Title: The same story or a unique novel? Within-participant principal component analysis of training load measures in professional rugby union skills training.

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ABSTRACT

Purpose: The study aimed to identify which combination of external and internal training load (TL) metrics capture similar or unique information for individual professional players during skills training in rugby union using principal component analysis (PCA). *Method:* TL data were collected from twenty-one male professional rugby union players across a competitive season. This included PlayerLoad™, total distance (TD), and individualised high-speed distance (HSD; >61% maximal velocity; all external TL) obtained from a micro-technology device worn by each player (Optimeye X4, Catapult Innovations, Melbourne, Australia) and the session-rating of perceived exertion (sRPE; internal TL). PCA was conducted on each individual to extract the underlying combinations of the four TL measures that best describe the total information (variance) provided by the measures. TL measures with PC "loadings" (PC_L) above 0.7 were deemed to possess well-defined relationships with the extracted PC. *Results:* The findings show that from the four TL measures, the majority of an individual's TL information (1st PC: 55 to 70%) during skills training can be explained by either sRPE (PC_L: 0.72 to 0.95), TD (PC_L: 0.86 to 0.98) or PlayerLoad™ (PC_L: 0.71 to 0.98). HSD was the only variable to relate to the *2nd* PC (PC_L: 0.72 to 1.00), which captured additional TL information (+19 to 28%). *Conclusions*: Findings suggest practitioners could quantify the TL of rugby union skills training with one of PlayerLoad™, TD, or sRPE plus HSD whilst limiting omitted information of the TL imposed during professional rugby union skills training.

Key words: monitoring; team-sport; GPS; RPE; principal component analysis

INTRODUCTION

Skills training is regularly prescribed to prepare professional rugby union players for the physical and technical-tactical requirements needed to succeed in competition.[1] This mode is one of several types of activity (i.e. interval-, sprint-, small-sided-games- and resistance-training) which is regularly prescribed by practitioners within a holistic training programme.[1-2] However, due to their differing characteristics (e.g., duration, intensity, energy system stimulus), balancing the training load (TL) imposed across these modes is challenging, yet important to manage negative training outcomes such as injury incidence.[3-4] Therefore, quantifying the collective TL imposed is a systematic approach taken by practitioners to maximise their understanding of this overall training process. A key part of this is to implement appropriate analyses and visualisations of TL data to facilitate its embedment into decision making for coaches during their planning of the training process.[5]

Within the age of technology[5], numerous TL methods and variables are now available to practitioners working in team-sports including microtechnology (e.g. global positioning systems [GPS]) and the session-rating of perceived exertion (sRPE).[6-7] These quantify one of two constructs; the external or internal TL, with both considered important to understand the overall training process.[8] The external load reflects the volume, intensity and composition of the activities (e.g. sprints, collisions, accelerations) completed by players. Conversely, the internal load is the psycho-physiological and mechanical response that results from both the external load and an individual's characteristics.[8-10]

As a monitoring procedure, the TL accrued for these numerous variables are reported to the coach for each daily training session and then collated over longer periods of time to understand the "dose-response" relationships between the accumulation and distribution of TL with outcomes such as injury incidence,[4,11] 'fatigue',[12-13] changes in markers of 'fitness'[14-

[15] or technical-tactical performance.[16-17] However, at present numerous studies have reported various external and internal TL variables to possess substantial associations with these important outcomes.[4,11-17] In some instances, multiple individual measures share very similar strengths of association with the same training outcome.[11,12] Therefore, understandably, practitioners often report multiple TL variables to coaches.[6] However, previous authors have highlighted the current dangers of 'data overload'[5] and the need to appropriately visualise and communicate this data to coaches.[18] This is important to consider as it is the coaching staff that decide the content and planning of the training programme and ultimately, the consequent positive (e.g. improved 'fitness') or negative training outcomes (e.g. injury).[5,18] By striving to improve the analysis and communication of TL data, it is hoped that coaches are able to utilise this information more effectively.

