Maughan, Patrick C. (2023) *Analysis and application of techniques to monitor training load in youth soccer players.* PhD thesis.

http://theses.gla.ac.uk/83613/

Analysis and Application of Techniques to Monitor Training Load in Youth Soccer Players

Patrick C Maughan

A thesis submitted in partial fulfilment of the requirement of requirements for the Degree of Doctor of Philosophy (PhD) in Sports Sciences

College of Medical, Veterinary & Life Science

The University of Glasgow

Date – 21-12-22

Thesis Abstract

Soccer is regarded as the world's most popular sport, performance in which depends on a range of factors generally characterised as being technical, tactical, physical, or psychological. The lucrative nature of the sport has allowed clubs to invest in academies in the hope of developing future players. These academies are supported by a range of practitioners, alongside investment in further understanding talent identification and talent development. A key role of practitioners within clubs is monitoring the load undertaken by players, with the aim of supporting training prescription to optimise performance and reduce the risk of injury. This thesis develops around five projects, analysing commonly used objective and subjective measures of training load to establish their relationships, developing novel methods of analysing subjective load, and testing the implementation of these methods within the transition from academy to full-time professional soccer.

The first data chapter aimed to describe and quantify relationships between subjective and external measures of training load in professional youth soccer players. Data from differential ratings of perceived exertion (dRPE) and seven measures of external load were collected from twenty youth professional soccer players over a 47-week season. Relationships were described via bivariate correlations and multivariate factor analysis methods. Results from these analyses suggested that there was a theoretical dispersion between measures which may be representative of volume, such as total distance covered, and measures which may be representative of intensity, such as sprint distance. Additionally, it was found that subjective measures of breathlessness and lower body muscle exertion provided limited additional insight over gestalt ratings of perceived exertion (sRPE) within the analysed population.

The second data chapter investigated the influence of training theme or competition on previously described relationships. Subjective load data was collected via sRPE and seven external load measures. General characteristics of training sessions were categorised based on their proximity to match day, with match-play also included within the analyses. Similarly to the first data chapter, analysis presented two, or three, readily interpretably components. The first component was represented by measures of volume, whilst the second and third components were generally represented by measures of intensity. This supports the finding of study one, that the identification of multiple components indicate that load monitoring should comprise multiple variables.

Whilst generally the findings of this study mirrored study one, there were minor differences which suggest that effective monitoring practices should account for the demands of different session types.

The third data chapter assessed the relationship between subjective and external load measures whilst accounting for the impact of phase of season. Subjective load relationships were collected via RPE, whilst data were collected via microelectromechanical system (MEMS) devices to analyse seven external load variables. Data were collected across a 47-week season with phases categorised as being pre-season phase, or competitive phases. Interestingly, when performing principal component analysis and using an alternative method to determine component extraction, only one component was retained for the competitive phases, whilst two components were retained for the pre-season phase. However, if using previously utilised methods similar results would have been found as to the previous data chapters. These findings highlight the importance of clearly defined methodology within factor analysis. Additionally, these results highlight that factoring load based on measures of volume and intensity may be considered as worthwhile practice by practitioners.

Given the collective results from the previous data chapters, the aim of the fourth data chapter was to investigate the structure of relationships between measures of training load and assess whether these can be modified through non-linear transformations. To control for the effects of session duration, sessions were categorised into short (≤ 60mins) or long (> 60mins), based on the mean session duration for both training and match-play. All sRPE were analysed in their raw form and with the inclusion of session duration (sRPE-TL). Additionally, sRPE and sRPE-TL was modified through non-linear transformations by raising to a series of exponentials to provide a metric termed "modified RPE" ($sRPE_{mod}$). Similarly, to previous data chapters, following PCA two components were retained which provided theoretical representations of volume or intensity. Non-linear transformations had little effect on loading profiles for long sessions. For short sessions the loading became more equal between intensity and volume for sRPE-TL, and more aligned to intensity for sRPE. The study demonstrated that sRPE and sRPE-TL predominantly reflect measures of training volume, however, these measures can be modified to better reflect intensity for training sessions less than 60mins in duration.

A key issue within soccer is optimising the transition of players going from academy to full-time professional soccer, therefor the aim of the fifth data chapter was to investigate the load experienced by players undergoing this transition. Additionally, the chapter aimed to determine whether subjective measures of load can provide useful insight into training volume, training intensity, or a combination of the two constructs in an applied setting. Data were collected from 4 academy players who had been identified as transitioning into full-time soccer. Data were then collected the following pre-season from the pre-determined transitioning players, and current development squad players. Subjective data were collected via sRPE and $sRPE_{mod}$, whilst external load measures were collected via MEMS devices. Results showed that there were significant differences between academy and transition phases for players with regards to $sRPE_{mod}$ and weekly sRPE and $sRPE_{mod}$. There were no significant differences identified between the academy and transition phase for daily sRPE or sRPE-TL. With regards to external measures of load, there were no significant differences between transition and development players in either sessional or weekly measures. These findings suggest that using a proposed modified subjective measure to identify differences in the load experienced by transition, academy, and development players, however the exact nature of these differences is unknown.

The collective findings in this thesis highlight relationships between subjective and external measures of load within youth soccer players. The results highlight the lack of additional information provided by dRPE, questioning the use of this measure within this population. Additionally, the results highlight that it appears logical to factor load based on volume and intensity, and that these relationships appear to remain relatively consistent regardless of training theme or stage of season. This thesis also highlights complexities involved in modifying subjective measures of load to provide a greater representation of intensity to allow practitioners who may not have access to external load measures to greater account for this. Whilst the methods proposed showed the relationship between subjective and external measures could be modified, this was only for short duration sessions. Finally, when monitoring the transition of players from academy to full-time professional soccer it was shown that $sRPE_{mod}$ highlighted differences within players undergoing a transition, however the exact nature of this was unclear. These findings can be used to enhance the monitoring approaches of practitioners working within professional soccer. Additionally, these findings provide evidence that practitioners who are limited to subjective measures of load should consider alternative methods if monitoring training intensity is required. Further research is required to investigate modifying subjective measures of load to greater represent intensity. Additionally, further research is required to understand the load experienced by players undergoing a transition from academy to full-time professional environments.

