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Athlete burnout and mental and physical health: A three-wave longitudinal study of direct and reciprocal effects

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The pre-registration, data, materials, and code for this study can be found on PsychArchives: Glandorf et al. (2022, pre-registration), Glandorf et al. (2024a, materials; 2024b, data; 2024c, code).

Abstract

Burnout is a mental health-related problem in athletes that may also be linked to further adverse mental and physical health problems. However, longitudinal research in this area is scarce. The studies that do exist have yet to test possible reciprocal effects while accounting for the multilevel structure of longitudinal data. Consequently, the aim of the present study was to examine longitudinal and reciprocal relationships between athlete burnout and a number of health variables. To do so, we used a random-intercept cross-lagged panel model to disaggregate between- and within-person effects. Based on existing literature, we chose to focus on physical symptoms, illness, depressive symptoms, sleep disruptions, and life satisfaction as the health variables of interest. Following a pre-registered protocol with open data, materials, and code, we recruited a sample of 267 competitive athletes who completed measures at three timepoints over six months. At the between-person level, we found athlete burnout to be associated with all examined health variables. At the within-person level, emotional and physical exhaustion was found to predict increases in depressive symptoms, sleep disruptions were found to predict increases in devaluation, and life satisfaction was found to predict decreases in total burnout, exhaustion, and reduced sense of accomplishment. The findings demonstrate that athlete burnout increases the risk for certain health consequences such as depressive symptoms, and reciprocal findings suggest that sleep and satisfaction-based interventions (e.g., sleep hygiene training and positive psychology interventions) may be able to protect against burnout development.

Keywords: stress, health, sport, wellbeing, exhaustion

Introduction

An individual's health is key to all areas of life (Verhagen et al., 2020). While physical training is known to facilitate health and wellbeing, preparing for and competing in sport may also increase athletes' risk for mental and physical health problems (e.g., Sabato et al., 2016). One mental health-related problem that appears to be increasingly prevalent in athletes is burnout (Madigan et al., 2022). Beyond representing a health concern in itself, burnout is also associated with further mental and physical health issues (Glandorf et al., 2023). In this regard, research has shown burnout to predict some health variables, such as depressive symptoms, over time (e.g., Amemiya & Skairi, 2021). Although such longitudinal examinations of burnout and health are key to further our understanding of burnout as a syndrome, its development, and severity to health, there are still too few of these examinations. Furthermore, no study has yet sought to examine possible reciprocal effects between burnout and health, while also considering the multilevel structure of longitudinal data. To forward our conceptual understanding, the present study examines the relationship between athlete burnout and selected health variables (physical symptoms, illness, depressive symptoms, sleep disturbances, life satisfaction) using a multilevel analytic approach that also tests for reciprocal effects.

Health

Health is important to athletes' wellbeing, training competence, and their performance in competition (Verhagen et al., 2020). According to the World Health Organisation (WHO, 1948), health is a multidimensional concept that is not only defined by the absence of disease but also the presence of general wellbeing. Following this definition, much contemporary research focuses on the dimensions of physical and mental health (e.g., Sabato et al., 2016). Physical health can be conceptualised as the overall condition of the body where both general physical symptoms (e.g., headaches, dizziness) and specific illness symptoms (e.g., respiratory symptoms) can be considered (Krahn et al., 2021). Mental health can be viewed both from a clinical and/or positive psychology perspective. From a clinical perspective, mental health is often conceptualised as mental illness as determined by officially recognised diagnostic criteria (APA, 2013), and can be supplemented by determining the frequency or severity of symptoms (e.g., depressive symptoms, sleep problems; Conway et al., 2021). From a positive psychology perspective (Seligman & Csikszentmihalyi, 2000), the positive aspects of mental health, such as to what extent an individual can maintain relationships, acquire skills, and are overall satisfied with their life, should be considered. Newer conceptualisations of mental health therefore consider both the debilitating aspects of mental illness and an individual's ability to value and engage with their life.

Athlete Burnout

Athlete burnout is a mental health-related problem that is defined as a multidimensional syndrome of three symptoms: emotional and physical exhaustion (emotional and physical fatigue), sport devaluation (reductions in interest and development of negative attitudes towards one's sport), and a reduced sense of accomplishment (reduced sense of athletic efficacy and accomplishment; Raedeke & Smith, 2001). While these symptoms are related, they may not develop at the same time. Instead, there is some evidence that suggests particular symptoms may precede others and thus contribute to the development of another (Lundkvist et al., 2018; Martinent et al., 2020). It is likely that the context of sport is conducive to the development of these burnout symptoms. Indeed, studies have shown that on average approximately 10-12% of athletes experience burnout symptoms (Raedeke & Smith, 2009; Gerber et al., 2018b). There is also evidence that the prevalence of burnout symptoms is increasing, at least in the context of average levels, and has been doing so for the past two decades (Madigan et al., 2022). This is a concerning proposition because burnout is associated with many negative consequences. These include reductions in motivation (Cresswell & Eklund, 2006), perceived performance (Moen et al., 2019), and an increased risk of dropout from sport (Isoard-Gautheur et al., 2016).

Athlete Burnout and Health

Burnout may also have consequences for athletes' health. Smith's (1986) cognitive-affective model of athlete burnout provides an explanation for why this could be the case. According to this model, stress is triggered when an athlete appraises their available resources to be outweighed by the demands of training and competition. While acute stress may have adaptive properties (e.g., improved performance), over time, chronic stress results in the development of burnout. Importantly for the present study, Smith suggests that burnout has physiological and behavioural consequences. These consequences include both physical health symptoms (e.g., general physical symptoms, illness susceptibility) as well as mental health symptoms (e.g., depression, poor sleep quality). This link between burnout and health has been reiterated in Gustafsson and colleagues' (2011) integrated model of athlete burnout. The integrated model also extends possible health consequences (such as impaired immune function and chronic inflammation) to also include reductions in positive mental health such as self-confidence that, over time, may translate to general life dissatisfaction.

The hypothesised link between burnout and health has been supported by empirical studies. This includes numerous studies outside of sport (Salvagioni et al., 2017), but also a recent systematic review and meta-analysis in sport (Glandorf et al., 2023). Across 54 studies, Glandorf and colleagues found athlete burnout to be positively associated with mental health issues such as depressive symptoms and sleep disruptions, and negatively associated with positive mental health such as life satisfaction. However, the evidence for a relationship between athlete burnout and physical health variables (e.g., physical symptoms, illness) was mixed and inconclusive. Overall, supporting both established and more recent theoretical propositions, athlete burnout appears to be associated with worse health.

Conceptual and Methodological Limitations of Previous Research

Further examinations of the relationship between burnout and health are key to build our conceptual understanding of burnout. Although burnout has been extensively studied both inside and outside of sport with and without connection to health, there is still considerable debate about whether it can be considered a medical condition (Parker & Tavella, 2022). So far, most burnout studies have focused on examining causes and associated factors instead of exploring how burnout relates to other health variables (Heinemann & Heinemann, 2017). Determining which and how health variables are related to burnout, however, is important to clarify the severity of burnout to health and the mechanisms by which this relationship operates. Examining how the three burnout symptoms may be differentially linked to health may also further inform our understanding of burnout. Studying burnout and health may thereby help refine existing theoretical models and conceptual understanding of burnout.

There are some notable limitations of previous work in the area which currently confound its conceptual contributions to our understanding of athlete burnout and health. First, nearly all of the current literature in this area is cross-sectional in nature (see Glandorf et al., 2023). While cross-sectional studies provide an indication of the health variables associated with athlete burnout, they provide limited information concerning causality and directionality. To examine whether changes in health are a *consequence* of athlete burnout, longitudinal studies are required (Eklund & DeFreese, 2020). The few longitudinal studies that do exist have focused almost exclusively on mental health variables. Among these, burnout has been shown to predict depressive symptoms, sleep disruptions, and life satisfaction which are, thus, considered potential health consequences of burnout (Amemiya & Skairi, 2021; Li et al., 2018; DeFreese & Smith, 2014). Further longitudinal work is required, however. Especially studies that incorporate physical health aspects such as an athlete's general physical condition (e.g., physical symptoms) or illness symptoms like respiratory infections (the most commonly reported infectious illness in athletes; Cox et al., 2004).

There are several different approaches to modelling the longitudinal relationship between burnout and health. Depending on the approach, conceptually informed hypotheses from longitudinal studies can be tested in one direction (unidirectional; e.g., regression models) or both directions (bidirectional; e.g., cross-lagged panel models). Bidirectional models are preferred as they allow us to examine which variables take precedence and whether any reciprocal effects exist (Baribeau et al., 2022). For example, life satisfaction could serve as a protective factor to burnout development or reduce as a consequence of the development of burnout symptoms. Such effects are important to consider because they provide a more accurate picture of the complexity of relationships between burnout and health and thereby improve our conceptual understanding of dynamics over time, including potential mechanisms at play (Hamaker et al., 2015). The few studies that have adopted such an approach to studying burnout and health so far are excellent examples of how to better understand burnout in sport (e.g., Frank et al., 2017; Li et al., 2018; Gerber et al., 2018a).

There is one further distinction that is important for longitudinal research in this area. This is the use of the statistical approach for examining bidirectional relationships. Research in this area so far has relied on traditional cross-lagged panel models (CLPMs) to study burnout and health (see Glandorf et al., 2023). Recent work, however, has questioned the use of traditional CLPMs, because they do not separate between- and within-person effects over time (Hamaker et al., 2015). Between-person effects reflect stable, trait-like individual differences between people, while within-effects reflect time-variant, state-like changes within the same person over time (Mulder & Hamaker, 2021). Not accounting for this multilevel structure of longitudinal data can bias the resulting cross-lagged estimates, allowing between-person effects to confound or, in some cases, reverse directional effects (Baribeau et al., 2022). Thus, the relationship between burnout and, for example, sleep disruptions or depressive symptoms may show an opposite directional effect when appropriately modelled for data nesting. There are several approaches to overcoming this limitation (e.g., DeFreese & Smith, 2014). One of the more recent advances in this regard is the development of the random-intercept cross-lagged panel model (Hamaker et al., 2015).