In reality, the presence of multiple individual TL variables demonstrating 'dose-response' relationships with training outcomes could be due to either data redundancy (i.e. variables sharing common information [i.e. collinearity]) or because these variables actually capture different aspects of the TL imposed during training. Indeed, many investigations, including meta-analyses,[19] have reported large relationships between TL methods suggesting that these share a substantial proportion of similar information (i.e. variance).[2,21-22] However, it is equally important to note that there is also a substantial proportion of unexplained information between these TL measures which is moderated (i.e. weaker or stronger relationships) by the mode of training.[2,19-20,22]

Adopting approaches that can combine common (i.e. redundant or co-linear data) information (i.e. variance) yet concurrently separate the unique information that is provided by these multiple TL variables could be useful to provide the most parsimonious representation of the TL constructs.[5] This could also optimise the reporting and visualisation of TL data to coaches and other decision makers, helping to translate this information into actionable manipulation of the training process.[5,18]

One such capable approach is principal component analysis (PCA), which attempts to explain the maximal amount of information (i.e. variance) within a dataset that consists of multiple variables, such as those often found in TL monitoring systems,[5-6] within the fewest number of transformed variables termed principal components.[2] Adopting PCA, Williams et al.[23] reported that different variables calculated from sRPE (e.g. weekly cumulative sRPE, week-to-week change in sRPE) provided distinct TL information in professional rugby union. Within professional rugby league, using PCA, Weaving et al.[2] observed the external TL to capture the greatest proportion of information (48%) provided by five TL variables during skills training, with internal TL methods capturing additional unique information (21%). This suggests that whilst the use of five TL measures by practitioners could be reduced to two and still capture ~70% of the overall information, the findings also provide an important suggestion that the use of a single TL variable (and subsequent derivative calculations) could underrepresent the true TL imposed during each session.

Although requiring large individual datasets, the inter-individual variability in response to training[8] suggests that understanding which of the multiple collected TL measures provide similar or unique information for an individual during a single mode of training (i.e. technical-tactical [skills] training), is important to optimise the monitoring process.[8-10] Indeed, appropriately quantifying the TL imposed on professional rugby union players during technical-tactical training (i.e. skills training) is a key focus as it contributes to the largest proportion of the weekly field-based TL.[1] If different TL measures capture different information (i.e. variance) within the individual, potentially important information that could help to improve the explanation of training outcomes (i.e. injury) could be omitted if practitioners and researchers adopt only a single measure to represent the TL imposed during this mode of training. Understanding these multivariate relationships through approaches such as PCA, can assist practitioners to identify which specific TL measure(s) capture the most information to represent the TL construct (i.e. content validity) for each individual and assist in the development of a parsimonious and time-efficient TL monitoring process.[5,18] In addition, as PCA captures the majority of the information provided by a multivariate dataset within a reduced number of composite variables (i.e. the principal components), it enables multivariate data to be visualised more clearly and concisely onto singular two dimensional scatterplots.

Therefore, the aims of this study were to identify multivariate within-participant external and internal load relationships during skills training in professional rugby union, through the use of PCA. In line with recent discussions[5,18], a secondary aim was to demonstrate how PCA can assist practitioners to condense the information provided by multiple TL methods to better visualise and communicate this information through the use of the principal component scores and a two-dimensional scatterplot.

METHODS

Subjects

Twenty-one male professional rugby union players were recruited and took part in the study (age: 27 ± 4 y; body mass: 102 ± 13 kg; height: 187 ± 7 cm), including 11 forwards (age: 27 ± 5 years; body mass: 105 ± 11 kg; height: 188 ± 7 cm; 30-15 intermittent fitness test [30-15 V_{IFT}]: 18.3 ± 0.9 km.h^{-1}; maximal velocity [V_{MAX}]: 8.6 ± 0.5 m.s^{-1}) and 10 backs (age: 26 ± 2 years; body mass: 92 ± 5 kg; height: 183 ± 4 cm; 30-15 V_{IFT}: 19.2 ± 0.7; V_{MAX}: 9.4 ± 0.4). Intra-positionally, the sample included 2 props, 2 hookers, 3 second rows, 4 back rows, 2 scrum halves, 2 fly-halves, 3 centres, and 3 outside backs. Ethics approval was granted by the university ethics committee and written consent was acquired from all subjects prior to data collection.