List of Tables

Table 1.1 - Structure of the project utilising a proposed applied model for research within sport sciences. Adapted from Bishop (Bishop, 2008). 4
Table 1.2 - Design of PhD Thesis using stages proposed by Bishop (Bishop, 2008). 7
Table 2.1– Descriptive match locomotor activity as reported by Sarmento et al. (Sarmento et al., 2014) 9
Table 2.2 - Match activity profiles in youth soccer 16
Table 2.3 - Match activity profiles in youth soccer reported by Buchheit et al. (2010) from an elite soccer academy (All data collected via GPS devices)........ 18
Table 2.4 – Match activity profiles in youth soccer reported by Harley et al. (2010) from an elite soccer academy (All data collected via GPS devices)........ 21
Table 2.5 - Weekly Training load in senior elite soccer players. 23
Table 2.6 - Weekly Training load in elite youth soccer players. 25
Table 2.7 – Validity of Global Positioning System Devices (1Hz) 39
Table 2.8 – Reliability of Global Positioning System Devices (1Hz) 42
Table 2.9 - Validity of Global Positioning System Devices (5Hz) 48
Table 2.10 - Reliability of Global Positioning System Devices (5Hz) 53
Table 2.11 - Validity of Global Positioning System Devices (10Hz) 58
Table 2.12 - Reliability of Global Positioning Systems (10Hz) 62
Table 2.13 - Validity of Global Positioning Systems (≥15Hz) 66
Table 2.14 - Validity of Global Positioning Systems (≥15Hz) 70
Table 2.15 - Reliability measures of accelerometer technology for measuring PlayerLoad and sport specific movements in team sports........ 80
Table 2.16 - Relationship between subjective and objective training load measures using the CR10 Borg Scale (Borg et al., 1987)........ 94
Table 2.17 - Relationship between subjective and objective training load measures using the CR100 centiMax scale (Borg and Borg, 2002);........ 97
Table 3.1 - Overview of participant characteristics for Chapters 4 – 8. Descriptive characteristics are presented as mean ± SD 103
Table 3.2 -Description of various competitions undertaken by Development Squad players in season 18/19........ 104
Table 3.3 – Training Drills Classification Criteria used throughout the data collection process of Chapters 4 – 8. 105
Table 4.1 - Load and Intensity measures categorised for match play and training for 20 male professional youth soccer players 113

Table 4.2 - Pearson correlations (r) for each training load measure for data collected from 20 male professional youth soccer players across a season 117
Table 4.3 - Between-Individual correlations (95% CI) Between sRPE and sRPE-TL and the External Measures of Training Load. 118
Table 4.4 - Results of Principal Component Analysis showing the eigenvalue, percentage of variance explained, and cumulative percentage of variance explained by each principal component for all variables. As well as the component loadings for the principal components maintained (PC1 & PC2). 119
Table 4.5 - Results of Exploratory Factor Analysis showing the loadings of each factor identified with a cut-off of 0.3. Each factor has been given a representative heading based on the variables with the heaviest loadings 121
Table 4.6 - Results of Exploratory Factor Analysis only including sRPE from subjective measures. Each factor has been given a representative heading based on the variables with the heaviest loadings 121
Table 5.1 – Distribution of mean training loads for match-day and each categorised training day across a season in professional youth soccer players.. 131
Table 5.2 – Principal component analysis results for each category of training and match-day data. 132
Table 6.1 - Mean (± SD) duration and load measures across an entire season, with phases categorised as pre-season or competitive phases... 143
Table 6.2 - Principal component analysis results across the pre-season phase. 144
Table 6.3 – Principal component analysis results across both competitive phases of the season 144
Table 7.1 - Descriptive Statistics (mean ± standard deviation [SD] of load variables across all sessions and categorised for 20 academy soccer players based on training duration 155
Table 8.1 - Descriptive Statistics (mean ± standard deviation [SD]) of training and match play frequency and duration, and subjective load data across all sessions for academy and development squad soccer players 169
Table 8.2 - Descriptive statistics (mean ± standard deviation [SD]) of objective load data for professional academy players categorised as transition or development squad. 169
Table 8.3 – Regression coefficients for duration and each subjective training load variable for transition and development squad players relative to academy players............................... 172
Table 8.4 – Regression coefficients for each external training load variable for transition players relative to development squad players within individual sessions during the pre-season phase.. 173
Table 8.5 – Regression coefficients for each external training load variable for training players relative to development squad players for weekly measures of training load 173

List of Figures

Figure 2.1 - Training process framework and measurable components for monitoring. Reproduced from Impellizzeri et al. (2020) ... 29
Figure 2.2- Calvert et al. (1976) Multicomponent model to explain effects of different forms of training on resultant performance. ... 31
Figure 2.3 – Key features of a commonly available microelectromechanical system device ... 34
Figure 2.4 – 15 point scale for ratings of perceived exertion (Borg, 1970) ... 85
Figure 2.5 - Further developed scale proposed by Borg (Borg, 1970). This scale was designed as a category scale with ratio properties ... 86
Figure 2.6 – Modification of the Borg CR10 scale (Foster, 1988, Foster et al., 1995) ... 87
Figure 2.7 – CR100 scale (Borg and Borg, 2002) ... 89
Figure 4.1 – PCA biplot showing scaled eigenvector arrows for each objective and subjective training load variable. Key; sRPE-TL – sessional RPE training load; LIR – low-intensity running; HSR – high-speed running Accel – accelerations; Decel – decelerations; Dim1 – Dimension 1 (1st principal component); Dim2 – Dimension 2 (2nd principal component) Contrib – scale of contribution value of each individual variable to relevant principal components. ... 120
Figure 5.1 - Pearson's product moment correlations between sRPE-TL and all external load measures (error bars represent 95% CI). TD - Total Distance, PL - PlayerLoad, LIR - Low intensity running, HSR – High- speed running, SPR - Sprinting, Accel - Accelerations, Decel - Decelerations. ... 132
Figure 6.1 - Pearson's product moment correlations between sRPE-TL and all external load measures (error bars represent 95% CI). TD, Total Distance; PL, PlayerLoad; LIR, low intensity running; HSR, running; SPR, sprinting; Accel, accelerations; Decel, decelerations. ... 145
Figure 7.1 - Normalised Rotated Component Loadings for ratings of perceived exertion (RPE) and sessional ratings of perceived exertion-training load (sRPE-TL) for pooled sessions. TD (total distance); PL (PlayerLoad); LIR (low-intensity running); HSR (high-speed running); Accel (accelerations); Decel (decelerations). ... 157
Figure 7.2 - Normalised Rotated Component Loadings for ratings of perceived exertion (RPE) and sessional ratings of perceived exertion-training load (sRPE-TL) for long (> 60mins) and short (≤ 60mins) sessions. TD (total distance); PL (PlayerLoad); LIR (low-intensity running distance); HSR (high-speed running distance); Sprint (sprinting distance); Accel (accelerations); Decel (decelerations). ... 158
Figure 7.3 - Normalised Rotated Component Loadings for unmodified and modified ratings of perceived exertion (RPE) for short (≤ 60 mins) and long (>60 mins) sessions. Ratios of volume : intensity are presented for each measure in brackets. ... 159