This new model offers a means to disaggregate between- and within-person effects, and in doing so, provide a more rigorous examination of the health variables that are related to athlete burnout to date.

The Present Study

Against this background, the aim of the present study was to forward our conceptual understanding of burnout and health while addressing the limitations of previous research in this area. To do so, we use a random-intercept cross-lagged panel model to disaggregate between- and within-person effects and thereby control for individual differences. This approach will allow to differentiate health variables that are solely associated with burnout from those that may precede (antecedents) or follow (consequences) the development of burnout. Based on existing literature, we chose to focus on physical symptoms, illness, depressive symptoms, sleep disruptions, and life satisfaction as the health variables of interest. To consider the possibility of bidirectional relationships over time, we also examined reciprocal effects (health affecting change in burnout; see Figure 1A). In doing so, we sought to test the following hypotheses: (1) At the between-person level, athlete burnout will be positively related to physical symptoms, illness, depressive symptoms, and sleep disruptions, (2) at the between-person level, athlete burnout will be negatively related to life satisfaction, (3) at the within-person level, athlete burnout will predict increases in physical symptoms, illness, depressive symptoms, and sleep disruptions, and (4) at the within-person level, athlete burnout will predict decreases in life satisfaction. We did not, however, have any formal hypotheses in relation to reciprocal effects and therefore these tests were considered exploratory[1].

Methods

[1]The random intercept cross-lagged panel model provides the best test of the aforementioned ideas and explicitly accounts for reciprocal effects. Burnout theory has not classically included such effects, and previous research with similar designs and analyses has predominantly shown unidirectional effects, hence the exploratory nature of this part of our study.

Design

The present study used a three-wave longitudinal design which was pre-registered prior to data collection on Psych Archives (see Transparency and Openness for details).

Participants

Prior to data collection, we ran an *a priori* power analysis in MPlus (Muthén & Muthén, 2011) which estimated a minimum required sample size of 250 participants for each of the three time points. This power analysis was based on a Monte Carlo simulation and modelling of our proposed analyses (random-intercept cross-lagged panel model) following the recommendations of Mulder (2022). We aimed to power the within effects from the predictor at Wave 1 and 2 to the outcome at Wave 2 and 3 (see supplemental Table A for details).

We recruited 398 athletes (176 female; M_{age} = 20.56 years, SD_{age} = 3.96) at Wave 1 through convenience sampling. Athletes were eligible to take part if they were aged 18 years and over and were competing at a regional level or higher in their sport. Athletes with a diagnosed mental health disorder or who were using pain medication regularly (more than once a week for more than a month) were ineligible. Of the 398 athletes from Wave 1, 263 completed Wave 2 and 178 completed Wave 3. As Wave 3 did not retain 250 athletes, this study is powered for our estimated effects from Wave 1 to 2, but not to Wave 3. As such, effects from Wave 2 to 3 will only show as significant if they are larger than estimated effect sizes.

After screening the data, the final longitudinal sample was 267 athletes (118 females) who completed at least two waves (see supplemental Table B for details). Athletes were on average 20.87 years of age (SD = 4.69) and participated in team (n = 161) and individual sports (n = 106). On average, they had competed for 8.8 years in their sport (SD = 5.5) with team sport athletes having about a year more of competition experience ($M_{individual}$ = 8.1, SD = 5.5, M_{team} = 9.3, SD = 5.4). Most athletes were at the beginning of their season at Wave 1 (n =

190; training 8.1 ± 5.0 hrs/week), in the middle of their season at Wave 2 (*n* = 165; training 8.45 ± 5.0 hrs/week) and at the end of their season at Wave 3 (*n* = 76; training 8.31 ± 6.14 hrs/week) with no significant differences in training load between waves (see Supplemental Table C). Individual sport athletes had slightly higher training load than team sport athletes on Wave 1 (individual: 9.68 ± 5.47 hrs/week; team: 7.01 ± 4.29hrs/week), Wave 2 (individual: 9.45 ± 5.29 hrs/week; team: 7.80 ± 4.77 hrs/week), and Wave 3 (individual: 9.43 ± 6.78 hrs/week; team: 7.41 ± 5.44 hrs/week), again, neither of those groups showed significant differences in training load between waves (see Supplemental Table C). Further information on the number of participants per season per wave and training load per season per wave (for individual sport athletes and team sport athletes) can be found in supplemental Table C.

Measures

Example items for each measure can be found in supplemental Table D.

Athlete burnout. We measured athlete burnout using the 15-item Athlete Burnout Questionnaire (ABQ; Raedeke & Smith, 2001). The ABQ has three dimensions: emotional and physical exhaustion (EPE), devaluation (DEV), and reduced sense of accomplishment (RSA), with five items each. Participants are asked to indicate the extent to which they have experienced each symptom and respond on a 5-point Likert scale from 1 (almost never) to 5 (almost always). Scores on the ABQ have previously demonstrated adequate internal consistency on each dimension (Gerber et al., 2018b) as well as good construct and structural validity (Cresswell & Eklund, 2006). Item responses are averaged for each dimension (dimensional scores; 5 items per dimension) and across the three dimensions (total score; 15 items).

Physical symptoms. We measured physical symptoms using the 18-item Physical Symptom Checklist (Emmons, 1991). Participants were asked to indicate how often they had experienced a number of symptoms (e.g., headache, chest pain, fatigue) over the past week.

Responses were rated on a 7-point Likert scale with anchors 1 (never) and 7 (almost always). Scores on this scale have previously been shown to be internally reliable for use with athletes (Reinboth & Duda, 2006). All items are summed to produce a total score.

Illness. We measured illness using the 11-item Wisconsin Upper Respiratory Symptom Survey-11 (WURSS-11; Barrett et al., 2005). The questionnaire includes one overall Upper Respiratory Infection (URTI) question, seven symptom questions, and two quality of life questions. The severity of URTI symptoms is rated on a 7-point Likert scale from 1 (very mild) to 7 (severe) with an option to indicate no symptoms (0), ultimately resulting in an 8-point scale. Scores on this scale have been validated in previous studies (Obasi et al., 2014). A total score is calculated by summing the overall URTI, the URTI symptom, and the quality-of-life scores (10 items).

Depressive symptoms. We measured depressive symptoms using the Centre of Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977). The CES-D is a 20-item questionnaire that measures depressive symptoms in the general population. Participants answer items on a 4-point Likert scale from 0 (rarely or none of the time) to 3 (most or all of the time), over the past week. Scores on the scale has been shown to be reliable and internally consistent in previous research on athletes (Frank et al., 2017). All items are summed to produce a total score.

Sleep disruptions. We measured sleep disruptions using the 19-item Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989). The PSQI has seven components: subjective sleep quality (1-item), sleep latency (2-items), sleep duration (1-item), sleep efficiency (3-items), sleep disturbance (9-items), sleep medication (1-item), and daytime dysfunction (2-item). Participants answer on a 4-point Likert scale ranging from 0 (not during the past month/no problem at all/very good) to 3 (three or more times a week/a very big problem/very bad). Previous studies have shown that scores on the PSQI to be valid and reliable in athletes (e.g., Li et al., 2018). Component scores are calculated first per manual instructions (see Buysse et al., 1989), then all components are summed to produce a total score.

Life satisfaction. We measured life satisfaction using the Satisfaction With Life Scale (SWLS; Diener et al., 1985). The SWLS is a short 5-item instrument designed to measure global cognitive judgement of satisfaction with one's life. Participants answer items on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). It has previously been used to assess life satisfaction in athletes (DeFreese & Smith, 2014) and scores have been shown to have acceptable convergent validity and internal consistency (Pavot et al., 1991). All items are summed to produce a total score.

Procedure

Before study commencement, ethical approval was received from the lead researchers' institutional ethics board. To maximise recruitment, we recruited athletes using both online (Qualtrics) and via paper-and-pen methods. At the beginning of Wave 1, athletes were informed about the study and asked screening questions, they then provided informed consent. At all waves, to minimise order effects (Krosnick & Alwin, 1987), measures were provided in a randomised order.

To maximise recruitment, each wave of data collection was open for approximately one month. This was followed by approximately two months of no data collection. As recommended by Hopwood et al. (2021), these time lags were chosen based on previous research (between 1-3 months; e.g., Cresswell & Eklund, 2006; DeFreese & Smith, 2014) and current recommendations for random-intercept cross-lagged panel models (~2 months; Orth et al., 2022).

Statistical Analysis

Preliminary analysis. All statistical analyses were carried out using R and R Studio (version 4.2.2; R Core Team, 2022). We first computed composite scores for each of the measures. In doing so, data were screened for extreme (mean ± 3 SDs; Howell, 1998) and missing values. Individuals with item non-responses that exceeded 5% were removed from the analysis. Where missing data remained after this stage, missing values were estimated by calculating an average of the remaining items under the same composite score/component (Graham et al., 2003).

Because we found evidence of skewness, we employed robust descriptive statistics to take into account these deviations; this included 20%-trimmed means, medium absolute deviations (MADs), and Spearman in addition to Pearson correlations. Internal consistency of each measure was determined by calculating McDonald's (1999) Omega. For modelling, a robust estimator that is asymptotically equivalent to the Yuan-Bentler estimator (1998) was chosen. Previous research has shown this estimator to appropriately correct for skewed data and calculating missing values (Yuan & Zhang, 2012), and was therefore suitable for athletes who may have missed a wave.