Design

To evaluate the relationships between internal and external TL measures, a longitudinal observational research design was conducted during professional rugby union field-based team skills training sessions across a single competitive season. These sessions primarily focused on team-based drills for enhancing rugby-union skills and rehearsing team strategy (e.g. set pieces and attacking/defensive patterns). Depending on the length of recovery cycle between-matches, sessions were completed 2 to 3 times per training microcycle. For each training session, internal and external TL were quantified by the sRPE method[6] and a microtechnology device (Optimeye X4, Catapult Innovations, Melbourne, Australia; firmware version: 7.17) which quantified a player's total distance (TD), their distance covered above an individualised high-speed-threshold (HSD) and PlayerLoad™ respectively. PCA was conducted on each individuals TL data to identify which of the four TL variables captured similar or unique information for each individual. To standardise the PCA, only players with greater than 40 skills training observations were included in the current study (21 players [session observation range: 40 to 62]).

Methodology

All players wore the same microtechnology unit during training and testing throughout the course of the study to limit potential between-unit variability in the reported metrics.[24] The device contains a 10Hz GPS, 100Hz tri-axial accelerometer, gyroscope and magnetometer worn as per typical methods.[22]

Running-based external TL metrics selected were TD and HSD due to their evidence of their practical utility and evidence of criterion validity to associate with training outcomes (i.e. injury),[4,11-12] their practical popularity[6] and their capability to be monitored in real-time.[25] HSD was determined as a percentage (> 61%) of the maximal velocity (V_{MAX})[26] achieved during a 40 m maximal sprint, which was assessed using GPS at regular intervals during the pre-and in-season periods.[27] Although both arbitrary and individualised thresholds have demonstrated some relationship with the training response[11-12,28] and different methods of individualisation are used[26,28-31], individualised thresholds are considered more useful to provide indication of the physiological cost of higher 'intensity' running.[29-31]

PlayerLoad™, expressed in arbitrary units (AU) and derived from the 100 Hz tri-axial accelerometer, was chosen as an overall measure of external load experienced by players which, unlike TD and HSD, is also suggested to include accelerations/decelerations and collision-based activity, which are key considerations within rugby union.[32] All microtechnology data (TD, HSD and PlayerLoad™) were downloaded using the proprietary Catapult Openfield software (version 1.12.0).

Each player provided their rating of perceived exertion (RPE) which was collected from each player with limited third-party observation ~30 minutes after the completion of each training session on a modified Borg category ratio-10 scale.[7] This rating was then multiplied by training session duration to give a TL (sRPE) in arbitrary units (AU).[7]

Statistical Analyses

PCA was undertaken for each individual as per previous methods[22-23], which transforms the combined information (i.e. variance) provided by the original TL measures (TD, HSD, PlayerLoad™, sRPE) into a new set of variables called principal components (PC), which always equal the number of original measures and which are transformed without losing any of the information provided by the original variables.[22-23] The first transformed PC captures the most information, with each subsequent PC explaining a reduced amount of information. An additional benefit to PCA is that each PC are uncorrelated so each capture distinct information within each individual's dataset. Therefore, a multi-faceted approach recommended by Hair et al.[33] was conducted to determine the optimal number of PCs to extract and interpret for each individual which included an examination of the scree plot, eigenvalues and the accumulation of the variance explained by each PC (Figure 1). Following this, orthogonal varimax rotation was performed to determine the contribution of the original variables to the variance explained for each extracted PC and to improve interpretability.[22-23] The original variables that demonstrated principal component "loadings" (PC_L) (i.e. eigenvectors of the covariance matrix) that exceeded ± 0.70 were considered indicative of a well-defined relationship with the extracted PC.[22-23]

All data were mean-centered and scaled prior to analyses PC "scores" were also calculated for every skills training session that comprised of a player's dataset, for each PC deemed important to extract. In the current study, PC "scores" were the mean centred TD, HSD, PlayerLoad™ and sRPE multiplied by their respective PC_L for each PC deemed important to extract and then summated.[33] In the presence of multiple extracted PC's, the PC "scores" of an individual were plotted on a two-dimensional scatterplot to provide practitioners with an example of how to visualise multivariate TL data. PCA was conducted using IBM SPSS Statistics for Windows (Version 24.0, Armonk, New York, USA).