Figure 8.1 – Rotated component loadings following PCA analysed including RPE (PCA1), sRPE (PCA2), mRPE (PCA3), msRPE-TL (PCA4). Key; TD - total distance; PL - PlayerLoad; LIR -low-intensity running distance; HSR - high-speed running distance; SPR - sprinting distance; Accel - accelerations; Decel – decelerations; RPE – rating of perceived exertion; sRPE-TL – session rating of perceived exertion training load; mRPE – modified rating of perceived exertion; msRPE-TL – modified session rating of perceived exertion training load. 171
Figure 9.1 – Session rating of perceived exertion (RPE) and session rating of perceived exertion training load (sRPE-TL) data from seven sessions for one player to highlight impact of aggregating load over training duration. Key; sRPE-TL - session rating of perceived exertion training load; RPE – rating of perceived exertion; au – arbitrary units. 181
Figure 9.2 – External load data from seven sessions for one player to highlight impact of aggregating load over training duration. Key; HSR – high-speed running distance; m - metres 182

List of Equations

Equation 1 – Original Fitness-Fatigue model proposed by Banister et al. (1975) 30

Equation 2 – Updated model proposed by Calvert et al. (Calvert et al., 1976)........................ 31

Equation 3– Busso (2003) proposed Fitness-Fatigue model. Where p is performance, w is training dose, k is gain in performance and t is a time constraint. 32

Equation 4- k2 calculation from Busso (2003) Fitness-Fatigue model 32

Equation 5 – The modified vector magnitude used to calculate PlayerLoad™ where:............ 75

Equation 6 – Training impulse method originally proposed by Banister (1991) where w(t) = assessment of the amount of training undertaken during a training session, and Y is a weighting factor applied to increase the magnitude of quantity of training nonlinearly at higher training intensities. where $Y = 0.64e^{1.92x}$ for males, $Y = 0.86e^{1.67x}$ for females, e = 2.712 and x = ΔHR ratio. 82

Equation 7 - Banister's TRIMP (Banister, 1991). D – Duration; HR_{ex} - mean exercising heart rate; HR_{rest} – resting heart rate; HR_{max} – maximal heart rate; Y – multiplication factor. 151

Equation 8 – Weighting factor of Banister's TRIMP (Banister, 1991). A = 0.64 for men and 0.86 for women, B = 1.92 for men and 1.67 for women. x = Δ HR ratio. 151

Equation 9 - Modified Banister's TRIMP equation for low-frequency measures where D = session duration, RPE = reported rating of perceived exertion for session, RPE_{min} = minimum reported rating of perceived exertion value across analysis period, RPE_{max} = maximum reported rating of perceived exertion value across analysis period, Y = weighting coefficient ranging from exp (1) to exp (3). 154

List of Abbreviations and definitions

Au – arbitrary units

dRPE - Differential rating of perceived exertion

EFA – Exploratory Factor Analysis

GPS – Global positioning systems

HR - Heart Rate

HR_{max} – maximum heart rate

HSR – high-speed running

KMO - Kaiser-Meyer-Olkin

LIR – low intensity running

LSG – Large-sided games

MEMS – Microelectromechanical system

MSG – Medium-sided games

PCA – Principal Component Analysis

RPE - Rating of perceived exertion – a numeric value assigned to the magnitude of effort perceived at a given point in time

RPEm – rating of perceived exertion with regards to contracting muscles in active limbs

RPEb – rating of perceived exertion with regards to breathing rate

sRPE – session rating of perceived exertion – a post-hoc appraisal of effort experienced during a period of training or competition

sRPE-TL – session rating of perceived exertion training load – sRPE multiplied by the duration of the exercise

$sRPE_{mod}$ – modified session rating of perceived exertion

$sRPE\text{-}TL_{mod}$ – modified session rating of perceived exertion training load

sRPETL-M – session rating of perceived exertion with regards to contracting muscles in active limbs sRPETL-B – session rating of perceived exertion with regards to breathing rate

SSG – Small-sided games

TRIMP - training impulse

Acknowledgements

The process of completing a part-time PhD whilst working in professional soccer, and latterly in academia, has been a challenging yet rewarding process. Whilst undoubtedly the academic skills I have developed will support me going forward in my professional career, I also believe this process has allowed me to become a more resilient and confident individual. Across the life-span of this PhD there are numerous people that I need to thank, and without whom I would not have completed this project.

Professor Niall MacFarlane

Thank you for your guidance and support throughout this process. You have allowed me to develop towards becoming an independent professional and I was lucky to have you as a supervisor. I have enjoyed working together, and I am grateful for your encouragement alongside your ability to challenge me. Finally, thank you for your patience!

Dr Paul Swinton

Your experience in statistical analysis has undoubtedly been invaluable, but your ability to question "why" things are done a certain way in professional sport has been equally crucial. I appreciated your ability to challenge my understanding, and your wisdom in directing me to further projects and levels of enquiry.

Scott Anderson, Paul Sheerin, Barry Robson, Steven Gunn, Graham Kirk, and all players and staff at Aberdeen Football Club

I am enormously grateful to all the players and staff I came across during my time at Aberdeen Football Club. I was fortunate to work with many hard working and talented players who made the process of data collection relatively straightforward. I was fortunate to spend my time at the club directly working with three patient, yet driven, coaches, who showed an interest in my research, but crucially challenged me to be a better practitioner. Steven, I am enormously grateful for your support in allowing me to carry out my PhD alongside full-time work. Graham, I am extremely grateful for your guidance and support professionally.

Mum and Dad

I am incredibly fortunate to have had two parents who have instilled a work ethic and an appreciation that things never come easy. I will be forever grateful for your support and guidance and would not be where I am today without it.

Steph

Undoubtedly this project wouldn't be where it is without you. Thank you for patiently listening to my whining about R and being a soundboard for everything from beginning to end. Thank you for constantly reminding me about having some sort of balance outside of work and study and being the person who I enjoy spending that time with! Thank you for the love and support you have given me throughout this process, and here's to our future.