RI-CLPM. The longitudinal associations between athlete burnout and the health variables of interest were examined using a random-intercept cross-lagged panel model (RI-CLPM; Hamaker et al., 2015; see supplemental Figure 1A for visualisation). In line with the pre-registration, we first fitted a standard RI-CLPM (i.e., without constraints). As we did not reach the required sample size on Wave 3 and following similar previous research (Madigan et al., 2019), so as to increase power for the last wave, we also fit a constrained model. In the standard RI-CLPM, between-person factors (random intercepts) were extracted from the repeated-measures of athlete burnout and the health variables of interest. Similar to previous RI-CLPMs in psychological research (Madigan et al., 2019), the random intercepts were allowed to covary, which captures the association between athlete burnout and the health variables that is constant over time (between-person effects). The random intercepts also isolate the contribution of other time-invariant confounding variables that are associated with both athlete burnout and the health variables. The within-person factor is then comprised of three estimates: (a) autoregressions that determine the stability of each construct over time,

(b) within-time covariances that reflect the strength and direction of associations between athlete burnout and the health variables within each individual at a single time point, and (c) cross-lags that capture the longitudinal and directional associations between athlete burnout and the health variables within individuals. In the constrained RI-CLPM, the strength of the autoregressions and cross-lags were fixed over time (i.e., effect from Wave 1 to Wave 2 fixed to be the same as effect from Wave 2 to Wave 3). These constraints were theoretically informed as it was expected that the strength of each autoregression would remain stable and the relationship between two variables over time for one direction would retain the same effect size. Therefore, these constraints were in line with Mulder and Hamaker's (2021) recommendations for the inclusion of constraints in such models. Both models were fit for each health variable and each burnout symptom (20 models in total).

Following Byrne's (2001) recommendations, we evaluated the fit of the models using a combination of absolute fit indices – Root Mean Square Error of Approximation (RMSEA) and Standardised Root Mean Square Residual (SRMR) – and incremental fit indices – Tucker-Lewis Index (TFI) and Comparative Fit Index (CFI). While appropriate ranges for these indices are still debated, based on similar previous research (Moen et al., 2019), we set ranges for acceptable (CFI and TFI > .90[2]; SRMR < .10; RMSEA < .08) and excellent fit (CFI and TFI > .95[1]; SRMR < .08; RMSEA < .06). The two models were then compared with $\bar{\chi}^2$ difference tests (Stoel et al., 2006) to determine whether the standard model fit significantly better than the constrained model. Effect sizes were classed as small, medium, or large for values of .03, .07, and .12, respectively, in line with recommendations by Orth et al. (2022).

Transparency and Openness

[2]Although the CFI and TLI are standardised to range between 0 and 1, they may exceed 1 in the case of a non-significant chi-squared test (see Marsh et al., 1996).

All data exclusions, manipulations, measures and deviations from the pre-registered analysis plan (see Glandorf et al., 2022) as well as how the sample size was determined are reported. All data, materials, and code have been made publicly available at PsychArchives and can be accessed at https://doi.org/10.23668/psycharchives.14066.

Results

Descriptive Statistics

Descriptive statistics for all variables can be found in Table 1. Internal consistency (Omega) for each measure was in the acceptable range (>.7) apart from the sleep disruptions measure (Ω = .15). To reach an acceptable internal consistency on this measure, two components (sleep efficiency and sleep medication) were removed before creating a total score (final Ω = .70).

Correlations between all variables on each wave are shown in supplemental Table E. Physical symptoms, upper respiratory symptoms, depressive symptoms, and sleep disruptions all showed small-to-medium significant positive associations with total burnout and the burnout dimensions at each wave and across waves. Life satisfaction showed small-to-large significant negative associations with total burnout and the burnout dimensions at each wave and across waves. Total burnout and the burnout dimensions showed small-to-large significant associations among each other at each wave and across waves.

RI-CLPM

Fit indices for both the standard and constrained RI-CLPM are presented in Table 2. Based on a $\bar{\chi}^2$ (chi-bar-squared) difference test, when the standard model did not provide a significantly better fit, we present the path estimates for the constrained RI-CLPM, otherwise those for the standard RI-CLPM are presented (see below and Table 3).

Physical Symptoms

The standard and constrained RI-CLPM for total burnout and physical symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .41, p < .01$). The regression results (see Table 3) showed autoregressive effects of total burnout only and no cross-lagged effects.

The standard and constrained RI-CLPM for EPE and physical symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .40, p < .01$). The regression results (see Table 3) showed no auto-regressive or cross-lagged effects.

The standard and constrained RI-CLPM for devaluation and physical symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant difference (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .34, p = .04$). The regression results (see Table 3) showed auto-regressive effects for devaluation but not physical symptoms and no cross-lagged effects.

The standard RI-CLPM for RSA and physical symptoms showed poor fit on the TLI but none of the other fit indices. The constrained RI-CLPM showed acceptable to excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .44, p < .01$). The regression results (see Table 3) showed autoregressive effects for both RSA and physical symptoms, but no cross-lagged effects.

Illness

The standard and constrained RI-CLPM for total burnout and illness showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors showed no significant co-variation ($Cov = .19, p = .84$). The regression results (see Table 3) showed auto-regressive effects for total burnout but not illness and no cross-lagged effects.

The standard RI-CLPM for EPE and illness did not converge. However, the constrained RI-CLPM showed excellent fit. The between-person factors significantly positively co-varied ($Cov = .38, p = .02$). The regression results (see Table 3) showed autoregressive effects for EPE, but not illness, and no cross-lagged effects.

The standard RI-CLPM for devaluation and illness was mis-specified. However, the constrained RI-CLPM showed excellent fit. The between-person factors showed no significant covariance ($Cov = .03, p = .86$). The regression results (see Table 3) showed autoregressive effects for devaluation but not illness, and no cross-lagged effects.

The standard and constrained RI-CLPM for RSA and illness showed excellent fit. The $\bar{\chi}^2$ difference test revealed a significant difference (see Table 3), so the standard model is presented hereafter. The between-person factors showed no significant covariance ($Cov = .22, p = .10$). The regression results (see Table 3) showed autoregressive effects for RSA, but not illness, and no cross-lagged effects.

Depressive Symptoms

The standard and constrained RI-CLPM for total burnout and depressive symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3) so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .55, p < .01$). The regression results (see Table 3) showed only significant auto-regressive effects for total burnout but not for depressive symptoms and no cross-lagged effects.

The standard and constrained RI-CLPM for EPE and depressive symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary in the constrained RI-CLPM ($Cov = .41, p < .01$). Regression results (see Table 3) showed significant auto-regressive effects for EPE only and large cross-lagged effects of EPE predicting depressive symptoms at both waves ($\beta =$

$.19; .23, 95\%CI[-0.01, 0.4]; [0.01, 0.46], p =$ .03). These are also visualised in supplemental Figure 1B.

The standard and constrained RI-CLPM for devaluation and depressive symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .53, p < .01$). The regression results (see Table 3) showed only significant auto-regressive effects for devaluation but not for depressive symptoms and no cross-lagged effects.

The standard and constrained RI-CLPM for RSA and depressive symptoms showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .53, p < .01$). The regression results (see Table 3) showed auto-regressive effects for both RSA and depressive symptoms, but no cross-lagged effects.

Sleep Disruptions

The standard and constrained RI-CLPM for total burnout and sleep disruptions showed acceptable and excellent fit, respectively. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .40, p < .01$). The regression results (see Table 3) showed only significant auto-regressive effects for total burnout but not for sleep disruptions and no cross-lagged effects.

The standard RI-CLPM for EPE and sleep disruptions showed poor fit across multiple fit indices. The constrained RI-CLPM showed acceptable fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .44, p < .01$). The regression results (see Table 3) showed no auto-regressive or cross-lagged effects.

The standard RI-CLPM for devaluation and sleep disruptions showed poor fit on the RMSEA but none of the other fit indices. The constrained RI-CLPM showed acceptable fit. The $\bar{\chi}^2$ difference test revealed a significant difference (see Table 3), so the standard model is presented hereafter. The between-person factors did not significantly co-vary ($Cov = .14, p = .19$). The regression results (see Table 3) showed only significant auto-regressive effects for devaluation but not for sleep disruptions. Sleep disruptions further significantly predicted devaluation with a large effect from Wave 1 to Wave 2, but not Wave 3 ($\beta = .26, 95\%CI[0.0,0.52], p = .05$). These are also visualised in supplemental Figure 1C.

The standard and constrained RI-CLPM for RSA and sleep disruptions showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant differences (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly positively co-vary ($Cov = .31, p < .01$). The regression results (see Table 3) showed no autoregressive or cross-lagged effects.

Life Satisfaction

The standard and constrained RI-CLPM for total burnout and life satisfaction showed excellent fit. The $\bar{\chi}^2$ difference test revealed a significant difference (see Table 3), so the standard model is presented hereafter. The between-person factors were shown to significantly negatively co-vary ($Cov = -.39, p < .01$). The regression results (see Table 3) showed autoregressive effects for total burnout and life satisfaction. Life satisfaction at Wave 1 further predicted total burnout at Wave 2 with a large effect ($\beta = -.48\ , 95\%CI[-0.81, -0.14], p < .01$,). These are also visualised in supplemental Figure 1D.

The standard and constrained RI-CLPM for EPE and life satisfaction showed excellent fit. The $\bar{\chi}^2$ difference test revealed a significant difference (see Table 3), so the standard model is presented hereafter. The between-person factors did not significantly co-vary ($Cov = -.17, p = .35$). The regression results (see Table 3) showed significant auto-regressive effects for life satisfaction but not EPE. Life satisfaction at Wave 1 further predicted EPE at Wave 2 with a large effect ($\beta = -.53, 95\% CI[-0.89, -0.16], p < .01$,). These are also visualised in supplemental Figure 1E.

The standard and constrained RI-CLPM for devaluation and life satisfaction showed excellent fit. The $\bar{\chi}^2$ difference test revealed no significant difference (see Table 3), so the constrained model is presented hereafter. The between-person factors were shown to significantly negatively co-vary ($Cov = -.34, p = .02$). The regression results (see Table 3) showed autoregressive effects for both devaluation and life satisfaction, but no cross-lagged effects.

