International Journal of Sports Physiology and Performance, **(Ahead of Print)**
https://doi.org/10.1123/ijspp.2020-0083

Human Kinetics
ORIGINAL INVESTIGATION

Data Reduction Approaches to Athlete Monitoring in Professional Australian Football

Samuel Ryan, Thomas Kempton, and Aaron J. Coutts

Purpose: To apply data reduction methods to athlete-monitoring measures to address the issue of data overload for practitioners of professional Australian football teams. ***Methods:*** Data were collected from 45 professional Australian footballers from 1 club during the 2018 Australian Football League season. External load was measured in training and matches by 10-Hz OptimEye S5 and ClearSky T6 GPS units. Internal load was measured via the session rate of perceived exertion method. Perceptual wellness was measured via questionnaires completed before training sessions with players providing a rating (1–5 Likert scale) of muscle soreness, sleep quality, fatigue, stress, and motivation. Percentage of maximum speed was calculated relative to individual maximum velocity recorded during preseason testing. Derivative external training load measures (total daily, weekly, and monthly) were calculated. Principal-component analyses (PCAs) were conducted for Daily and Chronic measures, and components were identified via scree plot inspection (eigenvalue > 1). Components underwent orthogonal rotation with a factor loading redundancy threshold of 0.70. ***Results:*** The Daily PCA identified components representing external load, perceived wellness, and internal load. The Chronic PCA identified components representing 28-d speed exposure, 28-d external load, 7-d external load, and 28-d internal load. Perceived soreness did not meet the redundancy threshold. ***Conclusions:*** Monitoring player exposure to maximum speed is more appropriate over chronic than short time frames to capture variations in between-matches training-cycle duration. Perceived soreness represents a distinct element of a player's perception of wellness. Summed-variable and single-variable approaches are novel methods of data reduction following PCA of athlete monitoring data.

Keywords: data reduction, PCA, training load, training response

Athlete-monitoring systems are commonly used in professional sport to provide insights into athlete training readiness and injury risk.[1] In the case of professional team sports such as Australian football (AF), readiness refers to a player's ability to complete planned training activities with no excessive physical impairment, mental fatigue, or psychological distress.[1] Player readiness can be informed by objective and subjective information including external training load measures,[2,3] internal load measures,[4] exposure to maximum speed,[5] and perceptual wellness assessments.[6] These data are typically analyzed over short and longer time frames to provide ongoing evaluations of how athletes are adapting to training and competition stimuli.

A challenge faced by coaches and scientists is synthesizing and communicating actionable information from a broad range of data sources to support decision making regarding a player's preparation for training and competition. Indeed, monitoring professional AF players is a complex process with inferences of player readiness derived from many data sources.[1] While extensive access to monitoring data allows practitioners to capture important information about the training process, this can lead to data overload, where data representing similar constructs (ie, training load, fitness, and fatigue) are analyzed and reported.[3] This likely results in data collinearity, which can cause accentuation of relationships between monitoring variables and outcome measures when conducting observational analysis of athlete preparation data.[7] This can lead to erroneous conclusions when assessing the effect of monitoring measures on outcomes such as injury risk and performance.[7]

One approach to address the issue of data overload in athlete monitoring is to selectively reduce the number of variables that are collected and analyzed to improve the efficiency of analysis without losing the veracity of the information provided by these data. One such method is principal-component analysis (PCA), a data reduction technique designed to evaluate the contribution of multiple variables to the variance of an entire dataset of correlated measures.[3,8]

Recent research has applied PCA to identify correlated training load measures in professional team sports.[3] One study examining derivative measures of internal load (session rate of perceived exertion [RPE]) in professional rugby league players reported cumulative load measures (ie, rolling values of load) to explain 57% of the variance in session training load, while 33% of the variance was explained by measures of change in load and acute load combined.[3] Other research in professional rugby league reported the most variance in individual training load from field-based skills sessions to be explained by either total distance (TD) covered, session RPE load, or Player Load.[8] Collectively, these studies demonstrate that PCA is an effective approach to data reduction in team sport training load monitoring systems. However, in practice player readiness is based on individual responses to training and matches (ie, perceptual wellness assessments) and derivative load measures (ie, cumulative weekly and monthly load). Indeed, no research has applied a data reduction method to commonly used player readiness measures to address the issue of data overload for practitioners of professional AF teams.