This thesis is dedicated to my father Frank Maughan, who supported me both financially and emotionally and gave me every opportunity to succeed. I hope this piece of work repays the faith.

Author's Declaration

I declare that I have carried out all the work submitted herein. Collaborative work is acknowledged where present.

Patrick Maughan (21-12-22)

Publications

Peer Reviewed First Author Publications from this series of Investigations

1. Maughan, P, Swinton, P, MacFarlane, N. Relationships between training load variables in professional youth football players. *International Journal of Sports Medicine*, 2021;42(7): 624-629.
2. Maughan, P.C., MacFarlane, N.G. and Swinton, P.A., 2021. Relationship between subjective and external training load variables in youth soccer players. *International journal of sports physiology and performance*, *16*(8), pp.1127-1133.
3. Maughan, P.C., MacFarlane, N.G. and Swinton, P.A., 2022. The influence of season phase on multivariate load relationships in professional youth soccer. *Journal of sports sciences*, *40*(3), pp.345-350.
4. Maughan, PC, MacFarlane, NG, Swinton, PA. Quantification of training and match-play load across a season in professional youth football players. *International Journal of Sports Science and Coaching.* 2021;16(5): 1169-1177.
5. Maughan, P.C., MacFarlane, N.G., Towlson, C., Barrett, S. and Swinton, P.A., 2022. Does transforming subjective measures of load better represent training and match-play intensity in youth soccer players?. *International Journal of Sports Science & Coaching*, p.17479541221114739.

Conference Communications from this series of Investigations

1. UKSCA September 2020 – Quantification of Individual Training Load Relationships in Professional Youth Football Players
2. UKSCA September 2020 – Context Specific Training Load Measures in Professional Youth Football Players

Contents

Thesis Abstract i

List of Tables v

List of Figures vii

List of Equations ix

List of Abbreviations and definitions x

Acknowledgements xii

Author's Declaration xiv

Publications xv

CHAPTER 1 - INTRODUCTION 1

1.1 General Introduction 1

1.2 Aims and Objectives of the Thesis 4

CHAPTER 2 - LITERATURE REVIEW 8

2.1 - Introduction 8

2.2 – Physical Demands of Training and Match Play in Senior and Youth Soccer 8

2.2.1 Match Analysis in Senior Soccer 8

2.2.2 - Match Analysis in Youth Soccer 14

2.3 - Training Load Monitoring in Soccer 22

2.3.1 - Training Loads in Elite Senior Soccer Players 23

2.3.2 - Training Loads in Youth Soccer Players 24

2.3.3 - Comparison of Training Load Values Between Elite Youth and Senior Soccer 25

2.3.4 - Summary 26

2.4 - Methods of Training Load Monitoring 26

2.4.1 - Modelling Training Load Dose and Response 29

2.5 - Monitoring External Training Load via Global Positioning Systems (GPS) 33

2.5.1 - Overview 33

2.5.2 - Validity and Reliability of GPS 35

2.5.3 - 1Hz Global Positioning System – Validity 36

2.5.4 - 1Hz Global Positioning System – Reliability 40

2.5.4 - 5Hz Global Positioning Systems – Device Overview **43**

2.5.6 - 5Hz Global Positioning Systems – Validity **43**

2.5.7 - 5Hz Global Positioning Systems - Reliability **50**

2.5.8 - 10Hz Global Positioning Systems Overview **55**

2.5.9 - 10Hz Global Positioning Systems – Validity **55**

2.5.10 - 10Hz Global Positioning Systems - Reliability **60**

2.5.11 - ≥15Hz Global Positioning Systems Overview **64**

2.5.12 - ≥15Hz Global Positioning Systems – Validity **64**

2.5.13 - ≥15Hz Global Positioning Systems – Reliability **68**

2.5.14 - Data Generation, Software, and Hardware Considerations for GPS Technology **72**

2.5.15 - Considerations for Commonly Used GPS Metrics in Athlete Monitoring **73**

2.6 – Accelerometery **74**

2.6.1 – Validity of Accelerometery **75**

2.6.2 – Reliability of Accelerometery **78**

2.6.3 Summary – GPS and Accelerometer Technology **81**

2.7 - Measuring Internal Load **82**

2.7.1 - Rating of Perceived Exertion **84**

2.7.2 - Validity of sRPE-TL Method using Borg CR10 Scale **91**

2.7.3 - Validity of sRPE-TL Method using Borg CR100 Scale **96**

2.7.4 - Reliability of RPE Method using Borg CR10 and Borg CR100 Scales **98**

2.7.5 Internal Load Monitoring Summary **98**

CHAPTER 3 EXPERIMENTAL APPROACH TO THE THESIS 99

3.1 – Literature Review Conclusion and Perspective and Thesis Rationale **99**

3.2 - Specific Aims of the Thesis **101**

3.3 – Participants **103**

3.4 – Research Design **103**

3.4.1 Chapters 4 to 7 **103**

3.5 – Methods of Measuring External Load **104**

3.5.2 – GPS Analysis of Match Play **105**

3.5.3 – GPS Analysis of Training **105**

3.5.4 – Arbitrary Velocity Thresholds **106**

3.5.5 - PlayerLoad™ **107**

3.5.6 – High Intensity Accelerations and Decelerations **107**

3.6 – Methods of Measuring Internal Load **108**

3.6.1 – Session Rating of Perceived Exertion **108**

3.7 – Statistical Analysis **108**

CHAPTER 4 - RELATIONSHIP BETWEEN SUBJECTIVE AND EXTERNAL TRAINING LOAD VARIABLES IN YOUTH SOCCER PLAYERS 110

4.1 Prelude **110**

4.2 Introduction **110**

4.3 Methods **112**

4.3.1 Experimental Approach to the Problem **112**

4.3.2 Participants **112**

4.3.3 Procedures **113**

4.3.4 Statistical Analysis **114**

4.4 Results **115**

4.5 Discussion **121**

4.6 Conclusion **125**

CHAPTER 5 – THE IMPACT OF TRAINING THEME ON TRAINING LOAD MEASURES IN YOUTH SOCCER PLAYERS 126

5.1 Prelude **126**

5.2 Introduction **127**

5.3 Methods **129**

5.3.1 Experimental Approach to the Problem **129**

5.3.2 Participants **129**

5.3.3 Procedures **129**

5.3.4 Statistical Analysis **130**

5.3.5 Results **131**

5.4 Discussion **134**

5.5 Conclusion **136**

CHAPTER 6 – THE IMPACT OF STAGE OF SEASON ON TRAINING LOAD MEASURES IN YOUTH SOCCER PLAYERS 136

6.1 Prelude **136**

6.2 Introduction **137**

6.3 Methods **139**

6.3.1 Experimental Approach to the Problem **139**

6.3.2 Participants **140**

6.3.3 Procedures **140**

6.3.4 Statistical Analysis **141**

6.4 Results **141**

6.5 Discussion **145**

6.6 Conclusion **148**

CHAPTER 7 – DOES TRANSFORMING SUBJECTIVE MEASURES OF LOAD BETTER REPRESENT TRAINING AND MATCH PLAY INTENSITY IN YOUTH SOCCER PLAYERS? 149

