Systematic Responses of Match High-Intensity Performance to Weekly External Training Load During a Play-off Mesocycle

Leonidas Papadakis [1 2], **Athanasios Angelis** [1] , **Konstantinos Patras** [3 4]

[1]Omonoia Nicosia FC, Nicosia 1061, Cyprus,[2]s11 Ltd, Nicosia, Cyprus,[3]Orthopaedic Sports Medicine Center, Department of Orthopaedic Surgery, Medical School, University of Ioannina, Ioannina 45110, Greece, and [4]Laboratory of Microbiology, Department of Laboratory Medicine, University Hospital of Ioannina, Ioannina 45110, Greece

GPS | Training Load | Within-Player Effect

Headline

Monitoring training/match load is crucial in identifying patterns and individual responses in adaptation to a training program, risk of non-functional overreaching, injury and illness and readiness to train/compete (1). Whilst previous research examined the effects of training load on match player rank- or skill-related performance (2-4), there is scarce evidence regarding its effects on match running performance (4).

Aim

We modeled how the within-player effect of different training load variables on match running performance varies systematically across levels of the between-player effect during a competitive mesocycle.

Design

A longitudinal observational study design was selected to examine the cross-level interaction of the within-player effect by the between-player effect.

Methods

Eleven professional football players (age: 28.1± 5.5years; height: 180.0±5.0cm; body mass: 77.5±7.3kg) from the same club participated in the present study. The study was conducted during the 2018-2019 season play-off round and there were 10 weekly microcycles with 1 game/microcycle. We analyzed outfield players that completed at least three full-time games, thus the final sample was 63 player-match observations. The experimental protocol complied according to the Declaration of Helsinki for research with human subjects. Ethical approval was granted by the local institutional Review Board and written consent was provided by the players. External training load and match running performance were recorded on all training sessions and official matches using GPS wearable devices sampling at 10 Hz (OptimEye S5, Catapult Innovations, Australia). The devices were activated according to the manufacturer's instructions and GPS data were downloaded onto a portable PC and analyzed using dedicated software (Catapult Open Field Software) and an electronic spreadsheet (Excel, Microsoft Corporation, USA).

The outcome variable was the amount of very high-speed running distance during the match ($VHSR_{game}$) whilst the predictor variables were total distance (TD_{micro}), fast running distance (FR_{micro}) and very high-speed running distance ($VHSR_{micro}$) accumulated during the preceding microcycle. FR_{micro} was defined as the sum of distance covered between 14-19.8km·h-1, whilst $VJSR_{micro}$ and $VHSR_{game}$ were defined as the sum of distance covered >19.8km·h-1.

The data were analyzed using a linear mixed-effects model (SPSS, v.23; Armonk, NY: IBM Corp). The $VHSR_{game}$ was log-transformed to reduce bias due to non-uniformity of errors. Separate analyses were conducted for each predictor variable and all effects were back-transformed to percent effects. Two fixed-effect parameters were specified to separate within-player and between-player effects of the training load variable on $VHSR_{game}$ (5, 6). The within-player effect was obtained by standardizing the external load variable to 2SD's of the mean of each player; it evaluates the magnitude of a change from a typical low to a typical high weekly load for a given player (6). To obtain the between-player effect the individual player's mean external load was standardized to 1 SD of the average of all players' mean; it gauges the systematic variation of the within-player effect for players with typical low, average and typical high mean training load (5). An additional predictor was a linear time trend that accounted for any systematic change of $VHSR_{game}$ during the observation period (5). The model was specified with random intercept for playerID; due to the limited number of games for some players, random effects could only be specified with a homogeneous variance which was deemed unrealistic. Thus we opted that the time-varying slopes varied systematically by specifying cross-level interactions with the time invariant-predictor (5). The random effects are presented as % SD and represent pure between-player variability (playerID) and within-player variability (residuals). The magnitudes of the effects are presented as standardized effect sizes (the effects divided by the square root of the sum of the playerID and residual variances), where <0.2, 0.2 to 0.6, 0.6 to 1.2, 1.2 to 2.0, and >2.0 are regarded as trivial, small, moderate, large, and very large effects, respectively. Nonclinical, magnitude-based inferences were used, where an effect was deemed unclear if the 90% CI included small positive and negative effects; the effect was otherwise deemed clear. Qualitative assessment of chances of clear outcomes was as follows: >25% to 75%, possibly; >75% to 95%, likely; >95% to 99%, most likely (7).

Results

The within-player and the time effect on $VHSR_{game}$ are presented in Table 1. The systematic response of the within-player effect on $VHSR_{game}$ is presented in Figure 1. The systematic response of the time effect on $VHSR_{game}$ is presented in Table 2. Finally the random effects are presented in Table 3.

Discussion

Whilst running performance on match day is a complex phenomenon given the observational nature of the present study,

Table 1. The within-player and between-player effect of the specific training load variable on $VHSR_{game}$ above and beyond systematic change in $VHSR_{game}$ over time.