Separately, to provide useful information to coaches and scientists, monitoring tests should possess measurement characteristics of validity (the ability of a test to measure what it is designed

Ryan and Coutts are with the Human Performance Research Centre, University of Technology Sydney (UTS), Sydney, NSW, Australia. Ryan, Kempton, and Coutts are with the Carlton Football Club, Melbourne, VIC, Australia. Ryan (sam.ryan@carltonfc.com.au) is corresponding author.

to measure), reliability (the consistency of results from a test), and sensitivity (the extent to which a test can detect changes beyond the typical error in results).[9,10] Moreover, these tools must be practical and time efficient to administer regularly without interrupting the training process.[11] Therefore, the inclusion of a variable into a professional athlete monitoring system should be based on measurement properties and feasibility, in addition to their statistical contribution (established via PCA). Consequently, the primary aim of this study was to apply a data reduction technique to athlete monitoring measures in professional AF using PCA. The second aim was to provide methods of applying the findings of PCA to inform selection of athlete monitoring measures based upon their statistical contribution and practicality.

Methods

Design and Subjects

Prospective, longitudinal data were collected from 45 professional Australian footballers (age, 24.6 [4.0] y; height, 1.9 [0.1] m; body mass, 86.0 [9.1] kg) from 1 club during the 2018 AFL competition season (week prior to round 1 to round 23, ie, March to August). Informed consent and institutional ethics approval were obtained from the University of Technology Sydney (UTS HREC: ETH17-1942).

Perceptual Wellness

Players completed a short questionnaire on their smartphone before the main field training session each week. Players provided a rating from 1 to 5 (1 representing a poor rating and 5 representing a good rating) in relation to their muscle soreness, sleep quality, fatigue level, stress, and motivation. While these methods were like those used in previous team sport research,[12–14] the questionnaire used in this study was customized for the observation group.

External Training Load

External training load was measured in training by 10-Hz Global Positioning System (GPS) units (OptimEye S5; Catapult Sports, Melbourne, Australia). Each unit was assigned to an individual player and worn in a small pouch in their training or match jerseys. After each session or match, data were downloaded using proprietary software (Openfield 1.20.0; Catapult Sports). External loads from 8 of 22 matches included in the analysis were collected via an alternative system (ClearSky T6; Catapult Sports) due to these matches being played indoors. All other match data were collected via the same system used for training sessions (OptimEye S5; Catapult Sports). Unpublished data from the technology manufacturer have reported distances covered at low and high speed over 80 m to have differences of <5% between the 2 systems (Catapult Sports). All data files were cleaned to ensure only recorded data from time spent on the field and/or during training activities was retained. Training and match files for each player were then exported and placed into a customized Microsoft Excel spreadsheet (Microsoft Corp, Redmond, MA) for analysis. This provided single figures to represent the total distance covered, total high-speed running (HSR; distance covered between 20 and 23 $km{\cdot}h^{-1}$), and very high-speed running distance (VHSR; distance covered >23 $km{\cdot}h^{-1}$)[15] covered by each player, their maximum speed ($km{\cdot}h^{-1}$) attained during a training session or match, and a total number of accelerations, decelerations, and changes of direction (inertial movement analysis). Maximum speed attained during the session was then compared with each player's highest maximum speed recorded in during preseason testing to generate a percentage of maximum. The primary GPS technology used in this study (OptimEye S5) is a valid and reliable method of quantifying movement in team sports; however, research has reported greater measurement error with higher movement speeds.[16,17]

Internal Training Load

Internal training load was measured via the session-RPE method within 30 min following every training session and competition match following standardized protocols.[18,19] Session RPE is a valid and reliable method of quantifying internal training load in professional AF.[19]

Derivative Load Measures

Training load was classified according to acute and chronic time frames[5] (Table 1). All load measures were inclusive of training and match loads.