7.1 Prelude **149**

7.2 Introduction **149**

7.3 Methods **152**

7.3.1 - Experimental Approach to the Problem **152**

7.3.2 Participants **153**

7.3.3 - Procedures **153**

7.3.4 Statistical Analysis **154**

7.4 Results **155**

7.5 Discussion **159**

7.6 Conclusions **161**

CHAPTER 8 – MONITORING THE LOAD EXPERIENCED BY PLAYERS DURING THE TRANSITION FROM ACADEMY TO YOUTH PROFESSIONAL SOCCER 163

8.1 Prelude **163**

8.2 Introduction **163**

8.3 Methods **166**

8.3.1 Experimental Approach to the Problem **166**

8.3.2 Participants **166**

8.3.3 Procedures **167**

8.3.4 Statistical Analysis **167**

8.4 Results **168**

8.6 Discussion **174**

8.7 Conclusion **176**

8.8 Perspective **177**

CHAPTER 9 – SYNTHESIS OF FINDINGS 178

9.1 Achievement of Aims and Objectives **178**

9.2 General Discussion **180**

9.3 Conclusions **186**

9.4 Project Limitations and Recommendations for Future Research **187**

9.5 – Practical Recommendations from the Present Thesis **189**

9.6 - Personal Reflections **191**

CHAPTER 10 - REFERENCES 193

Chapter 1 - Introduction

1.1 General Introduction

Soccer is regarded as the world's most popular sport (Reilly et al., 2000), and its influence on social and political issues is wide ranging (Numerato, 2018). Soccer is also an extremely lucrative sport, across the 2016 to 2019 period the English Premier League sold broadcasting rights for £8.3bn (Scelles, 2017). This financial environment has resulted in significant valuations being placed on players, with at least 10 transfers being made for ≥ €100m (Metelski, 2021). The fruitful nature of the game has also allowed clubs to invest in their academies, in the hope of developing future players (Ford et al., 2020). These academy operations are generally supported by administrative staff, technical coaches, sport scientists, scouts and medical teams (Ford et al., 2020). Alongside youth soccer operations, academic research interest has evolved with many practitioners interested in furthering understanding of talent identification practices and talent development in youth soccer (Ford et al., 2020, Williams, 2020).

Soccer academies aim to optimise the early detection and development of young players (Reilly et al., 2000, Buchheit et al., 2010). Whilst other aims have been highlighted, the predominant goal of youth academy programmes is to develop players for a clubs first team (Relvas et al., 2010). Additionally, it has been identified that consideration is given to having a positive impact on the personal development of individual players, and profit from future player sales (Relvas et al., 2010, Stratton et al., 2004). For clubs to achieve these goals they need to develop players, technically, tactically, and physically. There are several factors to consider which can influence a player's progression through youth academy programmes, such as, growth and maturational development, physiological advancement, technical and tactical learning, psychological development, and injury occurrence (Patel et al., 2020, Mills et al., 2012, Larruskain et al., 2021). Therefore, the development of players can be considered multifactorial in its nature, however within academic literature these facets of development are often considered, and explored, in isolation (Mills et al., 2012). To optimise physical development of players, the many facets of conditioning specific to soccer, such as, strength, speed, power and endurance, need to be enhanced to increase physical capacities and protect against injury (Stølen et al., 2005). In relation to this it is now common practice to monitor load to optimise performance and reduce injury risk (Gabbett, 2016, Drew and Finch, 2016, Salter et al., 2021).

To prepare players for senior-level competition, it is necessary to have some understanding of the demands of the game, and as such research concerning soccer match-play is prevalent (Whitehead et al., 2018). Soccer is an intermittent sport consisting of bouts of high-intensity linear and multidirectional activity interspersed with longer, variable recovery periods (Barnes et al., 2014, Varley and Aughey, 2013). It has been shown that players of a higher standard perform relatively more high-intensity running and sprinting during a game, as well as performing better at the Yo-Yo intermittent recovery test, than lower-level professional players (Mohr et al., 2003). Data analysed across a 7 year period in the English Premier League also showed that whilst total distance covered remained fairly consistent, high-intensity running distance and sprinting distance increased by ~30-35% (Barnes et al., 2014). Whilst sprinting only constitutes 1-4% of the distance covered within a soccer match, it often precedes significant moments (Di Salvo et al., 2009). This increase in explosive and intense movements, combined with improvements in technical measures such as pass completion rates (Barnes et al., 2014) highlights the need for the modern senior player to be both technically and physically prepared for the demands of the modern game.

To maximise performance and reduce risk of injury, it has become common practice for practitioners to monitor ‘load’. Load can be considered as a stimulus placed upon an athlete, and is generally categorised as being either ‘internal’ or ‘external’ (Drew and Finch, 2016). In basic terms, the external load can be considered as the physical work prescribed in a program, whilst the psychophysiological response to this can be considered as the internal load (Impellizzeri et al., 2020). Practitioners will prescribe load with the aim of maximising available training time with players alongside ensuring players cope with heightened physical demands across different phases of the training year (Iaia et al., 2009). A range of factors must be considered when prescribing load, particularly given that individual athletes will respond differently to a given stimulus (Hellard et al., 2005, Avalos et al., 2003, Skinner et al., 2000). The link between load and injury or illness is of significant interest to researchers and practitioners and there is moderate evidence of a dose-response relationship between the amount of training and match play load and injury and illness incidence (Drew and Finch, 2016). The ability to prescribe appropriate future load relies on monitoring of current training and physical fitness, alongside an understanding of competitive match-play demands.

