in first responders in South Africa. *International Journal of Environmental Research and Public Health*, *21*(12), Article 1684. https://doi.org/10.3390/ijerph21121684

Pedersen, J., Graversen, B. K., Hansen, K. S., & Madsen, I. E. H. (2024). The labor market costs of work-related stress: A longitudinal study of 52 763 Danish employees using multi-state modeling. *Scandinavian Journal of Work, Environment & Health*, *50*(2), 61–72. https://doi.org/10.5271/sjweh.4131

Robins, E., & Guze, S. B. (1970). Establishment of diagnostic validity in psychiatric illness: Its application to schizophrenia. *The American Journal of Psychiatry*, *126*(7), 983–987. https://doi.org/10.1176/ajp.126.7.983

Rogala, A., Shoji, K., Luszczynska, A., Kuna, A., Yeager, C., Benight, C. C., & Cieslak, R. (2016). From exhaustion to disengagement via self-efficacy change: Findings from two longitudinal studies among human services workers. *Frontiers in Psychology*, *6*, Article 2032. https://doi.org/10.3389/fpsyg.2015.02032

Rohrer, J. M., & Murayama, K. (2023). These are not the effects you are looking for: Causality and the within-/between-persons distinction in longitudinal data analysis. *Advances in Methods and Practices in Psychological Science*, *6*(1), Article 25152459221140842. https://doi.org/10.1177/25152459221140842

Salvagioni, D. A. J., Melanda, F. N., Mesas, A. E., González, A. D., Gabani, F. L., & Andrade, S. M. D. (2017). Physical, psychological and occupational consequences of job burnout: A systematic review of prospective studies. *PLOS ONE*, *12*(10), Article e0185781. https://doi.org/10.1371/journal.pone.0185781

Schaufeli, W. B., De Witte, H., & Desart, S. (2020). *Burnout Assessment Tool (BAT): Manual* (Version 2.0). https://burnoutassessmenttool.be/wp-content/uploads/2020/08/Test-Manual-BAT-English-version-2.0-1.pdf

Schaufeli, W. B., De Witte, H., Hakanen, J. J., Kaltiainen, J., & Kok, R. (2023). How to assess severe burnout? Cutoff points for the Burnout Assessment Tool (BAT) based on three European samples. *Scandinavian Journal of Work, Environment & Health*, *49*(4), 293–302. https://doi.org/10.5271/sjweh.4093

Schaufeli, W. B., Desart, S., & De Witte, H. (2020). Burnout Assessment Tool (BAT)-development, validity, and reliability. *International Journal of Environmental Research and Public Health*, *17*(24), Article 9495. https://doi.org/10.3390/ijerph17249495

Schaufeli, W. B., Leiter, M. P., Maslach, C., & Jackson, S. E. (1996). Maslach Burnout Inventory—General survey. In C. Maslach, S. E. Jackson, & M. P. Leiter (Eds.), *The Maslach Burnout Inventory—Test manual* (3rd ed., pp. 19–26). Consulting Psychologists Press.

Schaufeli, W. B., Maassen, G. H., Bakker, A. B., & Sixma, H. J. (2011). Stability and change in burnout: A 10-year follow-up study among primary care physicians. *Journal of Occupational and Organizational Psychology*, *84*(2), 248–267. https://doi.org/10.1111/j.2044-8325.2010.02013.x

Schaufeli, W. B., & Taris, T. W. (2005). The conceptualization and measurement of burnout: Common ground and worlds apart. *Work & Stress*, *19*(3), 256–262. https://doi.org/10.1080/02678370500385913

Schisterman, E. F., Cole, S. R., & Platt, R. W. (2009). Overadjustment bias and unnecessary adjustment in epidemiologic studies. *Epidemiology*, *20*(4), 488–495. https://doi.org/10.1097/EDE.0b013e3181a819a1

Shirom, A., & Melamed, S. (2006). A comparison of the construct validity of two burnout measures in two groups of professionals. *International Journal of Stress Management*, *13*(2), 176–200. https://doi.org/10.1037/1072-5245.13.2.176

Sørengaard, T. A., & Saksvik-Lehouillier, I. (2022). Associations between burnout symptoms and sleep among workers during the COVID-19 pandemic. *Sleep Medicine*, *90*, 199–203. https://doi.org/10.1016/j.sleep.2022.01.022

Spagnoli, P., Buono, C., Kovalchuk, L. S., Cordasco, G., & Esposito, A. (2021). Perfectionism and burnout during the COVID-19 crisis: A two-wave cross-lagged study. *Frontiers in Psychology*, *11*, Article 631994. https://doi.org/10.3389/fpsyg.2020.631994

Taris, T. W., Le Blanc, P. M., Schaufeli, W. B., & Schreurs, P. J. G. (2005). Are there causal relationships between the dimensions of the Maslach Burnout Inventory? A review and two longitudinal tests. *Work & Stress*, *19*(3), 238–255. https://doi.org/10.1080/02678370500270453

Toppinen-Tanner, S., Kalimo, R., & Mutanen, P. (2002). The process of burnout in white-collar and blue-collar jobs: Eight-year prospective study of exhaustion. *Journal of Organizational Behavior*, *23*(5), 555–570. https://doi.org/10.1002/job.155

Travis, D. J., Lizano, E. L., & Mor Barak, M. E. (2016). "I'm So Stressed!": A longitudinal model of stress, burnout and engagement among social workers in child welfare settings. *British Journal of Social Work*, *46*(4), 1076–1095. https://doi.org/10.1093/bjsw/bct205

Wang, J., & Wang, X. (2020). *Structural equation modeling: Applications using Mplus* (2nd ed.). Wiley. https://doi.org/10.1002/9781119422730

Received January 29, 2025
Revision received August 16, 2025
Accepted October 3, 2025 ■