Statistical Analyses

A total of 84,294 data points from 23 monitoring variables were collated into a customized Microsoft Excel spreadsheet (Microsoft Corp) for analysis. Two PCAs were undertaken to identify uncorrelated components to represent constructs of training load and training response. Components were named based on the nature of variables identified within each component, for example "Perceptual Wellness" for component 2 of "Daily" PCA. Prior to analyses, data were tested for sampling adequacy using the Kaiser-Meyer-Olkin measure (a threshold of 0.5) and for suitability for component analysis using the Bartlett test of sphericity (significance accepted at $P \leq .05$).[3,8,20] Orthogonal rotation was used to enhance interpretation of PCAs, while the components of each analysis were determined via inspection of a scree plot (Figures 1 and 2) in addition to eigenvalues of >1. Only variables with factor loadings of >0.70 were reported. These methods correspond with protocols described elsewhere.[3,8,20] Analyses were performed using jamovi statistical software (version 0.9; jamovi Project; https://www.jamovi.org).

Results

Three and 5 components were identified for Daily and Chronic measures, respectively. The percentage of variance that each component contributed, their eigenvalues and factor loadings for each variable are shown in Tables 2 and 3. Factor loadings denote correlations between each measure and the principal component it belongs to.[8] Kaiser-Meyer-Olkin measures were 0.80 and 0.59 for "Daily", and "Chronic" PCAs, while both PCAs passed the Bartlett test of sphericity for factor analysis ($P < .05$). Of the 23 monitoring measures analyzed, 1 displayed a factor loading below the redundancy threshold of 0.70 (perceived soreness). Three of the remaining 22 measures displayed a factor loading of between 0.70 and 0.80 (sleep quality, Times >85% last 7 d, and Times >90% last 7 d).

Discussion

The aim of this study was to apply a data reduction technique to common athlete monitoring measures in professional AF using

Table 1 Definition of Acute and Chronic Training Load Measures Used in PCA

Training load measure	Definition
Acute training load measures	
Daily load	Distance or arbitrary units completed in 1 d
Daily maximum speed	Highest speed (km·h^{-1}) reached in each field training session or competition match
Inertial movement analysis units, IMA	Count of IMA events completed in each field training session or competition match
Chronic training load measures	
Total weekly load	Distance or arbitrary units completed in last 7 d (rolling)
Total month load	Distance or arbitrary units completed in last 28 d (rolling)
Times >85% last 7 d	Number of instances >85% of maximum speed reached during the last 7 d (rolling)
Times >90% last 7 d	Number of instances >90% of maximum speed reached during the last 7 d (rolling)
Times >85% last 28 d	Number of instances >85% of maximum speed reached during the last 28 d (rolling)
Times >90% last 28 d	Number of instances >90% of maximum speed reached during the last 28 d (rolling)

Abbreviations: AU, arbitrary unit; IMA, inertial movement analysis; PCA, principal component analysis.

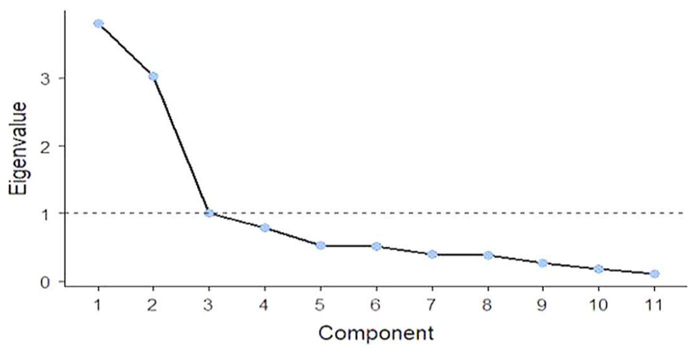

Figure 1 — Scree plot for principal-component analysis 1: daily monitoring measures.

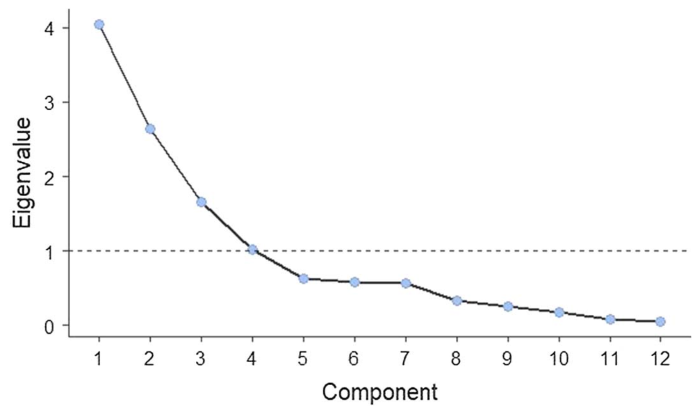

Figure 2 — Scree plot for principal-component analysis 2: chronic monitoring measures.