The standard and constrained RI-CLPM for RSA and life satisfaction showed excellent fit. The $\bar{\chi}^2$ difference test revealed a significant difference (see Table 3), so the standard model is presented hereafter. The between-person factors were shown to significantly negatively co-vary ($Cov = -.45, p < .01$). The regression results (see Table 3) showed autoregressive effects for life satisfaction, but not RSA. Life satisfaction at Wave 1 was further shown to predict RSA at Wave 2 with a large effect ($\beta = -.40\ , 95\% CI[-0.74, -0.05], p = .03$). These are also visualised in supplemental Figure 1F.

Discussion

The present study examined the relationship between athlete burnout and health using a three-wave design and random-intercept cross-lagged panel model. In line with our hypotheses, at the between-person level, athlete burnout was found to be positively related to physical symptoms, illness, depressive symptoms, and sleep disruptions, and negatively related to life satisfaction. At the within-person level, emotional and physical exhaustion was found to predict increases in depressive symptoms. Sleep disruptions were found to predict increases in devaluation. Life satisfaction was found to predict decreases in total burnout, exhaustion, and reduced sense of accomplishment. However, no relationship between athlete burnout and physical symptoms and illness was found at the within-person level. We now turn our attention to contextualising these main findings before moving on to their theoretical and practical implications as well as potential future directions.

Main Findings

We found significant between-person effects in all our models. These findings show that the stable aspects of athlete burnout are associated with the stable aspects of all considered health variables. Put another way, on average, individuals with higher burnout scores also experience worse health in the form of higher physical symptoms, illness, depressive symptoms, and sleep disruptions as well as less life satisfaction. These findings are in line with the large body of work outside of sport, including a range of longitudinal studies (Salvagioni et al., 2017). They are also consistent with work in sport showing that athlete burnout is positively associated with physical symptoms and negative mental health outcomes as well as negatively associated with positive mental health outcomes (Glandorf et al., 2023).

Much research has sought to examine how burnout and depression are related (Koutsimani et al., 2019). We found that exhaustion predicted increases in depressive symptoms at the within-person level. This effect was unidirectional and aligns with previous research in student athletes that found interpersonal exhaustion to predict future depressive symptoms (Amemiya & Skairi, 2021). However, it also contrasts with other studies that have shown a bidirectional relationship between burnout and depression (Frank et al., 2017). These conflicting findings could be the result of the difference in the statistical modelling approach that was applied. While Frank and colleagues (2017) used a traditional cross-lagged panel model, we instead adopted a random-intercept cross-lagged panel model to account for the limitations and bias of the traditional model. Our findings therefore provide further credence to the idea that not only are burnout and depression separate constructs, but that burnout may be a developmental antecedent of depression (see also: Toth-Kiraly et al., 2021, Meier & Kim, 2022).

We found that sleep disruptions predicted increases in devaluation at the within-person level. This finding stands in contrast to previous work in sport that found burnout to predict sleep disruptions (Gerber et al., 2019a; Li et al., 2018). Like with work on depression, the models used by Li and colleagues' (2018) and Gerber and colleagues' (2018a) did not consider the multilevel structure of longitudinal data. Their results therefore reflect a mix of time-invariant and time-variant associations, which could explain why they found opposite effects. It is also possible that internal consistency issues with the sleep measure in the present study have affected the results. The reduced sleep disruption scores we used lacked information on the use of sleep medication and sleep efficiency. These components therefore may be important in understanding the reciprocal nature of the relationship between burnout and sleep. As such, this relationship, especially potential cyclical effects, should be further examined in future studies utilising more psychometrically robust instruments of sleep disruptions.

Our next main finding was that life satisfaction predicted decreases in total burnout, exhaustion, and reduced sense of accomplishment at the within-person level. While previous research has examined within-person effects with these variables (DeFreese & Smith, 2014), the possibility of reciprocity was not examined. Contrary to previous work, it is possible, then, that when considering bidirectional effects, it is life satisfaction that is more important in the development of burnout than *vice versa*. We think this makes theoretical sense. Based on Smith's (1986) model, for example, an athlete's resources will determine whether they experience stress and, thus over time, burnout. Key resources can include social support and autonomy which are both associated with increased satisfaction in athletes (Rhind et al., 2013; Komenda et al., 2021). Consequently, high life satisfaction may be a sign of high available resources in athletes and therefore may be better situated as a predictor of burnout than a consequence.

Finally, contrary to our hypotheses, athlete burnout showed no relationship with physical symptoms and illness at the within-person level. These findings contrast with cross-sectional research in this area. For example, Daumiller and colleagues (2021) found a medium-sized significant correlation between athlete burnout and psychosomatic symptoms. This effect is supported by our between-person analyses, however, over time we cannot conclude the burnout predisposes athletes to increased risk of such symptoms. This is also contrary to work in other professions (Salvagioni et al., 2017). Despite upper respiratory tract infections being very common in athletes (Cox et al., 2008), it is still possible that our sample experienced very few or minor episodes (as evidenced by mean scores). Thus, while burnout may still be related, the size of effects is much smaller – requiring either larger samples or samples pre-selected for those with high burnout levels in the future to test this idea.

Theoretical Implications

Smith's (1986) cognitive-affective model suggests that athlete burnout develops in response to chronic stress and does so through a multi-stage process. According to this model, burnout develops with physiological consequences that include symptoms such as illness susceptibility, depression, and insomnia. The findings from the present study support the idea that burnout links to depressive symptoms as a specific health consequence. However, sleep disruptions and life satisfaction were instead shown to predict burnout. They may therefore represent risk/protective factors that are part of the resources the athlete evaluates during the cognitive appraisal process rather than a consequence of burnout. In addition, physical symptoms and illness showed only stable associations with burnout but no relationship over time. Accordingly, illness susceptibility may not in fact be linked to burnout development. Our findings also suggest that different mental and physical health variables may play into burnout development at different stages and may only link to specific burnout dimensions.

Overall, the findings challenge some of the propositions of Smith's theory, highlighting the potential need for theory development in this area. As a first step, this could be achieved by differentiating between health variables that heighten the risk for burnout development (e.g., sleep disruptions) and those that are health consequences of burnout (e.g., depression). A more detailed theory could also propose specific mechanisms for how these variables affect or are affected by burnout and its dimensions. Such work would likely need to convey psychobiological pathways through which burnout acts or is acted upon. There is research outside of sport that would guide such work (Bayes et al., 2021), and we note this is an area of special importance for future work.

Practical Implications

Against a backdrop of potentially increased depression as a consequence of burnout, our findings pose the need for effective intervention approaches. For example, integrating sleep hygiene and positive psychology-based interventions could be particularly beneficial. Sleep hygiene - behavioural and environmental recommendations to promote healthy sleep – may have a positive effect on athletes' recovery (Gerber et al., 2018a). It could also be beneficial in preventing burnout, which has been shown in intervention studies outside of sport (Brubaker et al., 2020; Dahlgren et al., 2022). In addition, mindfulness-based interventions (MBIs) may be of use, because mindfulness has previously been shown to predict life satisfaction (Xue & Xiang, 2022) and MBIs have been shown to reduce burnout in students (Madigan et al., 2023b) and athletes (Li et al., 2019). Testing such strategies further, especially using robust designs (e.g., RCTs), then, will allow us to build towards an evidence base to help athletes overcome burnout and its health consequences.

Limitations and Future Research

The present study has several limitations. First, due to attrition at each wave, the present study did not meet the required sample size at Wave 3, meaning that the study was only powered for our expected effects for the first two waves. Therefore, our models may have missed true positive effects from Wave 2 to 3. However, nonsignificant effects at these waves are still useful as future studies could use the effect sizes to inform their power calculations for a more accurate estimation of required sample sizes. Second, while our modelling approach allows us to control for stable trait factors that affect the observed scores, it does not control for covariates that vary over time, such as changes in social support. Future studies may aim to control for such factors while modelling the relationship between burnout and health. Third, the sleep disruptions measure showed low levels of internal consistency. Further psychometric examinations of the scale may be appropriate and future studies may use different scales such as the Insomnia Severity Index to measure sleep problems instead (Morin et al., 2011). Fourth, this study was likely affected by the healthy participant effect (see Chowdhury et al., 2017 for a review) as most participants showed normal burnout and health levels. This means relationships that only exist at higher burnout and worse health levels may have been missed. Future studies may consider pre-selection of participants to study the relationships in further detail. Fifth, the timing of the waves may not have been optimised for all participants. Due to inclusion of a range of sports, some athletes were at the beginning of their season during Wave 1, while other athletes were at the end of their season at the same time which could have affected burnout levels and the effect of burnout on health. Future studies may wish to focus their sample on those sports that follow a similar seasonable pattern. Finally, all health measures in this study were self-report measures that rely on the participants perception of their health status. While these types of measures are key to studying health, they would benefit from being supplemented with other measures such as biomarkers from saliva or blood (Glandorf et al., 2023).

Conclusion

We examined the relationship between burnout and a number of physical and mental health variables in athletes. We found burnout to be related to all health variables at the between-person level. At the within-person level, we found exhaustion to predict increased depressive symptoms, and we found that sleep disruptions and life satisfaction were found to contribute to burnout development. These findings highlight the health consequences of burnout as well as suggesting that sleep hygiene and positive psychology interventions may contribute positively to burnout prevention and intervention design.

References

Amemiya, R., & Sakairi, Y. (2021). Examining the relationship between depression and the progression of burnout among Japanese athletes. *Japanese Psychological Research*, 1-11. https://doi.org/10.1111/jpr.12332

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

Baribeau, D. A., Vigod, S., Brittain, H., Vaillancourt, T., Szatmari, P., & Pullenayegum, E. (2022). Application of transactional (cross-lagged panel) models in mental health research: An introduction and review of methodological considerations. *Journal of the Canadian Academy of Child and Adolescent Psychiatry*, *31*(3), 124–134.