Predictor Variables	Estimate (%)	ES (90% CI)	Inference
Time effect			
Model TD_{micro}*	-35.1	-1.81 (-1.11; -2.51)	most likely large
Model FR_{micro}**	-27.3	-1.44 (-0.89; -2.0)	most likely large
Model $VHSR_{micro}$***	-26.9	-1.75 (-1.04; -2.46)	most likely large
Within-player effect			
$ZTD_{microwithin2SD*}$	6.5	0.26 (-0.15; 0.67)	possibly small
$ZFR_{microwithin2SD**}$	13.5	0.57 (0.15; 0.99)	likely small
$ZVHSR_{microwithin2SD***}$	7.3	0.40 (-0.06; 0.85)	likely small
Between-player effect			
$ZTD_{microbetween\#}$	-10.1	-0.45 (0.25; -1.14)	unclear
$ZFR_{microbetween\#}$	1.9	0.08 (-0.45; 0.62)	unclear
$ZVHSR_{microbetween\#}$	7.7	0.41 (0.02; 0.81)	likely small
Cross-level interaction of the time effect			
Model TD_{micro}	24.4	0.92 (-0.11; 1.95)	likely moderate
Model FR_{micro}	13.0	0.55 (-0.10; 1.20)	likely small
Model $VHSR_{micro}$	18.3	0.94 (0.25; 1.62)	very likely moderate
Cross-level interaction of the within-player effect			
Model TD_{micro}	-7.2	-0.30 (0.27; -0.91)	unclear
Model FR_{micro}	-3.7	-0.17 (0.43; -0.77)	unclear
Model $VHSR_{micro}$	-5.1	-0.29 (0.18; -0.94)	possibly small

Abbreviations: *conditional at ZTDmicrobetween=0; **conditional at ZFRmicrobetween=0; ***conditional at ZVHSRmicrobetween=0. #conditional at time=0. The 2-way interactions modify the coefficients of the simple main effects.

Table 2. Systematic variation of the time effect as ES (90%CI) across levels of the between-player effect.

Model	Average-1 SD	Average	Average+1 SD
TD_{micro}	-2.73 (-1.17; -4.29)****	-1.81 (-1.11;-2.51)****	-0.89 (-0.08; -1.72)**
FR_{micro}	-1.99 (-1.13; -2.86)****	-1.44 (-0.89; -2.0)****	-0.89 (-0.05; -1.73)**
$VHSR_{micro}$	-2.69 (-1.77; -3.6)****	-1.75 (-1.04; -2.46)****	-0.81 (0.24; -1.86)

Abbreviations: *possibly, **likely, ***very likely, ****most likely. Unclear effects have no superscript.

Table 3. Random effects describing the variability (%) in $VHSR_{game}$ that is not explained by the specific training load variable.

	Between-player variablility		Within-player variability	
External load variable	CV (%)	90% CI	CV (%)	90% CI
Empty model	15.6	2 to 22.7	23.4	19 to 27.4
TD_{micro} model	17.1	3.7 to 24.7	19.5	15.7 to 22.7
FR_{micro} model	15.2	2.2 to 22	18.5	14.8 to 21.6
$VHSR_{micro}$ model	3.9	-5.8 to 8.4	19.1	15.4 to 22.4

no systematic change was expected on the outcome variable. However the presence of systematic change across the observation period may blunt the relationship between the outcome and the predictors (5, 8). Thus our approach models the relationship between training load and match running performance net the time effect (8).

Our results indicate that within-player variation in either FR_{micro} or $VHSR_{micro}$ (and to a lesser extend TD_{micro}) has clear, substantial effect on $VHSR_{game}$ across a short-term competitive period (Table 1). Furthermore the within-player effects of either FR_{micro} or $VHSR_{micro}$ appear to be equally effective which may indicate the plethora of programming possibilities that high intensity interval training may offer (9). Although individual responses could not be modeled properly, the within-player effect varied deterministically (non-randomly) as a function of the between-player effect (5). Thus it appears that a 2SD change of acute training load has the potential to differentiate match running performance for players with average or typical low mean training load (Figure 1).

$VHSR_{game}$ decreased substantially across the observation period; this decrease varied systematically across levels of mean training load (Table 2). Although a systematic change in match running performance was not considered previously (4) it appears that match performance may suffer in the short-