PCA. A secondary aim was to apply the findings of PCA to provide representative athlete monitoring measures based on their statistical contribution and practicality. Of the 23 monitoring measures analyzed, 1 displayed a factor loading below the redundancy threshold (0.70). The Daily PCA identified 3 components to represent daily external load, perceived wellness, and daily internal load, respectively. The Chronic PCA identified components to represent 4 monitoring constructs; chronic speed exposure, 28-d external load, 7-d external load, and chronic internal load.

Daily Monitoring Measures

The "Daily" PCA highlighted 3 components to represent daily collected monitoring measures, with component 1 contributing 34.4% of variance all Daily measures. Variables in this component were external load measures captured via GPS (TD, high-HSR and VHSR, maximum sprint speed, and inertial movement analysis count [captured via accelerometer within GPS units]). TD and distance covered at high-speed (>14 km h^{-1}) captured via GPS have been shown to be practical, valid and reliable measures of movement in team-sport athletes.[21,22] According to factor loadings of each running distance variable (ie, TD, HSR, and VHSR), TD displayed the strongest correlation with the component, followed by HSR and VHSR, suggesting TD provides the best representation of daily external load compared with HSR distances (>20 km·h^{-1}). In contrast, previous research in professional AF match play has reported greater variability in volume of HSR distances covered compared with TD and maximum speed,[23] indicating the former is more important when monitoring running output from matches as individual differences are likely derived from HSR output. However, it is well established that there is increased measurement error with increased movement speed when quantifying movement in team sport athletes using GPS,[21,22] hence it remains unclear whether variability in higher speed measures during training and matches can be attributed to device error or actual variance in player movement. The difference in findings may be because TD values (encompassing any locomotive movement) are always greater than HSR distance values; hence TD will have a greater loading on the component. When selecting variables to represent daily external load, we suggest using TD as it has the greatest loading on the daily external load component and is collected with less measurement error than HSR distance measures.

The second component consisted of 4 perceived wellness elements (motivation, stress, fatigue, and sleep quality), contributing 27.6% of the total variance of the dataset. Perceptual wellness questionnaires are commonly used in professional team sports as a practical method of assessing individual player recovery from a match and their readiness to train over acute time frames.[24] Our findings suggest that perceived motivation, stress, fatigue, and sleep represent the same construct, hence may be used interchangeably when assessing daily perceived wellness of professional AF players. Alternatively, these measures may be combined as a composite figure to provide an overall assessment of perceived wellness. Interestingly, perceived soreness displayed a factor loading below the redundancy threshold of 0.70 within the "Daily PCA" in the present study, indicating a relatively poor correlation with the wellness component identified. This suggests that perceived soreness represents a separate construct to the other 4 wellness elements examined here; fatigue, sleep quality, stress, and motivation measure one aspect of acute readiness while soreness represents an isolated element of a player's psychobiological response to training and match stressors and their readiness to train.

Table 2 PCA of "Daily" Monitoring Measures: Mean, SD, and Factor Loadings via Orthogonal Rotation

Component	Factor loading	Mean	SD
Component 1—daily external load (34.4% variance, eigenvalue: 3.8)			
TD daily load, m	0.92	6015.1	4125.6
HSR daily load, m	0.90	291.2	267.9
VHSR daily load, m	0.88	166.3	178.3
Daily maximum velocity, km h^{-1}	0.81	26.3	4.1
IMA, events	0.81	74.7	63.8
Component 2—perceived wellness (27.6% variance, eigenvalue: 3.0)			
Motivation, 1–5	0.84	3.6	.8
Stress, 1–5	0.84	3.5	.6
Fatigue, 1–5	0.81	3.3	.7
Sleep quality, 1–5	0.73	3.4	.7
Component 3—daily internal load (9.1% variance, eigenvalue: 1.0)			
SRPE daily load, AU	0.99	211.1	303.3

Abbreviations: AU, arbitrary units; HSR, high-speed running; IMA, inertial movement analysis; PCA, principal component analysis; SRPE, session rate of perceived exertion; TD, total distance; VHSR, very high-speed running. Note: VHSR (>23 km h^{-1}) and HSR (>20 km h^{-1}).