A range of methods are used to monitor the load experienced by athletes. The most common method used to measure external load in professional soccer players is time-motion analysis, with variables related to distance, time, acceleration, and distances covered above specific speed thresholds assessed (Akenhead and Nassis, 2016). Measures collected via accelerometers have also been shown to be commonly used in professional soccer, with industry developed metrics such as PlayerLoad and BodyLoad being utilised (Akenhead and Nassis, 2016). Objective internal load is generally measured via heart rate (HR) monitors, with average HR, maximal HR (HR_{max}), HR exertion, and durations above specific thresholds based on percentages of max, or physiological parameters generally used (Akenhead and Nassis, 2016). A commonly used measure of subjective internal load is the session rating of perceived exertion (sRPE) (Borg, 1970, Akenhead and Nassis, 2016). Integrating time with sRPE (sRPE-TL) provides some context to the exposure component of the activity alongside the athletes perception of effort (Drew and Finch, 2016). Measures of sRPE have been shown to be a valid and reliable assessment of training load, and has been used previously in soccer (Impellizzeri et al., 2004). Another benefit of using sRPE to monitor training load is its affordability in comparison to other methods (Foster et al., 2021).

Research regarding transitions from academy to senior professional environments have generally focused on psychological considerations (Finn and McKenna, 2010). More recently however, practitioners have aimed to better understand this transition by comparing physical demands of youth and senior players (Houtmeyers et al., 2021). Analysing data in U19 and first team Eredevisie players, Houtmeyers et al. (2021) showed that whilst younger players covered more total distance across a training week, this was generally at lower velocities ($<12 km•h^{-1}$). Distance covered at sprint speeds ($>25 km•h^{-1}$) however, was higher within first team players (Houtmeyers et al., 2021). This finding was not just present across the training week, but also during competitive match play. Whilst this research was carried out with one club, it is logical to assume some form of rank order effect exists between youth and first team players, thus placing novel demands, both physical and psychological, upon a transitioning player. An investigation of players transitioning from academy to first-team environments identified five subcategories which specifically contributed to strain experienced by athletes; physical intensity, self-management of beneficial behaviours and cognitions, coach relationships, performing under new levels of pressure, and earning respect from senior athletes and coaches (Finn and McKenna, 2010). Crucially, athletes entering a full-time environment will be subject to multiple novel sources of physiological and psychological stressors, and it is necessary for them to adapt to the demands of professional sport. Therefore, whilst the practice of monitoring physical load performed by players is a single factor within this transition, it is likely that the appropriate monitoring and prescription of load is crucial to optimise progression to first team environments.

Cost effective methods such as sRPE are attractive to clubs who may not be able to afford commercially available technology to monitor load of players progressing from youth academy programmes, into senior environments. However, previous research has shown that sRPE generally shows stronger relationships with measures of training volume, such as total distance covered, rather than measures of intensity such as high speed running (Lovell et al., 2013). Additionally, many previous studies have focused on bivariate assessments of relationships between training load measures. More recent research has assessed the relationships and underlying structures of load data in a multivariate fashion (Weaving et al., 2017, Weaving et al., 2014). It is possible that sRPE therefor does not account for changes in intensity across training progressions and as such, other methods of monitoring variation in intensity should be sought. Therefore, the aim of this thesis is to better understand sRPE and its relationship with other load variables, improved understanding of this measure will allow practitioners to maximise its use within transitions from academy to senior soccer.

1.2 Aims and Objectives of the Thesis

The overall aim and objective of this thesis is to assess the suitability of subjective measures, specifically sRPE, for measuring load during progression of soccer players from academy to senior environments. To do this the concept and design of this thesis shall follow a previously proposed research model for use in sports science (Bishop, 2008) (Figure 1.1). Briefly, this model was designed to allow research frameworks to be better integrated and directed towards improving sporting performance. The dynamic and flexible nature of this model also enforces its useability in research embedded within chaotic, professional sporting environments.

Table 1.1 - Structure of the project utilising a proposed applied model for research within sport sciences. Adapted from Bishop (Bishop, 2008).

	Stage	**Location within Thesis**

Description	1	Defining the problem	Chapters 2 & 3
	2	Descriptive research (hypothesis development)	Chapters 4, 5 & 6
	3	Predictors of performance	Chapter 7
Experimentation	4	Experimental testing of predictors	Chapter 8
	5	Determinants of key performance predictors	
	6	Efficacy studies (controlled laboratory or field)	
Implementation	7	Barriers to uptake	
	8	Implementation studies (real sporting setting)	

The structure of this PhD, and the accompanying aims of each stage, closely match the initial phases proposed within the Applied Research Model for the Sports Sciences (Table 1.1). The first phase of this model consists of clearly defining the problem and providing context. A key element of this is identifying the real-world problems facing practitioners, coaches, and athletes (Bishop, 2008). This PhD project was embedded within industry and investigated specific issues which had been highlighted at a strategic level by the club investigated, in this case how best to monitor players progressing from a club's academy to their senior environment. Chapter 2 defines this problem in the context of current academic literature, whilst Chapter 3 provides greater context regarding the approach taken to each element of the project. The seconds stage of the model is to carry out descriptive research, in this case profiling studies to describe what is currently occurring regarding load monitoring within the investigated club (Bishop, 2008). This process was carried out through Chapters 4, 5, and 6, where the relationship between various load measures, and the impact of factors such as training theme and phase of season were investigated. The next phase of this project involved proposing modified subjective measures, which may better allow practitioners to better understand and manage the intensity of training and match-play load undertaken by players (Chapter 7). Finally, this measure was investigated within an applied environment, investigating players transitioning from youth academy to senior soccer, to further investigate and describe previously identified associations (Chapter 8).

More specifically, the suitability of subjective measures shall be assessed using the following themes:

1. Consider the suitability of subjective measures of load by assessing relationships between subjective and objective measures across a competitive season in professional youth soccer players.
2. Investigate the influence of factors such as training theme and stage of season on relationships between subjective and objective measures of load.
3. Propose alternative subjective load measures and test these within a practical context.

The assessment and analysis of the above objectives will provide a greater understanding, albeit within the environment of a single club, of load experienced by professional youth soccer players for practitioners and coaches. To more specifically achieve these aims, using the stages defined by Bishop (2008) the following will be carried out:

Table 1.2 - Design of PhD Thesis using stages proposed by Bishop (Bishop, 2008).