**** INSERT FIGURE 1 ABOUT HERE****

RESULTS

The mean (± SD) field sessions completed by players during the observation period was 46 ± 7. The mean squad TL for skills training for TD, HSD, PlayerLoad™, and sRPE were 3096 ± 675 m, 127 ± 202 m, 292 ± 87 AU, and 178 ± 67 AU respectively.

For the *1st* PC, eigenvalues for each player ranged from 2.21 to 3.01 which explained 55 to 75% of the information (i.e. variance) provided by the four TL measures. For the *2nd* PC, eigenvalues ranged from 0.58 to 1.01 explaining 19 to 28% of TL information. The total accumulated variance for the *3rd* and *4th* PC, eigenvalues ranged from 0.14 to 0.71 and 0.03 to 0.38 explaining 4 to 12% and 1 to 9% of TL variance respectively.

Figure 1 demonstrates an example of the multifaceted approach to extract meaningful PCs. In line with this approach, the *1st* and *2nd* PC for each individual were retained for interpretation.

Figure 2 highlights the PC loadings (PC_L; i.e. eigenvectors of the covariance matrix) for each of the 4 original variables for the *1st* (Figure 2A) and *2nd* PC (Figure 2B) for all twenty-one participants.

Figure 3 highlights two scatterplot examples of the *1st* (x-axis) and *2nd* (y-axis) PC "scores" for each individual training session for a front-row forward (Figure 3A) and fly-half (Figure 3B) during skills training across professional rugby union season. X-axis values relate to the *1st* PC which comprises of meaningful (> 0.70) PC_L for PlayerLoad^{TM}, TD and sRPE. Y-axis values relate to the the *2nd* PC which comprises of a meaningful PC_L for HSD.

****INSERT FIGURE 2 ABOUT HERE****

****INSERT FIGURE 3 ABOUT HERE****

DISCUSSION

By identifying common variance between multiple TL measures, the current study is the first to demonstrate a systematic process to identify TL variables that provide similar or distinct information for individual professional rugby union players through PCA. The findings show that from the four TL measures used in the current study, the majority of TL information (60 to 70%) for an individual during field-based skills training across a complete season can be explained by either sRPE (PC_L: 0.72 to 0.95), TD (PC_L: 0.86 to 0.98) or PlayerLoad^{TM} (PC_L: 0.71 to 0.98) (Figure 2A). This suggests that practitioners should be confident that they would not be omitting information by only reporting one of these three variables to coaches. However, in the current study, HSD captured unique additional variance (19 to 28%) to sRPE, TD and PlayerLoad™ as it possessed a well-defined relationship (PC_L: > 0.7) with the 2nd PC for each player (Figure 2B). In total, 75 to 95% of the variability in four TL measures could be reflected by the two constructed PC's.

A large amount of shared information within-individual players has previously been reported between sRPE and TD within Australian rules football (r = 0.81)[34] and rugby league skills training (r = 0.69).[20] Bartlett et al.[35] also found TD to be the most important predictor of sRPE utilising an individualised machine learning technique within Australian Footballers. Previous research has also reported weaker associations between sRPE and HSD (r = 0.53)[20] and reported that two PC were needed to explain a meaningful proportion of the information provided by five TL methods during professional rugby league skills training.[2] Collectively, current and previous study findings provide evidence that multiple measures can be reduced for an individual without losing TL information, which can assist in the development of a parsimonious and time-efficient TL monitoring system for practitioners working in professional rugby union.[5] However, at the same time, more than one TL variable is needed to capture the largest proportion of the total information provided by multiple TL variables.

The findings from this study can also be used in conjunction with practical considerations to inform the efficient reporting and quantification of field-based training. For example, if microtechnology is always available to players then practitioners might consider adopting TD and HSD, as these variables allow real-time control of the training stimulus[25] and current study findings suggest practitioners can be confident that TD is likely to reflect a players perceived exertion at the completion of skills training. However, practitioners must also consider that sRPE is collected for other modes of training which microtechnology cannot quantify (e.g. resistance training, off-feet conditioning) and therefore, by omitting the collection of sRPE practitioners would be unable to quantify a cumulative global measure of TL across all modes of training.