Barrett, B., Brown, R., Mundt, M., Safdar, N., Dye, L., Maberry, R., & Alt, J. (2005). The Wisconsin Upper Respiratory Symptom Survey is responsive, reliable, and valid. *Journal of Clinical Epidemiology*, *58*(6), 609–617. https://doi.org/10.1016/j.jclinepi.2004.11.019

Bayes, A., Tavella, G., & Parker, G. (2021). The Biology of Burnout: Causes and consequences. *The World Journal of Biological Psychiatry*, *22*(9), 686–698. https://doi.org/10.1080/15622975.2021.1907713

Brubaker, J. R., Swan, A., & Beverly, E. A. (2020). A brief intervention to reduce burnout and improve sleep quality in medical students. *BMC Medical Education*, *20*(1). https://doi.org/10.1186/s12909-020-02263-6

Buysse, D. J., Reynolds, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh Sleep Quality index: A new instrument for psychiatric practice and Research. *Psychiatry Research*, *28*(2), 193–213. https://doi.org/10.1016/0165-1781(89)90047-4

Byrne, B.M. (2001). *Structural equation modelling with AMOS: Basic concepts, applications, and programming.* Lawrence Erlbaum Associates, Inc.

Chowdhury, R., Shah, D., & Payal, A. (2017). Healthy worker effect phenomenon: Revisited with emphasis on statistical methods – a review. *Indian Journal of Occupational and Environmental Medicine*, *21*(1), 2-8. https://doi.org/10.4103/ijoem.ijoem_53_16

Conway, C. C., Krueger, R. F., Cicero, D. C., DeYoung, C. G., Eaton, N. R., Forbes, M. K., Hallquist, M. N., Kotov, R., Latzman, R. D., Ruggero, C. J., Simms, L. J., Waldman, I. D., Waszczuk, M. A., Watson, D., Widiger, T. A., & Wright, A. G. (2021). Rethinking the diagnosis of mental disorders: Data-driven psychological dimensions, not categories, as a framework for mental-health research, treatment, and training. *Current Directions in Psychological Science*, *30*(2), 151–158. https://doi.org/10.1177/0963721421990353

Cox, A. J., Gleeson, M., Pyne, D. B., Callister, R., Hopkins, W. G., & Fricker, P. A. (2008). Clinical and laboratory evaluation of upper respiratory symptoms in elite athletes. *Clinical Journal of Sport Medicine*, *18*(5), 438–445. https://doi.org/10.1097/jsm.0b013e318181e501

Cresswell, S. L., & Eklund, R. C. (2006). Changes in athlete burnout and motivation over a 12-week league tournament. *Medicine & Science in Sports & Exercise*, 37, 1957-1966. https://doi.org/10.1249/01.mss.0000176304.14675.32

Dahlgren, A., Tucker, P., Epstein, M., Gustavsson, P., & Söderström, M. (2022). Randomised control trial of a proactive intervention supporting recovery in relation to stress and irregular work hours: Effects on sleep, burn-out, fatigue and somatic symptoms. *Occupational and Environmental Medicine*, *79*(7), 460–468. https://doi.org/10.1136/oemed-2021-107789

Daumiller, M., Rinas, R., & Breithecker, J. (2021). Elite athletes' achievement goals, burnout levels, psychosomatic stress symptoms, and coping strategies. *International Journal* *of Sport and Exercise Psychology, 20*(2), 416-435. https://doi.org/10.1080/1612197X.2021.1877326

DeFreese, J. D., & Smith, A. L. (2014). Athlete social support, negative social interactions, and psychological health across a competitive sport season. *Journal of Sport and Exercise Psychology, 36*(6), 619–630. https://doi.org/10.1123/jsep.2014-0040

Diener, E., Emmons, R., Larsen, R., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal Of Personality Assessment*, *49*(1), 71-75. https://doi.org/10.1207/s15327752jpa4901_13

Eklund, R. C., & DeFreese, J. D. (2020). Athlete burnout. In G. Tenenbaum, R. C. Eklund, & N. Boiangin (Eds.), *Handbook of sport psychology: Exercise, methodologies, & special topics* (pp. 1220–1240). John Wiley & Sons, Inc.. https://doi.org/10.1002/9781119568124.ch60

Emmons, R. (1991). Personal strivings, daily life events, and psychological and physical well-being. *Journal Of Personality*, *59*(3), 453-472. https://doi.org/10.1111/j.1467-6494.1991.tb00256.x

Frank, R., Nixdorf, I., & Beckmann, J. (2017). Analyzing the relationship between burnout and depression in junior elite athletes. *Journal Of Clinical Sport Psychology*, *11*(4), 287-303. https://doi.org/10.1123/jcsp.2017-0008

Gerber, M., Best, S., Meerstetter, F., Isoard-Gautheur, S., Gustafsson, H., & Bianchi, R. et al. (2018a). Cross-sectional and longitudinal associations between athlete burnout, insomnia, and polysomnographic indices in young elite athletes. *Journal Of Sport And Exercise Psychology*, *40*(6), 312-324. https://doi.org/10.1123/jsep.2018-0083

Gerber, M., Gustafsson, H., Seelig, H., Kellmann, M., Ludyga, S., Colledge, F., Brand, S., Isoard-Gautheur, S., & Bianchi, R. (2018b). Usefulness of the Athlete Burnout Questionnaire (ABQ) as a screening tool for the detection of clinically relevant burnout symptoms among young elite athletes. *Psychology of Sport and Exercise*, *39*, 104–113. https://doi.org/10.1016/j.psychsport.2018.08.005

Glandorf, H. L., Madigan, D. J., Kavanagh, O., & Mallinson-Howard, S. H. (2023). Mental and physical health outcomes of burnout in athletes: A systematic review and meta-analysis. *International Review of Sport and Exercise Psychology*, 1–45. https://doi.org/10.1080/1750984x.2023.2225187

Glandorf, H., Madigan, D., Kavanagh, O., Mallinson-Howard, S., Donachie, T., Olsson, L., & Rumbold, J. (2022). *Athlete burnout and mental and physical health outcomes: A three-wave longitudinal study*. PsychArchives. https://doi.org/10.23668/psycharchives.8214

Glandorf, H., Madigan, D., Kavanagh, O., Mallinson-Howard, S., Donachie, T., Olsson, L., & Rumbold, J. (2024a). *Materials for: Athlete burnout and mental and physical health outcomes: A three-wave longitudinal study*. PsychArchives. https://doi.org/10.23668/psycharchives.14064

Glandorf, H., Madigan, D., Kavanagh, O., Mallinson-Howard, S., Donachie, T., Olsson, L., & Rumbold, J. (2024b). *Data for: Athlete burnout and mental and physical health outcomes: A three-wave longitudinal study* [Data set]. PsychArchives. https://doi.org/10.23668/psycharchives.14066

Glandorf, H., Madigan, D., Kavanagh, O., Mallinson-Howard, S., Donachie, T., Olsson, L., & Rumbold, J. (2024c). *Code for data analysis for: Athlete burnout and mental and physical health outcomes: A three-wave longitudinal study*. PsychArchives. https://doi.org/10.23668/psycharchives.14065

Graham, J. W., Cumsille, P. E., & Elek-Fisk, E. (2003). Methods for handling missing data. *Handbook of Psychology*, 87–114. https://doi.org/10.1002/0471264385.wei0204

Gustafsson, H., Genttä, G., & Hassmén, P. (2011). Athlete burnout: An integrated model and future research directions. *International Review of Sport and Exercise Psychology*, *4*(1), 3–24. https://doi.org/10.1080/1750984x.2010.541927

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102–116. https://doi.org/10.1037/a0038889

Hopwood, C., Bleidorn, W., & Wright, A. (2021). Connecting theory to methods in longitudinal research. *Perspectives On Psychological Science*, *17*(3), 884-894. https://doi.org/10.1177/17456916211008407

Howell, D. C., Rogier, M., Yzerbyt, V., & Bestgen, Y. (1998). Statistical methods in human sciences. *New York: Wadsworth, 721.*

Isoard-Gautheur, S., Guillet-Descas, E., & Gustafsson, H. (2016). Athlete burnout and the risk of dropout among young elite handball players. *The Sport Psychologist*, *30*(2), 123-130. https://doi.org/10.1123/tsp.2014-0140

Komenda, S., Springstein, T., Zrnić, I., Zeilinger, E., Franken, F., & Weber, G. (2021). Satisfaction with life in special olympic athletes: The role of autonomy support and basic need fulfilment. *International Journal of Developmental Disabilities*, *68*(6), 964–972. https://doi.org/10.1080/20473869.2021.1917110

Koutsimani, P., Montgomery, A., & Georganta, K. (2019). The relationship between burnout, depression, and anxiety: A systematic review and meta-analysis. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00284

Krahn, G. L., Robinson, A., Murray, A. J., Havercamp, S. M., Havercamp, S., Andridge, R., Arnold, L. E., Barnhill, J., Bodle, S., Boerner, E., Bonardi, A., Bourne, M. L., Brown, C., Buck, A., Burkett, S., Chapman, R., Cobranchi, C., Cole, C., Davies, D., … Witwer, A. (2021). It’s time to reconsider how we define health: Perspective from disability and chronic condition. *Disability and Health Journal*, *14*(4), 1-5. https://doi.org/10.1016/j.dhjo.2021.101129

Krosnick, J. A., & Alwin, D. F. (1987). An evaluation of a cognitive theory of response-order effects in survey measurement. *Public Opinion Quarterly*, *51*(2), 201-219. https://doi.org/10.1086/269029