The third component consisted of only session RPE daily load, with a factor loading of 0.98. Session RPE has been established as a valid, reliable, and feasible (cost and time efficient) method of training load quantification[18,19] and is widely used by professional sporting teams. Our findings indicate that session RPE measures a construct of daily load separate to external load measures, in agreement with previous research in rugby league using the same statistical analysis technique.[25] This study reported session RPE to have the highest factor loading among internal and external load measures during conditioning sessions,[25] indicating that a combination of internal and external load measures is required to quantify daily training load among professional team sport athletes. It is also well established that a combination of external and internal load measures is necessary to comprehensively describe load completed by athletes.[26] Moreover, session RPE is a practical method of measuring load completed via other training modalities such as cross-training and resistance training.[1] Therefore, we suggest monitoring session RPE load alongside TD (external load measure) when quantifying daily load in professional AF.

Chronic Monitoring Measures

The "Chronic" PCA identified 4 components to represent monitoring variables collected at rolling time points at 7 and 28 d. The first component consisted of exposures to maximum speed, with 28-d measures displaying stronger correlations to the component compared with 7-d measures. Indeed, players will have more exposures to their maximum speed across 28 d than 7 d, which may explain this observation. However, it is likely that a period of 28 d encompasses different between-match training microcycles (6 or 8 d) compared with 7 d and therefore provides a more stable indication of maximum speed exposure over a chronic period. Interestingly, research in professional AF has suggested that optimal maximum speed exposure (>85% of maximum speed) to reduce noncontact injury risk is between 5 and 8 instances over a 28-d period, indicating that monitoring speed exposure over a chronic (28 d) period may be more practical than acute periods

Table 3 PCA of "Chronic" Monitoring Measures: Mean, SD, and Factor Loadings via Orthogonal Rotation

Component	Factor loading	Mean	SD
Component 1—chronic maximum speed exposure (33.6% variance, eigenvalue: 4.0)			
Times >90% last 28 d, instances	0.83	3.3	1.8
Times >85% last 28 d, instances	0.82	6.2	2.1
Times >85% last 7 d, instances	0.79	1.6	0.84
Times >90% last 7 d, instances	0.77	0.86	0.76
Component 2—28 d external load (21.9% variance, eigenvalue: 2.6)			
TD total month load last 28 d, m	0.89	71,045.3	24,056.1
HSR total month load last 28 d, m	0.89	3452.5	1388.7
VHSR total month load last 28 d, m	0.84	1976.2	980.3
Component 3—7 d external load (13.7% variance, eigenvalue: 1.6)			
HSR total week load, m	0.90	998.4	465.6
VHSR total week load, m	0.85	570.9	326.1
TD total week load, m	0.82	494.1	245.1
Component 4—chronic internal load (8.4% variance, eigenvalue: 1.0)			
SRPE total month load last 28 d, AU	0.91	5687.1	1333.5
SRPE total week load last 7 d, AU	0.90	376.8	409.2

Abbreviations: AU, arbitrary units; HSR, high-speed running; PCA, principal component analysis; SRPE, session rate of perceived exertion; TD, total distance; VHSR, very high-speed running. Note: VHSR (>23 km h^{-1}) and HSR (>20 km h^{-1}).

relative to injury risk.[5] Taken together, we suggest monitoring maximum speed exposure over a 28 d period in professional AF players based on statistical contribution and practicality (ie, association with injury risk and variations in between-match training cycle duration).

The second component identified 28-d external load variables (TD, HSR, and VHSR distance), with TD and HSR distance displaying the equal-greatest factor loading on the component (0.89). This indicates that both variables contribute the same amount of variance to the dataset and therefore may be interchangeable when evaluating 28-d external load completed by players. However, given the increased measurement error associated with increased movement speed using GPS reported previously,[21,22] we suggest using TD to represent external load over a chronic period of 28 d. Separately, component 3 highlighted 3 measures to represent 7-d external load (TD, HSR, and VHSR distance) with HSR displaying the highest factor loading (0.90). This finding contrasts with the Daily PCA, possibly indicating that individual variation in player HSR output is more pronounced over a 7-d period compared with a single training session and is therefore more suitable to represent 7-d external load based on statistical contribution to the component.