The current study has also demonstrated that by understanding the unique and similar information provided by the four TL variables through PCA, the information provided by the investigated TL variables can be condensed into a smaller number of orthogonalised variables (i.e. the principal components scores) whilst still capturing the majority of the total information (i.e. variance). This allows high dimensional data to be summarised more concisely for a given latent construct (i.e. training load) which can allow practitioners to better visualise data and avoid 'data overload'.[5] For example, in Figure 3A, 89% of the total information provided by TD, sRPE, PlayerLoad™ (all x-axis) and HSD (y-axis) across 48 training sessions (i.e. 192 data points) for a front-row forward can be captured and visualised within a single 2-D scatterplot. In comparison, without PCA, to capture the same amount of information for each TL measure individually, practitioners would need to plot 6 separate 2-D scatterplots (e.g. TD *vs* HSD, TD *vs* sRPE etc).

The findings of the current study also provide evidence that although multiple TL methods share a large proportion of information (i.e. variance) and can be reduced, the use of a single TL variable is likely suboptimal to capture the actual variability between different field-based skills training sessions across a season. This supports previous research,[2,22,36] and suggests practitioners and researchers should consider adopting more than one measure in "dose-response" analyses to provide a better representation of the TL imposed. This is highlighted by the black data points within the scatterplot in Figure 3A, where the 1st PC scores (TD, sRPE and PlayerLoad™; *x*-axis) are similar across multiple skills sessions for a front-row forward yet the 2nd PC (HSD; *y*-axis) during these sessions were vastly different. Therefore, if a practitioner adopted solely sRPE, TD or PlayerLoad™ to represent the TL, these sessions would be interpreted as providing similar TL, although the actual acute (e.g.

fatigue) responses for this player could be different.[12-13,37] Ultimately this could lead to suboptimal training prescription and training outcomes.

This is supported by previous ‘dose-response’ investigations where lower perceived ratings of perceived recovery were associated with greater accumulations of HSD across two to four training days in professional football players (*r* range = -0.28 to -0.42).[13] Greater accumulations of HSD have also been associated (r = 0.76) with increases in creatine kinase concentration 24 h after professional rugby league match play.[12] Multiple TL methods have also been found to possess differing contributions to injury incidence in professional rugby league players.[36] Collectively, current and previous findings suggest a combination of measures are needed to be included in ‘dose-response’ analyses (i.e. logistic regression) such as the association between the acute and chronic training load ratio and injury incidence.[3-4]

A limitation of the current study is that skills training is one of many modes of training that professional rugby union players undertake[1] and therefore, how the magnitude of similar or unique information captured by these specific TL measures changes across other modes of training was not established. Additionally, other TL measures are also collected by practitioners, such as differential ratings of perceived exertion or the individualised training impulse (iTRIMP) which have also demonstrated substantial associations with training outcomes.[1,14] Therefore, future research should look to investigate whether these within-individual relationships change during other modes of training (e.g. contact *vs* non-contact skills training, sprint-training, small-sided-games) with additional TL measures and particularly if this influences the relationships with acute (e.g markers of fatigue) and chronic (e.g. injury or changes in ‘fitness’) training responses. However, the study still demonstrates a systematic process for practitioners to determine which variables capture similar or unique information for the collective TL variables that they deem important to quantify during their daily practice. Future research is needed to confirm which combination of TL variables provides the most valid representation of the TL to provide the most reproducible relationships with the important outcomes of the training process in professional rugby union.

PRACTICAL APPLICATIONS

- Practitioners working in professional rugby union should consider that for an individual, TD and PlayerLoad™ will respond similarly to sRPE across multiple skills training sessions. However, HSD provides additional unique information of the load imposed.
- Practitioners could therefore consider reporting either TD, PlayerLoad™ or sRPE plus HSD for an individual to reflect the load imposed during skills training in professional rugby union.
- The current study has demonstrated PCA as a useful process to determine similarity and disparity in the information provided by TL measures. This could be a useful approach to adopt if practitioners collect different measures to the ones investigated in the current study.

CONCLUSIONS

The study has demonstrated a systematic process (i.e. PCA) to determine that for an individual, more than one measure is needed to capture a meaningful proportion of the total information provided by multiple TL measures. TD, sRPE and PlayerLoad™ reflect similar, yet capture the greatest amount of information provided by the four TL methods and subsequently only one could be reported to coaches. However, HSD captures unique additional information. Therefore, this provides evidence that multiple measures are needed to provide the most valid representation of the load imposed during professional rugby union skills training.