Li, C., Ivarsson, A., Stenling, A., & Wu, Y. (2018). The dynamic interplay between burnout and sleep among elite blind soccer players. *Psychology Of Sport And Exercise*, *37*(1), 164-169. https://doi.org/10.1016/j.psychsport.2017.08.008

Li, C., Zhu, Y., Zhang, M., Gustafsson, H., & Chen, T. (2019). Mindfulness and athlete burnout: A systematic review and meta-analysis. *International Journal of Environmental Research and Public Health*, *16*(3), 449. https://doi.org/10.3390/ijerph16030449

Lundkvist, E., Gustafsson, H., Davis, P. A., Holmström, S., Lemyre, N., & Ivarsson, A. (2017). The temporal relations across burnout dimensions in athletes. *Scandinavian Journal of Medicine & Science in Sports*, *28*(3), 1215–1226. https://doi.org/10.1111/sms.13000

Madigan, D. J., Kim, L. E., & Glandorf, H. L. (2023b). Interventions to reduce burnout in students: A systematic review and meta-analysis. *European Journal of Psychology of Education*. https://doi.org/10.1007/s10212-023-00731-3

Madigan, D. J., Kim, L. E., Glandorf, H. L., & Kavanagh, O. (2023a). Teacher burnout and physical health: A systematic review. *International Journal of Educational Research*, *119*, 102173. https://doi.org/10.1016/j.ijer.2023.102173

Madigan, D., Olsson, L., Hill, A., & Curran, T. (2022). Athlete burnout symptoms are increasing: A cross-temporal meta-analysis of average levels from 1997 to 2019. *Journal Of Sport & Exercise Psychology*, *44*(3), 153-168. https://doi.org/10.1123/jsep.2020-0291

Madigan, S., Browne, D., Racine, N., Mori, C., & Tough, S. (2019). Association between Screen Time and Children's performance on a developmental screening test. *JAMA Pediatrics*, *173*(3), 244-250. https://doi.org/10.1001/jamapediatrics.2018.5056

Marsh, H.W., Balla, J.R., & Hau, K-T. (1996). An evaluation of incremental fit indices: A clarification of mathematical and empirical properties. In G.A. Marcoulides & R.E. Schumacker (Eds.), *Advances in structural equation modeling: Issues and techniques* (pp. 315-353). Erlbaum.

Martinent, G., Louvet, B., & Decret, J.-C. (2020). Longitudinal trajectories of Athlete Burnout Among Young Table Tennis Players: A 3-wave study. *Journal of Sport and Health Science*, *9*(4), 367–375. https://doi.org/10.1016/j.jshs.2016.09.003

McDonald R. P. (1999). Test theory: A unified treatment. Mahwah, NJ: Lawrence Erlbaum.

Meier, S. T., & Kim, S. (2022). Meta-regression analyses of relationships between burnout and depression with sampling and measurement methodological moderators. *Journal of Occupational Health Psychology*, *27*(2), 195–206. https://doi.org/10.1037/ocp0000273

Moen, F., Hrozanova, M., Stiles, T. C., & Stenseng, F. (2019). Burnout and perceived performance among junior athletes—associations with affective and cognitive components of stress. *Sports*, *7*(7), 171. https://doi.org/10.3390/sports7070171

Morin, C. M., Belleville, G., Bélanger, L., & Ivers, H. (2011). The insomnia severity index: Psychometric Indicators to detect insomnia cases and evaluate treatment response. *Sleep*, *34*(5), 601–608. https://doi.org/10.1093/sleep/34.5.601

Mulder, J. D. (2022). Power analysis for the random intercept cross-lagged panel model using the "powriclpm" R-package. *Structural Equation Modeling: A Multidisciplinary Journal*, *30*(4), 645–658. https://doi.org/10.1080/10705511.2022.2122467

Mulder, J. D., & Hamaker, E. L. (2021). Three extensions of the random intercept cross-lagged panel model. *Structural Equation Modeling, 28*(4), 638–648. https://doi.org/10.1080/10705511.2020.1784738

Muthén, L. K., & Muthén, B. O. (1998-2011). *Mplus user's guide* (6th Ed.). Muthén & Muthén.

Obasi, C., Brown, R., & Barrett, B. (2014). Item reduction of the Wisconsin Upper Respiratory Symptom Survey (WURSS-21) leads to the WURSS-11. *Quality Of Life Research*, *23*(4), 1293-1298. https://doi.org/10.1007/s11136-013-0561-z

Orth, U., Meier, L., Bühler, J., Dapp, L., Krauss, S., Messerli, D., & Robins, R. (2022). Effect size guidelines for cross-lagged effects. *Psychological Methods*, 1-14. https://doi.org/10.1037/met0000499

Parker, G., & Tavella, G. (2022). The diagnosis of Burnout. *Journal of Nervous & Mental Disease*, *210*(7), 475–478. https://doi.org/10.1097/nmd.0000000000001492

Pavot, W., Diener, E., Colvin, C., & Sandvik, E. (1991). Further validation of the satisfaction with life scale: Evidence for the cross-method convergence of well-being measures. *Journal Of Personality Assessment*, *57*(1), 149-161. https://doi.org/10.1207/s15327752jpa5701_17

R Core Team. (2022). *R: A language and environment for statistical computing*. The R Project for Statistical Computing. https://www.R-project.org/

Radloff, L. (1977). The CES-D Scale. *Applied Psychological Measurement*, *1*(3), 385-401. https://doi.org/10.1177/014662167700100306

Raedeke, T. D., & Smith, A. L. (2001). Development and preliminary validation of an athlete burnout measure. *Journal of Sport and Exercise Psychology, 23*, 281-306.

Raedeke, T. D., & Smith, A. L. (2009). The athlete burnout questionnaire manual. Morgantown, WV: Fitness Information Technology

Reinboth, M., & Duda, J. L. (2004). The motivational climate, perceived ability, and athletes' psychological and physical well-being. *The Sport Psychologist*, *18*(3), 237–251. https://doi.org/10.1123/tsp.18.3.237

Rhind, D., Jowett, S., & Lorimer, R. (2011). The impact of social support on student athletes' satisfaction in individual sports. *Journal for the Study of Sports and Athletes in Education*, *5*(1), 73–84. https://doi.org/10.1179/ssa.2011.5.1.73

Sabato, T., Walch, T., & Caine, D. (2016). The elite young athlete: strategies to ensure physical and emotional health. *Open Access Journal of Sports Medicine, 7*(2016), 99-113.

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

Seligman, M. E. P., & Csikszentmihalyi, M. (2000). Positive psychology: An introduction. *American Psychologist, 55*(1), 5–14. https://doi.org/10.1037/0003-066X.55.1.5

Smith, R. (1986). Toward a cognitive-affective model of athletic burnout. *Journal of Sport Psychology*, *8*(1), 36-50. https://doi.org/10.1123/jsp.8.1.36

Stoel, R. D., Garre, F. G., Dolan, C., & van den Wittenboer, G. (2006). On the likelihood ratio test in structural equation modelling when parameters are subject to boundary constraints. *Psychological Methods, 11*(4), 439–455. https://doi.org/10.1037/1082-989x.11.4.439

Tóth-Király, I., Morin, A. J. S., & Salmela-Aro, K. (2021). Reciprocal associations between burnout and Depression: An 8-year longitudinal study. *Applied Psychology*, *70*(4), 1691–1727. https://doi.org/10.1111/apps.12295

Verhagen, E., Mellette, J., Konin, J., Scott, R., Brito, J., & McCall, A. (2020). Taking the lead towards healthy performance: the requirement of leadership to elevate the health and performance teams in elite sports. *BMJ Open Sport & Exercise Medicine*, *6*(1), 1-2. https://doi.org/10.1136/bmjsem-2020-000834

World Health Organization. (1948). *Constitution of the World Health Organization* (1st Ed.).

Xue, Y., & Xiang, Y. (2022). How daily mindfulness predicts life satisfaction: From the perspective of mindfulness coping model. *The Journal of Psychology*, *156*(8), 568–581. https://doi.org/10.1080/00223980.2022.2085236

Yuan, K.-H. & Bentler, P. M. (1998). Normal theory based test statistics in structural equation modelling. *British Journal of Mathematical and Statistical Psychology*, 51, 289-309.

Yuan, KH. & Zhang, Z. (2012). Robust structural equation modeling with missing data and auxiliary variables. *Psychometrika,* 77, 803-826.

Table 1

Descriptive Statistics of all Included Measures

	Wave 1			Wave 2			Wave 3			Omega
Measure	20% TM	MAD	Range	20% TM	MAD	Range	20% TM	MAD	Range	
TB	2.22	0.59	1 – 4.6	2.39	0.69	1.07 – 4.53	2.38	0.69	1 – 4.47	0.85
EPE	2.15	0.89	1 – 4.8	2.24	0.89	1 – 5	2.20	0.89	1 – 4.8	0.88
DEV	1.94	0.59	1 – 4.8	2.17	0.89	1 – 4.6	2.16	0.89	1 – 4.4	0.73
RSA	2.47	0.59	1 – 5	2.68	0.89	1 – 5	2.69	0.74	1 – 5	0.80
DS	13.93	7.41	2 – 45	14.85	6.67	2 – 43	14.55	8.15	4 – 41	0.85
SDR (SDR-r)	8.62 (5.94)	1.48 (1.48)	3 – 15 (0 – 13)	8.96 (6.25)	1.48 (1.48)	3 – 15 (0 – 15)	8.31 (5.60)	1.48 (1.48)	3 – 16 (1 – 14)	0.15 (0.7)
PS	37.82	14.83	18 - 112	38.68	14.83	18 – 91	35.88	14.09	18 – 82	0.88
URS	15.50	17.79	0 - 70	10.57	10.38	0 – 59	7.85	8.90	0 – 50	0.92
LS	24.21	5.93	5-35	24.20	5.93	5 – 35	24.83	5.93	9-35	0.85