Chronic internal load measures were represented by 1 component of the "Chronic" PCA, with average daily (over the past 28 d) and total weekly session RPE load displaying strong correlations with the component (factor loadings of >0.90). Interestingly, session RPE measures showed stronger correlations over longer time frames (28 d) than those over shorter periods (7 d), suggesting the former may be a more appropriate period to assess global training load. This is likely due to the fact that any given 7 d period during a competition season may not include a competition match (ie, 8 d between some matches) which represents a substantial portion of a player's in-season load.[27] Therefore, we suggest monitoring internal load over 28 d in contrast to 7 d when evaluating player readiness based on total load completed.

One aim of the present study was to apply a PCA to common monitoring measures to reduce their number based on correlations between variables. However, while several studies have used PCA to reduce correlated athlete monitoring data, no research has proposed ways of using these components to inform selection of athlete monitoring measures on their statistical contribution and practicality. We propose 2 methods of applying the findings of PCA to enhance parsimony in athlete monitoring; single-variable approach and summed variable approach, with examples using the findings of the "Daily" PCA conducted in the present study.

Single Variable

The single-variable approach requires selecting 1 variable from each component of the PCA to represent an athlete monitoring construct based on the measurement characteristics and practicality. This is advantageous as it reduces a group of similar variables assessing the same construct to one valid, reliable, and practical measure. For example, component 1 of the "Daily" PCA undertaken in the present study identified 5 external load variables above the redundancy threshold. TD, HSR, and VHSR all demonstrated factor loadings of 0.88 to 0.92; hence their statistical contribution to the component is similar. Previous studies have reported GPS to be a valid and reliable method of time-motion analysis,[21,22] however this research also reported increased measurement error with increased speeds. Therefore, if practitioners prefer to select a single measure to represent a construct of daily external training load, we suggest selecting TD to represent daily external load among the variables examined in this study due to lower measurement error than HSR and VHSR distance covered. The benefit of the single-variable approach is that it reduces a group of measures that provide similar statistical contribution to a single variable that best represents a monitoring construct and is most practical. However, the reductionist nature of this method can neglect the statistical contribution of other variables within the component that may provide a similar contribution but are not as reliable or practical.

Summed Variable

The summed variable approach involves taking the values of each variable within a principal component and multiplying it by the factor loading identified via PCA, and then summing these values together to produce an arbitrary figure to represent each construct.[28] An example is shown in Table 4 using component 1 of the "Daily" PCA undertaken in the present study. The advantage of this approach is that it provides a single arbitrary figure to represent a monitoring construct while accounting for the contribution of other variables in a component. While this approach is more inclusive than the single-variable method, a limitation is that it dilutes the variance in contribution of variables to each component. Moreover, the summed variable is an arbitrary figure and may also be less interpretable that the single-variable approach.

While this study was the first to apply a data reduction analysis technique to athlete monitoring measures in professional AF, our findings should be interpreted with caution. First, external load during 8 of 22 matches included in the analysis were collected using an alternative positioning system due to these matches being played at an indoor stadium, and while both methods are valid measures of player movement in team sport activity,[22,29] no research has established the technical agreement between these 2 systems. Second, this research did not model changes in any of the 23 variables examined against outcomes measures. Future research may assess the utility of the approaches presented here by establishing associations between a parsimonious collection of monitoring variables and match performance. Finally, our data were collected from 1 cohort of professional AF players during 1 season, hence may reflect the demographics of the group and the periodization strategies adopted during the observation period. Nonetheless, the single-variable and summed variable approaches may be applied to monitoring data from any cohort of professional athletes.

Practical Applications

1. Summed variable and single-variable approaches are novel methods of athlete monitoring data reduction following principal component analyses.

Table 4 Summed Variable Approach to Component 1 of "Daily" PCA

Variable	Equation
TD daily load, m	(1) TD daily load, m × 0.92
HSR daily load, m	(2) HSR daily load, m × 0.90
VHSR daily load, m	(3) VHSR daily load, m × 0.88
Daily maximum speed, km h^{-1}	(4) Daily maximum speed, km h^{-1} × 0.81
IMA	(5) IMA × 0.81

Abbreviations: HSR, high-speed running; IMA, inertial movement analysis; PCA, principal component analysis; TD, total distance; VHSR, very high-speed running.

