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Identifying mediators of training effects on performance-related psychobiosocial states: A single-case observational study in an elite female triathlete

Anthony Barnett[a,*], Ester Cerin[a], Peter Reaburn[b], Sue Hooper[c]

[a] Institute of Human Performance, University of Hong Kong, Hong Kong SAR, China
[b] Institute for Health and Social Science Research, CQ University, Rockhampton, Australia
[c] Centre of Excellence for Applied Sport Science Research, Queensland Academy of Sport, Brisbane, Australia

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ABSTRACT

Objectives: Relationships between training load, psychobiosocial (PBS) states and performance are dynamic and individual-specific. The nature of these relationships can be investigated using a combination of dynamic linear models (DLMs) and mediating variable analysis, potentially assisting applied sports psychologists in planning and monitoring of individual elite athletes' intervention programmes.
Design: We illustrate this approach by examining the relationships of training loads with a performance-related state ('self-efficacy') and the role of potential mediating PBS variables ('fatigue/lack of energy' and 'being in shape') in explaining these relationships in an elite triathlete across time.
Method: Self-reports of PBS states (twice weekly) and training data were collected over 137 days. Using DLMs and mediating variable analysis, direct (unmediated) and indirect (mediated) short-term associations of training load with 'self-efficacy' were examined.
Results: In this triathlete, we found evidence for positive effects of training on 'self-efficacy', which were partly explained by feelings of 'being in shape' and suppressed by feelings of 'fatigue/lack of energy'. Changes in the relationship between lagged training load and 'fatigue/lack of energy' were observed across time and were particularly pronounced in temporal proximity of an injury.
Conclusion: Strengths of the presented approach are its dynamic nature enabling the observation of changes occurring over time, use of statistical inference rather than visual data interpretation, and quantification of mediating effects to identify potential pathways of intervention. Additionally, the DLM method can identify complex nonlinear associations by examining correspondence between changes in levels of predictors and changes in magnitude and direction of predictor-outcome associations.

Applied sports scientists strive to understand and quantify how physical training impacts on the performance of individual elite athletes. Psychobiological (PBS) states may mediate the relationship between training and performance. Performance-related PBS states have been defined as comprising of at least cognitive, affective, motivational, volitional, bodily, kinaesthetic, operational (skill-related), and communicative forms (Bortoli, Bertollo, & Robazza, 2009; Hanin, 2010). In this context, the role of applied sport psychologists is to understand and quantify how physical training impacts on an athlete's PBS states and, eventually, how these states are related to performance. This information can help develop effective individualized intervention programs aimed at the regulation of performance-related PBS states. It may also assist the identification of signs of impending staleness or "overtraining syndrome" episodes defined as an athlete's negative response to overtraining characterized by decrements in performance and performance-related states persisting even after a rest period or reduced training (Raglin & Wilson, 2000).

The observed substantial inter-individual variability in the effects of training (Borresen & Lambert, 2009) and PBS states (Hanin, 2000, 2007) on performance, and of training on PBS states (Raglin & Wilson, 2000; Sawka et al., 2007) requires the adoption of an idiographic approach focussing on an in-depth understanding of individual athletes (Barnett, Cerin, Reaburn, & Hooper, 2010). The strongest and most accurate evidence of the causal effects among an athlete's physical training, PBS states and performance comes from experimental studies (Thomas, Nelson, & Silverman, 2005). However, elite athletes are reluctant to participate in such trials as they are disruptive to their established training regimen

* Corresponding author. Tel.: +852 25890590; fax: +852 2818 8042.
E-mail addresses: abarnett@hku.hk (A. Barnett), ecerin@hku.hk (E. Cerin), p.reaburn@cqu.edu.au (P. Reaburn), Sue.Hooper@communities.qld.gov.au (S. Hooper).

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and may lead to performance decrements. In these circumstances, a naturalistic, observational approach without research-driven manipulation of training or PBS states becomes the only viable alternative.

Apart from being more acceptable to athletes and coaches, naturalistic studies also have the advantage of being more easily implemented over extended periods. This facilitates the study of the short- and long-term dynamics of an athlete's adaptation and responses to training (Avalos, Hellard, & Chatard, 2003; Coyle, 2005; Jones, 2006) and PBS state–performance relationships (Hanin, 2000). Athletes change and evolve across time (intra-individual variability). Therefore, it is important for idiographic studies on training–PBS states–performance relationships to be dynamic in nature and identify changes in such relationships (Barnett et al., 2010; Cerin, Szabo, Hunt, & Williams, 2000; Hanin, 2000, 2007).

Ways to analyse dynamic relationships of training with PBS states and performance in observational single-case studies

Relationships among training, PBS states, and performance in single-case studies have often been examined using visual analyses of graphical representations or profiles of PBS states (e.g., Hanin, 2000; Kellmann & Kallus, 2001; Kinugasa, Cerin, & Hooper, 2004). Although easy to implement, this type of analysis may lead to erroneous conclusions due to its inability to account for the effects of confounders and autocorrelation. The former referring to factors that mask the true independent relationships between explanatory and outcome variables, the latter referring to successive observations being correlated (Barnett et al., 2010; Bengali & Ottenbacher, 1998; Kinugasa et al., 2004). Another major weakness of visual analysis is its inability to quantify dose–response relationships and how these change across time, which makes the planning of effective individually-tailored intervention programs more difficult and less accurate.