Stage		Chapter within Thesis
1	Defining the Problem	Chapter 2 - Literature Review Chapter 3 – Experimental Approach to the Thesis
2	Descriptive Research (hypothesis development)	Chapter 4 - Relationships Between Subjective and External Training Load Variables in Youth Soccer Players
		Chapter 5 – The Impact of Training Theme on Training Load Measures in Youth Soccer Players
		Chapter 6 – The Impact of Stage of Season on Training Load Measures in Youth Soccer Players
3	Predictors of Performance	Chapter 7 – Does Transforming Subjective Measures of Load Better Represent Training and Match Play Intensity in Youth Soccer Players?
4	Experimental Testing of Predictors	Chapter 8 – Monitoring the Load Experienced by Players During the Transition from Academy to Youth Professional Soccer

Chapter 2 - Literature Review

2.1 - Introduction

The aims of this literature review are to introduce, synthesise, and evaluate the current practices regarding the monitoring of training load in soccer players. The initial section of this review will describe the match play and training demands of both senior and youth soccer players. This is appropriate given the broad theme of this thesis concerns the progression of players from youth to senior soccer. It will then analyse and describe the validity, reliability, and practical application of commonly used objective and subjective training load measures, and provide an overview of methods used to analyse training load dose and response.

2.2 – Physical Demands of Training and Match Play in Senior and Youth Soccer

This section of the literature review will aim to give some context of the physical activity performed in both youth and senior soccer during training and match play. Both internal and external load measures will be discussed. External load variables such as total distance covered, and distances covered in specific locomotor thresholds will be reported. External load data has generally been collected via GPS or camera-based technology. Internal measures such as heart rate and subjective measures such as sRPE shall also be discussed.

2.2.1 Match Analysis in Senior Soccer

Time-motion analysis and technology such as GPS have been widely used in professional soccer to quantify match demands of senior players (Whitehead et al., 2018, Cummins et al., 2013, Sarmento et al., 2014). Senior players have been shown to cover distances of between 9 – 12km (Taylor et al., 2017) or 9 -14km (Sarmento et al., 2014) during a match. Additionally, total sprinting distance has been reported between 117m to 831m, with distance of 222m to 1900m categorised as high-intensity running (Taylor et al., 2017). The intermittent nature of the game has also been evidenced, with an average of 1379 to 1459 activity changes during match play (Taylor et al., 2017). When analysing peak match demands of professional players, Delaney et al. (2018)

reported ranges of ~129 to 148m•min^{-1} across 5-min moving averages. A range of factors have been investigated to further understand their effect on movement demands including playing position and competitive level (Sarmento et al., 2014).

A range of total distance covered has been reported in the literature in senior men's soccer (Table 2.4). In English Premier League fixtures (n = 14) and an international friendly match, it was shown that the average distance covered by players was 10841 ± 950m, with no difference reported between international match play and domestic competition (Bradley et al., 2010). In both settings, the distance covered in the 1st Half was greater than in the second half, with players covering 5469 ± 507m in the first half, and 5372 ± 498m in the second half (Bradley et al., 2010). Similarly in English Premier League games during the 2005 - 2006 season, average total distance covered of 10714 ± 991m was reported (Bradley et al., 2009). Again, a greater distance was covered in the first half (5422 ± 561m) than the second half (5292 ± 508m) (Bradley et al., 2009). Also, in assessing English Premier League match play total distances of 11229 ± 434m were reported to be covered during a game (Lovell and Abt, 2013). In English Premier League Reserve League match play, Akenhead et al. (Akenhead et al., 2013) recorded a similar mean value of total distance covered of 10451 ± 760m with a range of 9376 to 12247m. Again, a larger total distance was covered in the first half (5345 ± 413m) than the second half (5106 ± 408m). During the UEFA Euro 2016 tournament, across 15 matches, an average of 10350m, ranging from 8446 to 12982m was reported (Kubayi, 2019). Similar findings have been shown in Brazilian First Division Championship match play (10012 ± 1024m) (Barros et al., 2007), the Australian National Football League, now referred to as the A-League, (10.1km ± 1.4km) (Burgess et al., 2006) professional Norwegian teams (11046 ± 1015m and 11230 ± 992m) (Dalen et al., 2016, Ingebrigtsen et al., 2015), Ivorian international players (11173 ± 524m) (Dellal et al., 2012) , friendly matches of a Spanish La Liga team (10793 ± 1153m) (Mallo et al., 2015), professional European players (11019 ± 331m) (Rampinini et al., 2007) and English Premier League players during the 2008 - 2009 season (10794 ± 374m) (Weston et al., 2011).

Table 2.1– Descriptive match locomotor activity as reported by Sarmento et al. (Sarmento et al., 2014)

Reference	Standard	Participants (n)	Method	Measure and Distance Covered (Mean ± SD)
Barros et al. (2007)	Brazilian First Division	55 players	CAVA	TD - 10012m ± 1024m Standing/Walking/Jogging (0-11km•h^{-1}) - 5537m ± 263m Low-Speed Running (11-14km•h^{-1}) - 1615m ± 351m Moderate-Speed Running (14 - 19km•h^{-1}) - 1731m ± 399m High-Speed Running (19-23km•h^{-1}) - 691m ± 190m Sprinting (≥23km•h^{-1}) - 437m ± 171m
Di Salvo et al. (2007)	Spanish Premier League	300 players	CAVA	TD - 11393 ± 1016m
Rampinini et al.(2007)	Champions League Level Team	20 players	CAVA (ProZone)	TD - 11019m ± 331m HIR (>14.4km•h^{-1}) - 2738m ± 220m VHIR (>19.8km•h^{-1}) - 903m ± 115m
Bradley et al. (2010)	14 competitive league matches & one non-competitive international match	100 domestic and 10 international players	ProZone	TD - 10841m ± 950m HIR (≥14.4km•h^{-1}) - 2725m ± 656m VHIR (19.8km•h^{-1}) - 980m ± 294m
Gregson et al. (2010)	English Premier League	485 players	CAVA (ProZone)	<u>THSR (m, >19.8km•h^{-1})</u> CD – 604 ± 164m WD – 951 ± 231m CM – 916 ± 253m WM – 1162 ± 247m ATT – 941 ± 250m <u>HSR (m, 19.8 to 25.2km•h^{-1})</u> CD – 459 ± 115m WD – 698 ± 155m CM – 718 ± 181m WM – 856 ± 172m ATT – 670 ± 161m <u>TSD (m, (>25.2km•h^{-1})</u> CD – 145 ± 65m WD – 253 ± 96m CM – 198 ± 90m WM – 307 ± 109m ATT – 272 ± 117m
Vigne et al. (2010)	Italian Serie A	25 players	CAVA (SICS)	TD- 8930 ± 3515 Walk (<5km•h^{-1})– 3478 ± 1433m