2. Monitoring player exposure to maximum sprint speed is more appropriate over chronic periods to capture variations in between-match training cycles.
3. Subjective ratings of soreness represent an element of a player's perceived readiness to train that is separate from stress, motivation, fatigue, and sleep quality.

Conclusions

This study applied a data reduction technique to an athlete-monitoring data set and proposed methods for selecting monitoring measures to represent training load and response based on their statistical contribution and practicality. We presented 2 methods for applying the findings of PCA; a single-variable approach and a summed-variable approach. While both methods have advantages and disadvantages, we encourage practitioners to consider the exact nature and number of monitoring variables they collect within their training environment to determine the most appropriate approach. Indeed, the inclusion of a variable into an athlete monitoring system should be based on measurement properties and feasibility (cost and time) in addition to statistical contribution. The techniques presented in the current study can assist in reducing the amount of monitoring data collected and analyzed, which is an important consideration for practitioners working in professional sport to ensure the best use of human and financial resources.

References

1. Ryan S, Kempton T, Impellizzeri F, Coutts A. Training monitoring in professional Australian football: theoretical basis and recommendations for coaches and scientists. *Sci Med Football*. 2020;4(1):52–58. doi:10.1080/24733938.2019.1641212
2. Weaving D, Marshall P, Earle K, Nevill A, Abt G. Combining internal- and external-training-load measures in professional rugby league. *Int J Sports Physiol Perform*. 2014;9(6):905–912. PubMed ID: 24589469 doi:10.1123/ijspp.2013-0444
3. Williams S, Trewartha G, Cross MJ, Kemp SPT, Stokes KA. Monitoring what matters: a systematic process for selecting training-load measures. *Int J Sports Physiol Perform*. 2017;12(suppl 2):S2101–S2106. PubMed ID: 27834553 doi:10.1123/ijspp.2016-0337
4. Impellizzeri FM, Rampinini E, Coutts AJ, Sassi A, Marcora SM. Use of RPE-based training load in soccer. *Med Sci Sports Exerc*. 2004;36(6):1042–1047. PubMed ID: 15179175 doi:10.1249/01.MSS.0000128199.23901.2F
5. Colby MJ, Dawson B, Peeling P, Heasman J, Rogalski B, Drew M, Stares J. Improvement of prediction of noncontact injury in elite Australian footballers with repeated exposure to established high-risk workload scenarios. *Int J Sports Physiol Perform*. 2018;13(9):1130–1135. PubMed ID: 29543079 doi:10.1123/ijspp.2017-0696
6. 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;13(8):1021–1027. PubMed ID: 29466065 doi:10.1123/ijspp.2017-0640
7. Weaving D, Jones B, Ireton M, Whitehead S, Till K, Beggs CB. Overcoming the problem of multicollinearity in sports performance data: a novel application of partial least squares correlation analysis. *PLoS One*. 2020;14(2):e0211776. PubMed ID: 30763328 doi:10.1371/journal.pone.0211776
8. Weaving D, Dalton NE, Black C, Darrall-Jones J, Phibbs PJ, Gray M, Jones B, Roe GAB. The same story or a unique novel? Within-participant principal-component analysis of measures of training load in professional rugby union skills training. *Int J Sports Physiol Perform*. 2018;13(9):1175–1181. PubMed ID: 29584514 doi:10.1123/ijspp.2017-0565
9. Currell K, Jeukendrup AE. Validity, reliability and sensitivity of measures of sporting performance. *Sports Med*. 2008;38(4):297–316. PubMed ID: 18348590 doi:10.2165/00007256-200838040-00003
10. Robertson S, Kremer P, Aisbett B, Tran J, Cerin E. Consensus on measurement properties and feasibility of performance tests for the exercise and sport sciences: a Delphi study. *Sports Med*. 2017;3(1):2.
11. Ryan S, Pacecca E, Tebble J, Hocking J, Kempton T, Coutts AJ. Measurement characteristics of athlete monitoring tools in professional Australian football. *Int J Sports Physiol Perform*. 2020;15(4):457–463. doi:10.1123/ijspp.2019-0060
12. Gallo TF, Cormack SJ, Gabbett TJ, Lorenzen CH. Self-reported wellness profiles of professional Australian football players during the competition phase of the season. *J Strength Cond Res*. 2017;31(2):495–502. PubMed ID: 27243912 doi:10.1519/JSC.0000000000001515
13. Gastin PB, Meyer D, Robinson D. Perceptions of wellness to monitor adaptive responses to training and competition in elite Australian football. *J Strength Cond Res*. 2013;27(9):2518–2526. PubMed ID: 23249820 doi:10.1519/JSC.0b013e31827fd600
14. Buchheit M, Racinais S, Bilsborough JC, Bourdon PC, Voss SC, Hocking J, Cordy J, Mendez-Villanueva A, Coutts AJ. Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players. *J Sci Med Sport*. 2013;16(6):550–555. PubMed ID: 23332540 doi:10.1016/j.jsams.2012.12.003
15. Johnston RJ, Watsford ML, Pine MJ, Spurrs RW, Murphy A, Pruyn EC. Movement demands and match performance in professional Australian football. *Int J Sports Med*. 2012;33(2):89–93. PubMed ID: 22095328 doi:10.1055/s-0031-1287798
16. Nicolella DP, Torres-Ronda L, Saylor KJ, Schelling X. Validity and reliability of an accelerometer-based player tracking device. *PLoS One*. 2018;13(2):e0191823. PubMed ID: 29420555 doi:10.1371/journal.pone.0191823
17. Whitehead S, Till K, Weaving D, Jones B. The use of microtechnology to quantify the peak match demands of the football codes: a systematic review. *Sports Med*. 2018;48(11):2549–2575. PubMed ID: 30088218 doi:10.1007/s40279-018-0965-6
18. Foster C, Florhaug JA, Franklin J, et al. A new approach to monitoring exercise training. *J Strength Cond Res*. 2001;15(1):109–115. PubMed ID: 11708692
19. Scott TJ, Black CR, Quinn J, Coutts AJ. Validity and reliability of the session-RPE method for quantifying training in Australian football: a comparison of the CR10 and CR100 scales. *J Strength Cond Res*. 2013;27(1):270–276. PubMed ID: 22450253 doi:10.1519/JSC.0b013e3182541d2e
20. Hair JF. *Multivariate Data Analysis: A Global Perspective*. Upper Saddle River, NJ/London, UK: Pearson Education; 2010.
21. Johnston RJ, Watsford ML, Kelly SJ, Pine MJ, Spurrs RW. Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *J Strength Cond Res*. 2014;28(6):1649–1655. PubMed ID: 24276300 doi:10.1519/JSC.0000000000000323
22. Coutts AJ, Duffield R. Validity and reliability of GPS devices for measuring movement demands of team sports. *J Sci Med Sport*. 2010;13(1):133–135. PubMed ID: 19054711 doi:10.1016/j.jsams.2008.09.015
23. Kempton T, Sullivan C, Bilsborough JC, Cordy J, Coutts AJ. Match-to-match variation in physical activity and technical skill measures in