Note. TB = Total Burnout, EPE = Emotional and Physical Exhaustion, DEV = Devaluation, RSA = Reduced Sense of Accomplishment, DS = Depressive Symptoms, SDR = Sleep Disruptions, PS = Physical Symptoms, URS = Upper Respiratory Symptoms, LS = Life Satisfaction

Table 2

Fit Indices for All Standard and Constrained RI-CLPMs

	Standard RI-CLPM						Constrained RI-CLPM						Diff test
BO	Chi	*p*	CFI	TLI	RMSEA	SRMR	Chi	*p*	CFI	TLI	RMSEA	SRMR	Chi-bar (*p*)
						Physical Symptoms							
TB	1.41	0.24	1.00	0.99	0.04	0.013	6.67	0.25	1.00	0.99	0.05	0.025	5.26 (0.09)
EPE	0.04	0.85	1.00	1.05	0.00	0.003	5.88	0.32	1.00	1.00	0.01	0.026	5.84 (0.07)
DEV	0.10	0.75	1.00	1.05	0.00	0.004	3.17	0.67	1.00	1.02	0.00	0.020	3.07 (0.26)
RSA	6.87	**0.01**	0.99	0.85	0.15	0.027	10.35	0.07	0.99	0.96	0.082	0.037	3.48 (0.21)
						Upper Respiratory Symptoms							
TB	0.00	0.98	1.00	1.07	0.00	0.000	3.45	0.63	1.00	1.02	0.00	0.026	3.45 (0.21)
EPE			Does not converge				4.43	0.49	1.00	1.02	0.00	0.032	NA
DEV			Miss-specified				1.87	0.87	1.00	1.04	0.00	0.019	NA
RSA	0.01	0.94	1.00	1.08	0.00	0.001	7.44	0.19	0.99	0.98	0.04	0.038	7.43 (**0.03)**
						Depressive Symptoms							
TB	0.30	0.59	1.00	1.03	0.00	0.006	3.01	0.69	1.00	1.01	0.00	0.016	2.71 (0.30)
EPE	0.63	0.43	1.00	1.02	0.00	0.010	6.73	0.24	1.00	0.98	0.06	0.027	6.10 (0.06)
DEV	0.23	0.63	1.00	1.05	0.00	0.006	5.49	0.36	1.00	1.00	0.01	0.025	5.26 (0.09)
RSA	1.62	0.20	1.00	0.99	0.05	0.015	6.04	0.30	1.00	1.00	0.01	0.032	4.42 (0.14)
						Sleep Disruptions							
TB	2.85	0.09	1.00	0.94	0.11	0.021	6.08	0.30	1.00	0.99	0.04	0.033	3.23 (0.24)
EPE	8.13	**<0.01**	0.99	0.78	0.19	0.035	9.50	0.07	0.99	0.96	0.08	0.044	1.37 (0.54)
DEV	2.42	0.12	1.00	0.95	0.09	0.019	9.70	0.08	0.99	0.97	0.08	0.035	7.29 (**0.04)**
RSA	0.06	0.81	1.00	1.03	0.00	0.003	3.33	0.72	1.00	1.02	0.00	0.024	3.27 (0.23)
						Life Satisfaction							
TB	0.03	0.86	1.00	1.03	0.00	0.002	8.45	0.13	1.00	0.99	0.05	0.032	8.42 (**0.02)**
EPE	0.40	0.53	1.00	1.03	0.00	0.009	7.14	0.21	1.00	0.99	0.03	0.034	6.74 (<**0.05)**
DEV	0.22	0.64	1.00	1.02	0.00	0.005	6.24	0.28	1.00	1.00	0.03	0.030	6.02 (0.07)
RSA	0.42	0.52	1.00	1.03	0.00	0.008	8.06	0.15	0.99	0.99	0.05	0.037	7.64 (**0.03)**

Note. BO = Burnout Dimension; Diff test = Chi-bar-squared differences test; TB = Total Burnout, EPE = Emotional and Physical Exhaustion, DEV = Devaluation, RSA = Reduced Sense of Accomplishment

All standard RI-CLPM have 1 degree of freedom in the chi-squared test, all constrained RI-CLPM have 5 degrees of freedom.

Table 3

Overview of Estimated Model for RI-CLPM of Total Burnout and Burnout Dimensions with each Health Variable

		Total burnout Estimate[a]	95% CI	p-value	EPE Estimate[a]	95% CI	p-value	DEV Estimate[a]	95% CI	p-value	RSA Estimate[a]	95% CI	p-value
PS	Between[b] factors												
	RI-Cov	0.41	0.19 – 0.63	0.001	**0.40**	0.17 – 0.64	**0.008**	**0.34**	0.04 – 0.63	**0.035**	**0.44**	0.14 – 0.74	**0.003**
	Within												
	Auto-reg												
	BO1~BO2	**0.27**	0.12 – 0.42	**0.00**	0.21	-0.03 – 0.45	0.10	**0.39**	0.19 – 0.59	**0.00**	**0.25**	0.07 – 0.43	**0.007**
	BO2~BO3	**0.50**	0.27 – 0.72	**0.00**	0.28	-0.05 – 0.61	0.10	**0.61**	0.44 – 0.78	**0.00**	**0.39**	0.12 – 0.65	**0.007**
	PS1~PS2	0.20	-0.07 – 0.46	0.13	0.21	-0.07 – 0.50	0.13	0.22	-0.02 – 0.47	0.06	**0.26**	0.00 – 0.51	**0.03**
	PS2~PS3	0.27	-0.08 – 0.61	0.13	0.29	-0.08 – 0.65	0.13	0.31	-0.01 – 0.62	0.06	**0.35**	0.05 – 0.66	**0.03**
	Cross-lags												
	BO1~PS2	0.13	-0.03 – 0.28	0.10	0.15	-0.10 – 0.39	0.21	0.06	-0.09 – 0.21	0.41	0.04	-0.10 – 0.18	0.58
	BO2~PS3	0.22	-0.04 – 0.49	0.10	0.20	-0.12 – 0.51	0.21	0.11	-0.15 – 0.38	0.41	0.07	-0.16 – 0.29	0.58
	PS1~BO2	-0.05	-0.19 – 0.08	0.44	0.10	-0.12 – 0.33	0.36	-0.07	-0.21 – 0.07	0.35	-0.13	-0.28 – 0.02	0.10
	PS2~BO3	-0.08	-0.27 – 0.12	0.44	0.13	-0.15 – 0.41	0.36	-0.08	-0.26 – 0.09	0.35	-0.17	-0.35 – 0.02	0.10
URS	Between[b] factors												
	RI-Cov	0.19	-0.06 – 0.44	0.84	**0.38**	0.09 – 0.68	**0.024**	0.03	-0.30 – 0.37	0.86	0.22	-0.06 - 0.48	0.10
	Within												
	Auto-reg												
	BO1~BO2	**0.27**	0.12 – 0.43	**0.00**	**0.31**	0.09 – 0.52	**0.002**	**0.37**	0.17 – 0.58	**0.00**	-0.022	-0.44 - 0.40	0.92
	BO2~BO3	**0.49**	0.27 – 0.70	**0.00**	**0.43**	0.17 – 0.68	**0.002**	**0.58**	0.39 – 0.77	**0.00**	**0.33**	0.10 - 0.55	**0.004**
	URS1~ URS2	0.03	-0.23 – 0.28	0.84	0.02	-0.24 – 0.28	0.88	0.04	-0.21 – 0.29	0.75	0.08	-0.17 - 0.33	0.53
	URS2~ URS3	0.02	-0.21 – 0.26	0.84	0.02	-0.21 – 0.25	0.88	0.04	-0.19 – 0.27	0.75	0.012	-0.38 - 0.40	0.95

	Cross-lags												
	BO1~URS2	0.05	-0.11 – 0.21	0.51	-0.01	-0.18 – 0.16	0.92	0.07	-0.11 – 0.25	0.42	-0.22	-0.50 - 0.05	0.14
	BO2~URS3	0.09	-0.19 – 0.37	0.51	-0.01	-0.26 – 0.23	0.92	0.13	-0.18 – 0.44	0.42	0.08	-0.16 - 0.32	0.50
	URS1~BO2	0.07	-0.11 – 0.24	0.44	-0.001	-0.17 – 0.17	0.99	0.11	-0.04 – 0.26	0.14	0.17	-0.07 - 0.42	0.15
	URS2~BO3	0.06	-0.09 – 0.21	0.44	-0.001	-0.14 – 0.14	0.99	0.08	-0.03 – 0.19	0.14	-0.15	-0.40 - 0.10	0.26
DS	Between[b] factors												
	RI-Cov	**0.55**	0.40 - 0.71	**0.00**	**0.41**	0.21 – 0.62	**0.004**	**0.53**	0.26 – 0.81	**0.00**	**0.53**	0.31 – 0.75	**0.00**
	Within factors												
	Auto-reg												
	BO1~BO2	**0.25**	0.08 – 0.42	**0.001**	**0.25**	0.023 – 0.47	**0.03**	**0.38**	0.18 – 0.58	**0.00**	**0.21**	0.015 - 0.41	**0.032**
	BO2~BO3	**0.45**	0.20 – 0.69	**0.001**	**0.31**	0.035 – 0.65	**0.03**	**0.59**	0.40 – 0.78	**0.00**	**0.33**	0.04 – 0.62	**0.032**
	DS1~DS2	0.16	-0.06 – 0.37	0.16	0.17	-0.02– 0.37	0.08	0.18	-0.04– 0.41	0.11	0.18	0.00 – 0.37	0.04
	DS2~DS3	0.20	-0.10 – 0.50	0.16	0.23	-0.05 – 0.50	0.08	0.24	-0.08 – 0.56	0.11	0.29	-0.01 – 0.50	0.04
	Cross-lags												
	BO1~DS2	0.09	-0.07 – 0.26	0.25	0.19	0.01 – 0.40	**0.03**	-0.003	-0.16 – 0.16	0.98	0.04	-0.12 – 0.20	0.64
	BO2~DS3	0.14	-0.10 – 0.37	0.25	0.23	0.01 – 0.46	**0.03**	-0.004	-0.25 – 0.24	0.98	0.05	-0.17 – 0.27	0.64
	DS1~BO2	0.04	-0.09 – 0.17	0.57	0.05	-0.10 – 0.20	0.50	0.01	-0.12 – 0.13	0.94	0.05	-0.09 – 0.19	0.50
	DS2~BO3	0.06	-0.14 – 0.26	0.57	0.08	-0.14 – 0.29	0.50	0.01	-0.16 – 0.17	0.94	0.08	-0.15 – 0.30	0.50
SDR	Between[b] factors												
	RI-Cov	**0.40**	0.24 – 0.55	**0.00**	**0.44**	0.26 – 0.62	**0.00**	0.14	-0.06 – 0.35	0.19	**0.31**	0.11 – 0.50	**0.003**
	Within												
	Auto-reg												
	BO1~BO2	**0.22**	0.08 – 0.36	**0.001**	0.21	-0.01 – 0.42	0.06	0.19	-0.39 – 0.77	0.47	0.19	-0.002 – 0.39	0.056
	BO2~BO3	**0.39**	0.16 – 0.61	**0.001**	0.28	-0.01 – 0.56	0.06	0.58	0.36 – 0.81	**0.00**	0.29	-0.006 – 0.58	0.056