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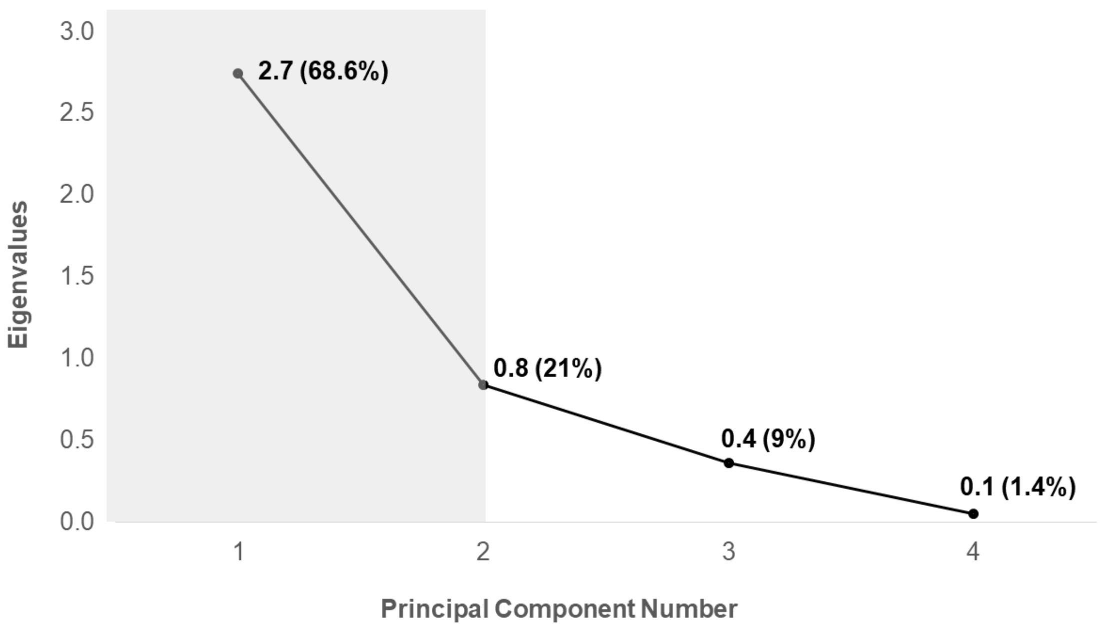


Figure 1. Example of a scree plot and the multifaceted approach to extract meaningful PCs for an individual. Each data point relates to the eigenvalue for each principal component along with the percentage of total variance captured by each principal component (bracketed value). Grey shaded area represents the principal components deemed to be 'meaningful'.