professional Australian Football. *J Sci Med Sport*. 2015;18(1):109–113. PubMed ID: 24444753 doi:10.1016/j.jsams.2013.12.006
24. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med*. 2016;50(5):281–291. PubMed ID: 26423706 doi:10.1136/bjsports-2015-094758
25. Weaving D, Jones B, Marshall P, Till K, Abt G. Multiple measures are needed to quantify training loads in professional rugby league. *Int J Sports Med*. 2017;38(10):735–740. PubMed ID: 28783849 doi:10.1055/s-0043-114007
26. Impellizzeri F, Marcora S, Coutts A. Internal and external training load: 15 years on. *Int J Sports Physiol Perform*. 2019;14(2):270–273. PubMed ID: 30614348 doi:10.1123/ijspp.2018-0935
27. Ritchie D, Hopkins WG, Buchheit M, Cordy J, Bartlett JD. Quantification of training and competition load across a season in an elite Australian football club. *Int J Sports Physiol Perform*. 2016;11(4):474–479. PubMed ID: 26355304 doi:10.1123/ijspp.2015-0294
28. Henderson M, Fransen J, McGrath JJ, Harries SK, Poulos N, Coutts A. Situational factors affecting rugby sevens match performance. *Sci Med Football*. 2019;3(4):275–280. doi:10.1080/24733938.2019.1609070
29. Hoppe MW, Baumgart C, Polglaze T, Freiwald J. Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PLoS One*. 2018;13(2):e0192708. PubMed ID: 29420620 doi:10.1371/journal.pone.0192708