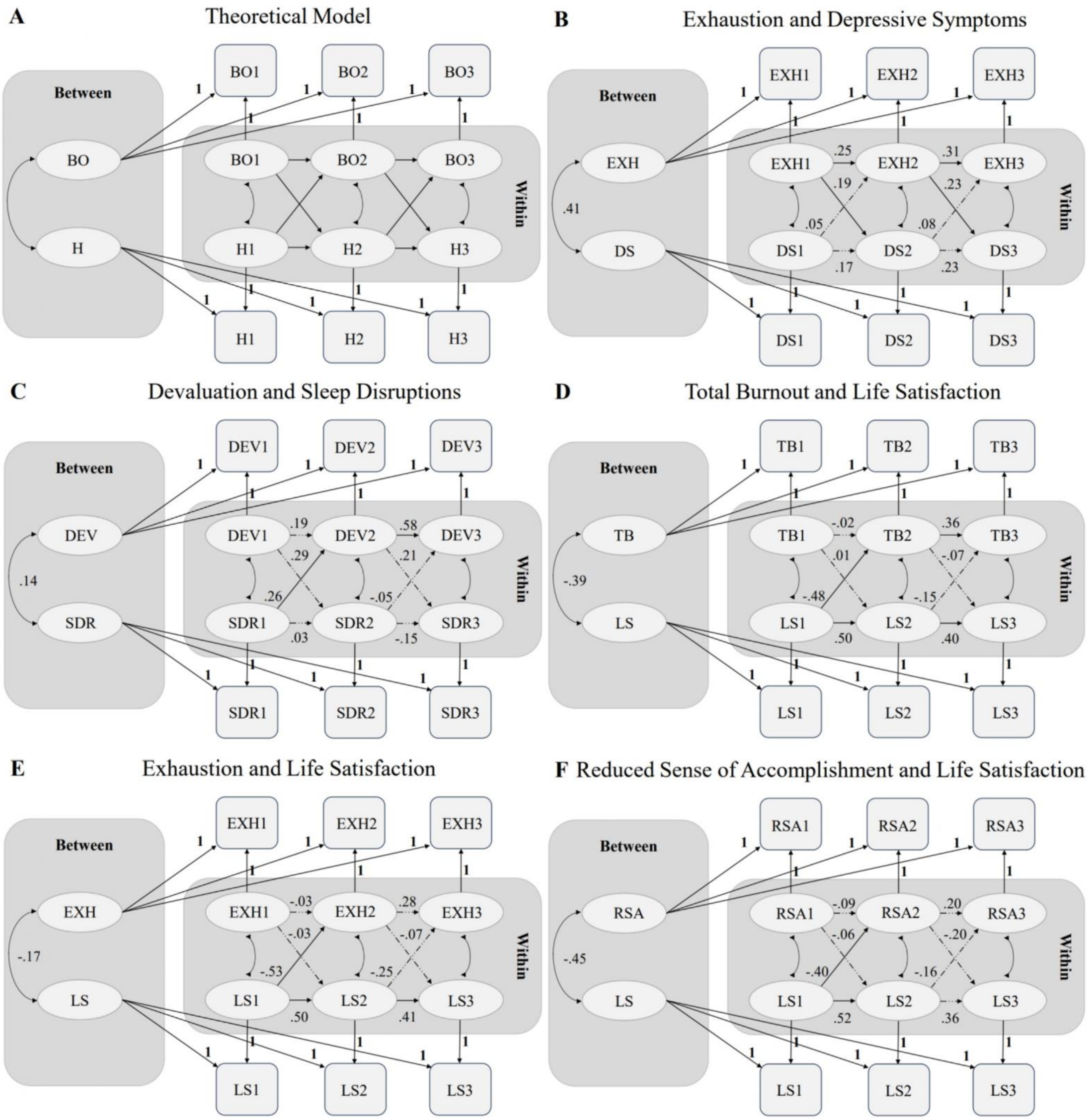
	SDR1~SDR2	-0.08	-0.36 – 0.20	0.56	-0.06	-0.36 – 0.25	0.71	0.03	-0.30 – 0.36	0.85	-0.018	-0.266 – 0.23	0.88
	SDR2~SDR3	-0.08	-0.35 – 0.18	0.56	-0.06	-0.37 – 0.25	0.71	-0.15	-0.56 – 0.27	0.49	-0.021	-0.31 – 0.26	0.88
	Cross-lags												
	BO1~SDR2	0.12	-0.06 – 0.30	0.18	0.14	-0.07 – 0.35	0.18	0.29	-0.03 – 0.61	0.14	0.03	-0.17 – 0.23	0.76
	BO2~SDR3	0.19	-0.08 – 0.45	0.18	0.17	-0.08 – 0.43	0.18	0.21	-0.20 – 0.61	0.32	0.05	-0.26 – 0.35	0.76
	SDR1~BO2	0.11	-0.05 – 0.27	0.15	0.13	-0.07 – 0.32	0.20	**0.26**	0.003 – 0.52	**0.046**	0.04	-0.15 – 0.23	0.67
	SDR2~BO3	0.13	-0.05 – 0.32	0.15	0.14	-0.07 – 0.35	0.20	-0.05	-0.28 – 0.18	0.67	0.05	-0.17 – 0.26	0.67
LS	Between[b] factors												
	RI-Cov	**-0.39**	-0.60 – -0.18	**0.007**	-0.17	-0.48 - 0.14	0.35	**-0.34**	-0.57 - - 0.11	**0.017**	**-0.45**	-0.68 - - 0.22	**0.007**
	Within												
	Auto-reg												
	BO1~BO2	-0.02	-0.41 - 0.37	0.93	-0.03	-0.42 - 0.37	0.90	**0.35**	0.14 – 0.56	**0.00**	-0.09	-0.40 - 0.23	0.59
	BO2~BO3	**0.36**	0.12 - 0.61	**0.005**	0.28	-0.012 - 0.56	0.062	**0.54**	0.32 – 0.76	**0.00**	0.20	-0.07 - 0.47	0.15
	LS1~LS2	**0.50**	0.26 - 0.74	**0.00**	**0.50**	0.24 - 0.77	**0.00**	**0.26**	-0.02 – 0.53	**0.025**	**0.52**	0.31 - 0.73	**0.00**
	LS2~LS3	**0.40**	0.058 - 0.746	**0.025**	**0.41**	0.074 - 0.75	**0.019**	**0.35**	0.03 – 0.67	**0.025**	0.36	-0.008 - 0.73	0.059
	Cross-lags												
	BO1~LS2	0.005	-0.26 - 0.27	0.97	-0.026	-0.25 - 0.19	0.81	0.01	-0.14 – 0.15	0.94	-0.064	-0.30 - 0.73	0.59
	BO2~LS3	-0.07	-0.34 - 0.20	0.61	-0.065	-0.37 - 0.24	0.67	0.01	-0.21 – 0.23	0.94	-0.20	-0.48 - 0.08	0.16
	LS1~BO2	**-0.48**	-0.81- - 0.14	**0.006**	**-0.53**	-0.89 – -0.16	**0.003**	-0.11	-0.27 – 0.06	0.12	**-0.40**	-0.74 – -0.05	**0.033**
	LS2~BO3	-0.15	-0.47 - 0.16	0.35	-0.25	-0.58 - 0.088	0.15	-0.15	-0.35 – 0.05	0.12	-0.16	-0.5 – 0.19	0.38

Note. RI-Cov = Random Intercept Covariance, Auto-reg = Auto-regressions, BO = Burnout Variable of Model, TB = Total Burnout, EPE = Emotional and Physical Exhaustion, DEV = Devaluation, RSA = Reduced Sense of Accomplishment, PS = Physical Symptoms, URS = Upper Respiratory Symptoms, DS = Depressive Symptoms, SDR = Sleep Disruptions, LS = Life Satisfaction

[a] Pathways to RI are constrained to 1.0 to isolate the between-person factors. [b] Estimate is covariance for between and β for within factors.

Figure 1

Theoretical Model and Models with Significant Cross-Lagged Effects



Note. Between = Between-factors; Within = Within-factors, BO = Burnout; H = Health; TB = Total Burnout, EPE = Emotional and Physical Exhaustion, DEV = Devaluation, RSA = Reduced Sense of Accomplishment, DS = Depressive Symptoms, SDR = Sleep Disruptions, LS = Life Satisfaction; 1 = Wave 1, 2 = Wave 2, 3 = Wave 3; Covariances of within factors at each individual wave are not shown.