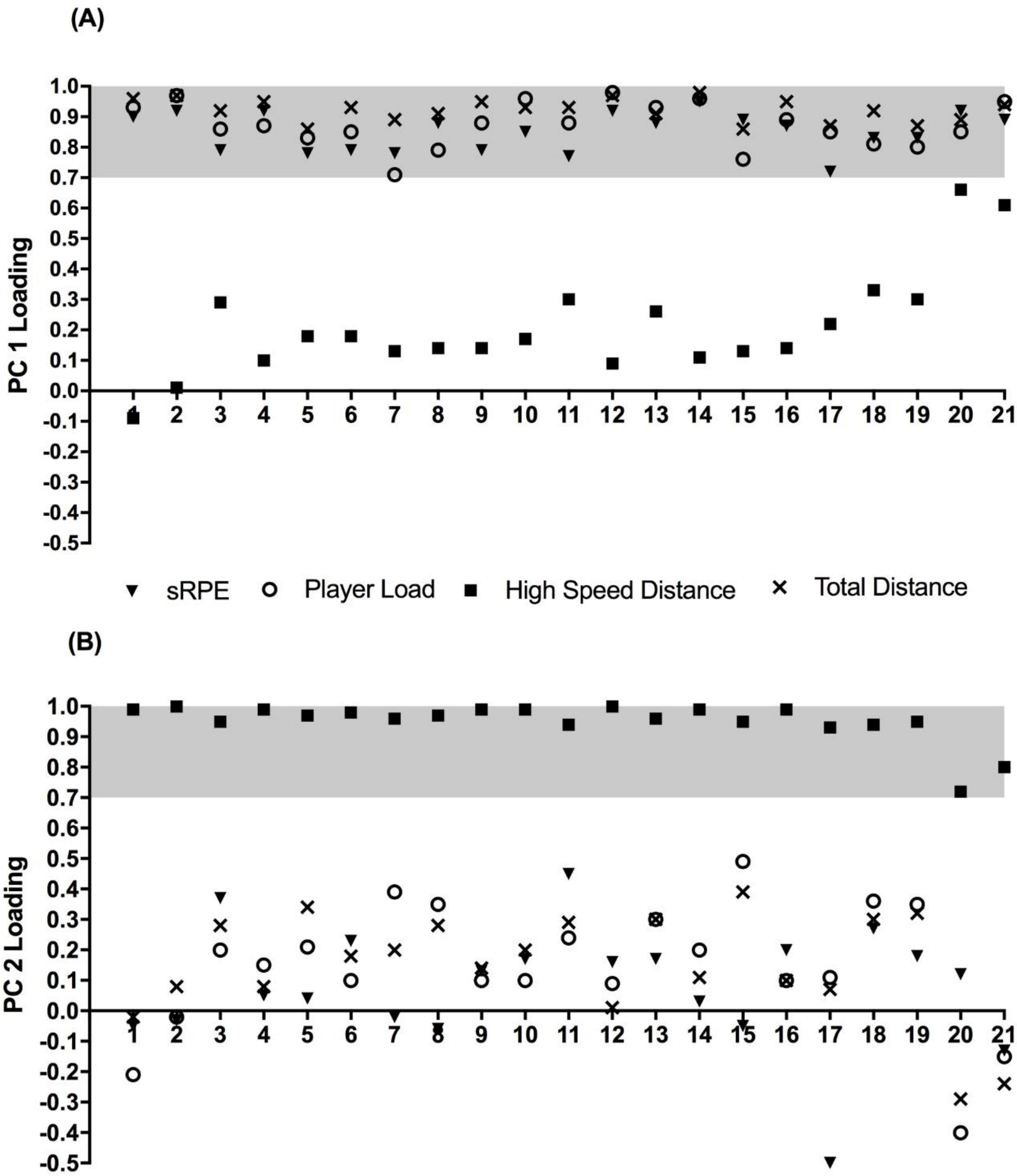
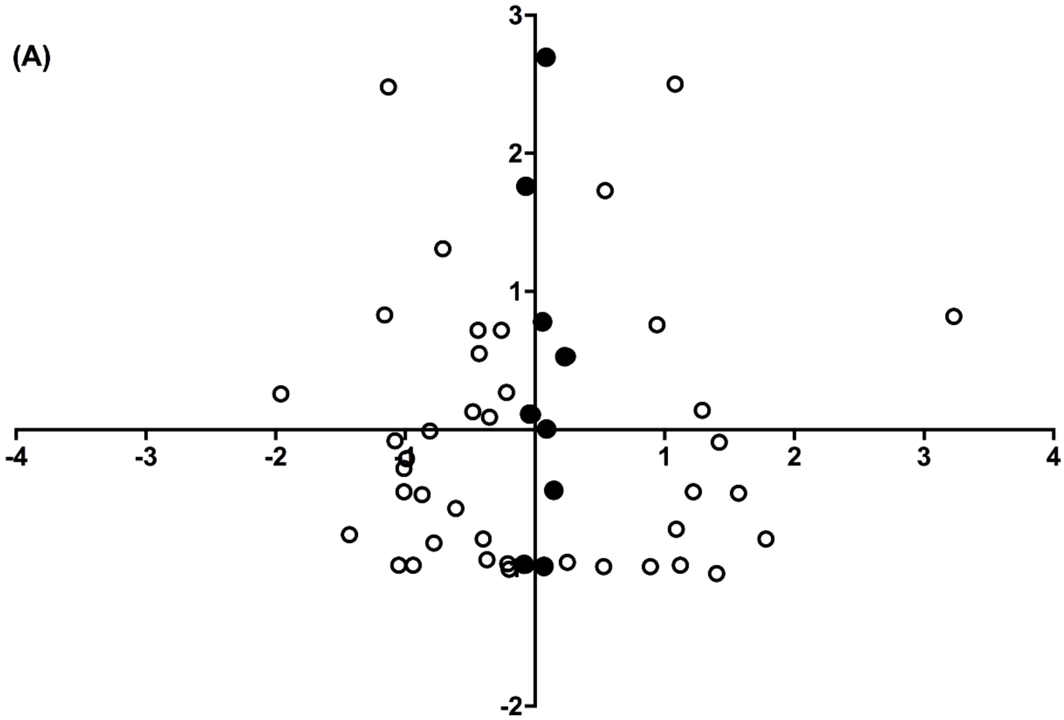