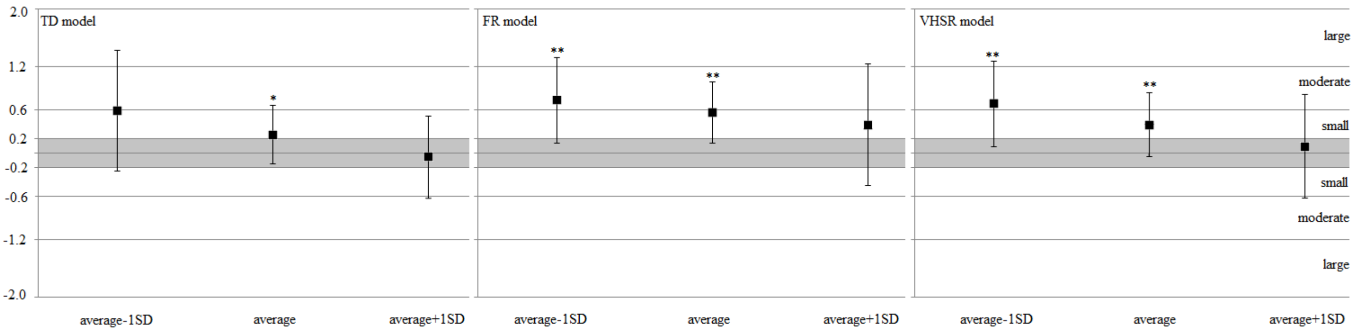

Fig. 1. Systematic response of the within-player effect on $VHSR_{game}$ across levels of the between-player effect. Abbreviations: *possibly, **likely; unclear effects have no superscript.

term. $VHSR_{game}$ decreased almost uniformly across levels of mean training loads with the exception of typical high mean $VHSR_{micro}$ (Table 2). The unclear change may indicate that the player who accumulated 1SD more than average mean $VHSR_{micro}$ across the observation period may have had less pronounced performance reductions.

The random effects from the model estimate variability in $VHSR_{game}$ that is not explained by the predictors (Table 3). The between-player variability represents the unexplained variability in $VHSR_{game}$ due to player differences (positional, tactical, etc). $VHSR_{micro}$ was the only variable that explained a significant portion of the between-player CV and in addition had a substantial between-player effect. Thus between-player differences in match running performance across the observation period could be explained by the amount of mean $VHSR_{micro}$. The within-player variability represents the individual players' variability in a typical match after adjusting for the external load. It appears that TD_{micro}, FR_{micro} and $VHSR_{micro}$ when used in isolation can explain only a small fraction of the within-player variation (Table 3); modeling the relationship between FR_{micro} and match running performance net the time effect explained at best 1/5 of the original within-player variability in the empty model.

Practical Applications

- Lower (FR_{micro}) were as effective as higher ($VHSR_{micro}$) training intensities in producing clear, substantial effects upon $VHSR_{game}$.
- Practitioners have more choices for effective training solutions by either prescribing the specific training volumes at lower (FR; 14-19.8km·h-1) or higher intensities (VHSR; >19.8km·h-1) on an individual player basis.
- However in terms of predictive ability either FR_{micro} or $VHSR_{micro}$ explain only a small fraction of the within-player match running performance variation even after accounting for any systematic change in the outcome.

Limitations

- The limited number of games for some players did not allow proper modeling of (any) individual responses; this was partly off-set by modeling systematic responses.
- Whilst we used specifically external training load, differences in team cultures may favor other predictors of match running performance.

Conflicts of Interest

The authors declare no financial, institutional, and/or personal conflicts of interest that might inappropriately influence actions or statements of the present study.

Dataset

Data will be made available to all interested researchers upon request from the corresponding author (KP).

References

1. Bourdon PC, Cardinale M, Murray A, Gastin P, Kellmann M, Varley MC, Cable NT. Monitoring Athlete Training Loads: Consensus Statement. Int J Sports Physiol Perform. 2017 Apr;12(Suppl 2):S2161-S70.
2. Lazarus BH, Stewart AM, White KM, Rowell AE, Esmaeili A, Hopkins WG, Aughey RJ. Proposal of a global training load measure predicting match performance in an elite team sport. Front Physiol. 2017 Nov 21;8:930.
3. Rowell AE, Aughey RJ, Hopkins WG, Esmaeili A, Lazarus BH, Cormack SJ. Effects of Training and Competition Load on Neuromuscular Recovery, Testosterone, Cortisol, and Match Performance During a Season of Professional Football. Front Physiol. 2018 Jun 7;9:668.
4. Ryan S, Coutts AJ, Hocking J, Dillon PA, Whitty A, Kempton T. Physical Preparation Factors That Influence Technical and Physical Match Performance in Professional Australian Football. Int J Sports Physiol Perform. 2018 Sep 1;13(8):1021-1027.
5. Hoffman L. Longitudinal analysis: Modeling within-person fluctuation and change. New York & London: Routledge/Taylor & Francis Group; 2015.287p.
6. Wiig H, Andersen TE, Luteberget LS, Spencer M. Individual Response to External Training Load in Elite Football Players. Int J Sports Physiol Perform. 2020 Jan 30;15(5):696-704.
7. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. Med Sci Sports Exerc. 2009 Jan;41(1):3-13.
8. Wang L, Maxwell SE. On disaggregating between-person and within-person effects with longitudinal data using multilevel models. Psycol Methods. 2015 Mar;20(1):63-83.
9. Laursen PB, and Buchheit M. Science and Application of High Intensity Interval Training: Solutions to the Programming Puzzle. Champaign: Human Kinetics; 2018.