Several alternative regression-based statistical methods addressing the drawbacks of visual analyses have been proposed (Barnett et al., 2010; Kinugasa et al., 2004). The most suited to a dynamic naturalistic approach to monitoring training-PBS states–performance relationships are dynamic linear models (DLMs; West & Harrison, 1997), as they can gauge the temporal stability of associations and describe their temporal patterns (Barnett et al., 2010; West & Harrison, 1997). Importantly, unlike other types of time-series models [i.e., models for sets of sequences of data points measured at successive times (Gorman & Allison, 1997)], DLMs allow the integration of relevant expert knowledge (i.e., from sport scientists, athletes and coaches) about the studied relationships or plausible ranges of values prior to and during data collection. Therefore, compared to other modelling approaches the number of data points required to obtain reliable regression estimates is reduced and the ability of the model to adapt to foreseeable changes in the system is increased (West & Harrison, 1997). When accurate prior information is available, non-volatile simple models including a level component (intercept) and a predictor may produce robust regression estimates with as few as five data points. As the complexity the models and volatility of the underlying processes increases, the number of required data points increases (>50 or 100). This is especially the case if no prior information on the possible distributional characteristics of the regression parameters is available.

In contrast to other time-series models, such as multivariate Box–Jenkins seasonal auto-regressive integrated moving average models (SARIMA; Gorman & Allison, 1997), and other models for longitudinal data (multilevel models), DLMs do not assume time-invariant effects of a predictor on the outcome. To identify change in relationships of a predictor with an outcome, the former models require that time by predictor interaction terms be included. These interaction terms represent simple linear or quadratic changes in associations. However, changes in associations may follow irregular and unpredictable patterns due to the effect of unmeasured events and states (e.g., stress at work, injury). These changes can be easily captured by DLMs (Barnett et al., 2010). In the context of sport performance, the ability to identify changes in effects facilitates the study of the dynamics of athletes' long-term adaptations to training (Coyle, 2005) and changes in responses to training across time (Avalos et al., 2003), including impending staleness episodes (Raglin & Wilson, 2000).

An in-depth understanding of an individual athlete's system requires the identification of PBS mechanisms through which training may affect performance. If performance measures are scarce, indicators of perceived readiness to perform may be used. One such indicator is performance-related self-efficacy defined as an athlete's belief in his/her ability to perform so as to obtain a desired performance-related outcome (Feltz, 1988). PBS mechanisms explaining the relationships between training and performance or perceived readiness to perform can be identified using a combination of DLMs and mediating variable analysis. Fig. 1 shows a simplified version of a mediation model of performance-related self-efficacy. A PBS state mediates the effects of training on performance-related self-efficacy if (1) training is significantly related to the state (i.e., the regression coefficient α is statistically significant) and (2) the variable is significantly related to performance-related self-efficacy after controlling for training (i.e., the regression coefficient β is statistically significant). The amount of the effect of training on performance-related self-efficacy through a specific PBS state can be quantified by multiplying the coefficients α and β (Cerin, 2010; MacKinnon, 2008). Thus, for example, if a 1-unit increase in training yields a 2-unit increase in fatigue ($\alpha = 2$) and a 1-unit increase in fatigue results in a 3-unit decrease in readiness to perform ($\beta = -3$), the effect of training on performance-related self-efficacy through fatigue would be $\alpha \times \beta = -6$ units (a 6-unit decrement in self-efficacy). The coefficient τ' in Fig. 1 represents the so-called direct (unmediated by fatigue or being in shape) association of training with performance-related self-efficacy, while the regression coefficient τ represents the total association (sum of mediated and unmediated effects) of training with performance-related self-efficacy.

Importantly, mediating variable analyses using sets of DLMs do not require as many observations as applications of large-sample methods, such as structural equation modelling. This is because,

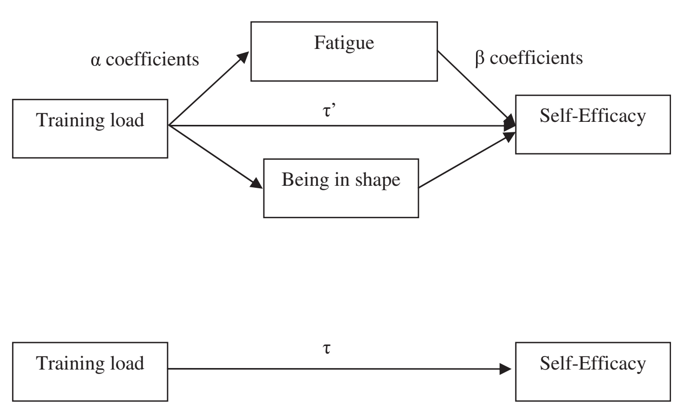

Fig. 1. Diagrammatic representation of direct (τ') and indirect (through fatigue and being in shape; coefficients α and β) effects of training load on performance-related self-efficacy.