Figure 2. The principal component “loadings” (y-axis) on the 1st (A) and 2nd (B) principal component for each training load measure (TD, sRPE, PlayerLoadTM and HSD) for each individual (x-axis). Grey area represents meaningful “loadings”.


(A)
3
2
1
-2
-4
-3
-2
-1
1
2
3
4

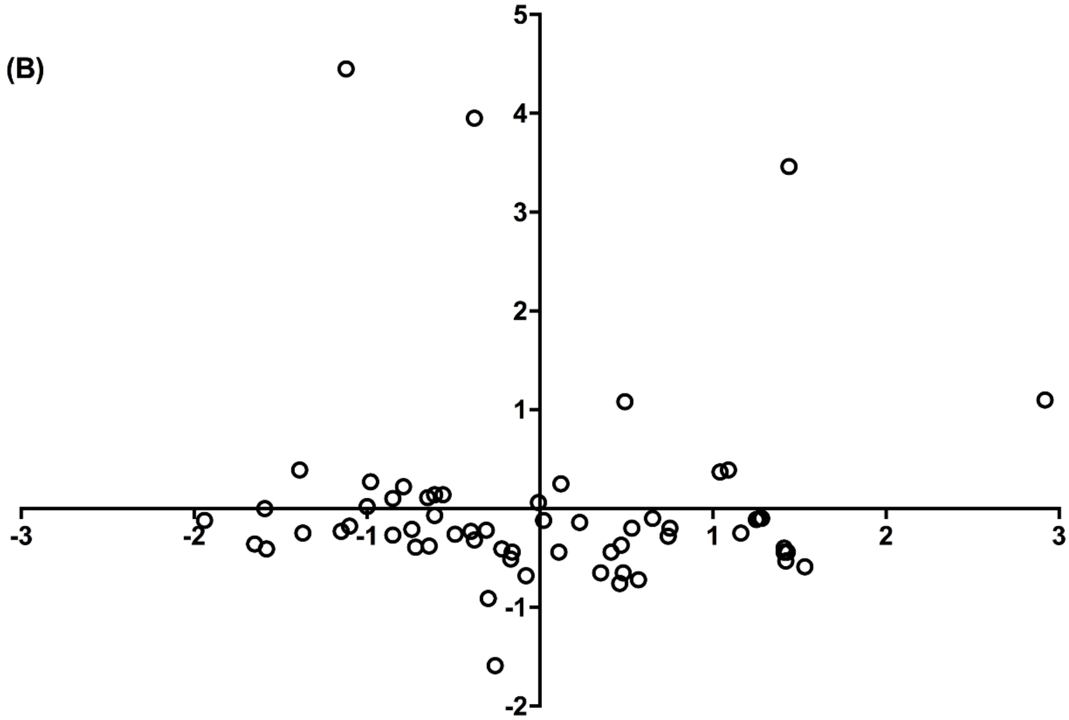

(B)
5
4
3
2
1
-1
-2
-3
-2
-1
1
2
3

Figure 3. Scatterplot of the 1st (x-axis) and 2nd (y-axis) PC "scores" for each individual training session for a frontrow forward (A) and fly-half (B) during skills training across professional rugby union season. X-axis values relate to the 1st PC which comprises of meaningful (> 0.70) principal component "loadings" for PlayerLoadTM, TD and sRPE. Y-axis values relate to the the 2nd PC which comprises of a meaningful component "loadings" for HSD.