				Jog (5-13km•h^{-1}) – 2631 ± 1098m 13-16km•h^{-1} – 1192 ± 478m 16-19km•h^{-1} – 751 ± 314m >19km•h^{-1} – 878 ± 433m

Key; CAVA – computer assisted video analysis, TD – total distance, HIR – high-intensity running, VHIR – very-high intensity running, THSR – total high-speed running, HSR– high-speed running, TSD – total sprint distance, CD – central defender, WD – wide defender, CM – central midfielder, WM – wide midfielder, ATT - attacker

A range of contextual factors including position, level, and formation have been highlighted as influencing match play demands of players. Differences have been highlighted in total distance covered by players of different positions. In Brazilian First Division Championship players Barros et al. (2007) showed that Wide Defenders (10642 ± 663m) and Wide Attackers (10598 ± 890m), covered greater distance than central defenders (9029 ± 860m), central midfielders (10476 ± 702m) and forwards (9612 ± 772m). In English Premier League players, it was found that wide (11535 ± 933m) and central midfielders (11450 ± 608m) covered a greater total distance than wide defenders (10710 ± 589m), attackers (10314 ± 1175m) and central defenders (9885 ± 555m) (Bradley et al., 2009). In professional Norwegian players it was found that wide defenders (11426 ± 648m), central midfielders (11573 ± 768m), and wide midfielders (11990 ± 771m) covered more distance than central defenders (9951 ± 491m) and attackers (10429 ± 874m) (Dalen et al., 2016). Whilst there are trends in differences between positions, with wide players generally covering more distance than central players, and central midfield players generally covering greater distance than central defenders or attackers, these are also likely to be affected by technical and tactical strategies. Previous analysis of commonly used playing formations has shown that, with regards to total distance covered, “3-5-2” is the most demanding formation for players (10528 ± 565m) (Tierney et al., 2016). The formation played is also likely to influence positional differences in distance covered, with CM in a “4-3-3” formation (10643 ± 1093m) shown to cover 11% greater distance than CM in a “4-4-2” formation (9886 ± 1516m) (Tierney et al., 2016). Therefore, the effect of playing position, as well as different playing styles, should be considered when comparing locomotor demands covered between teams or individual players.

A factor that may be considered when comparing physical outputs in professional soccer is the physical evolution of the game. Comparing data across seven consecutive

English Premier League seasons, from 2006-07 to 2012-13, Barnes et al. (Barnes et al., 2014) showed that total distance covered varied only by a trivial magnitude. They showed that average distance covered during a match in 2006-07 was 10679 ± 956m, whilst in the 2012-13 season they reported values of 10881 ± 885m. Positionally, further research showed that central midfielders and central defenders were the only positions to show increases in distance covered (Bush et al., 2015). Whilst there were limited differences in total distance covered, high-intensity running, and sprint distances displayed more evidence of evolution within English Premier League match play. The evolution of elite level soccer is likely to continue, with increases in the frequency of match play, tactical changes, and subsequent impacts on both physical performance and injury risk being highlighted as areas of concern for practitioners and coaches (Nassis et al., 2020)

Due to methodological differences concerning arbitrary speed thresholds used, comparison between studies regarding distances covered at specific speed thresholds can be problematic. Using speed thresholds of 14.4km•h^{-1} to 19.7km•h^{-1}, 19.8km•h^{-1} to 25.1km•h^{-1} and ≥ 25.2km•h^{-1}, Bradley et al. (2010) reported running, high-speed running and sprinting distance values, respectively. The authors also reported high-intensity running (≥14.4km•h^{-1}) and very high-intensity running (≥19.8km•h^{-1}). Mean distances covered in high-intensity running were 2725 ± 656m, whilst distances of 980 ± 294m were reported in very high-intensity running. Comparisons between stages of the game showed that high-intensity running distance covered was 18% lower in the last 15 minutes (391 ± 117m) than in the first 15 minutes of match play (478 ± 141m), with similar decreases reported in very high-intensity running distance covered (Bradley et al., 2010). Further analysis of English Premier League match play by Bradley et al. (2009), using the same arbitrary speed thresholds, reported mean high-intensity and very high-intensity running distances of 2492 ± 625m and 905 ± 285m, respectively. Again, temporal differences were found in high-intensity profiles, with 17% less high-intensity running performed in the last 15 minutes of the first half (391 ± 131m), and 21% less in the last 15 minutes of the match (374 ± 119m) versus the first 15 minutes of match play (466 ± 137m) (Bradley et al., 2009).

Using thresholds of > 5.8m•s^{-1} (20.88km•h^{-1}) and > 6.78m•s^{-1} (24.41km•h^{-1}), Akenhead et al. (2013) reported high speed and sprint distance in English Premier League Reserve match play. They reported high-speed running distances of 505 ± 209m, with a range of

116 to 973m, and sprint distances of 194 ± 101m, with a range of 0 to 450m. Whilst comparison between studies can be troublesome due to a lack of conformity when categorising speed thresholds, the evolution of high-intensity running is evident (Barnes et al., 2014, Bush et al., 2015). Using effect sizes of < 0.2 (trivial), > 0.2 – 0.6 (small), > 0.6 – 1.2 (moderate), and > 1.2 – 2.0 (large), an analysis comparing external workload variables across a 7-year period in the English Premier League showed that high-intensity running distance, categorised as any distance covered above 19.8km•h^{-1}, showed a moderate increase (ES = 0.82) from 890 ± 299m in the 2006-07 season to 1151 ± 337m in the 2012-13 season (Barnes et al., 2014). This increase was, as expected, associated with a large increase (ES = 1.41) in high-intensity running actions (Barnes et al., 2014). Large increases (ES = 1.31) were also shown in the number of sprints, from 31 ± 14 to 57 ± 20, whilst moderate (ES = 1.02) increases were seen in maximal running speed attained from 9.12 ± 0.43m•s^{-1} to 9.55 ± 0.4m•s^{-1}. Additionally, Barnes et al. (2014) considered what they defined “explosive sprints” which were categorised as sprinting efforts (> 25.1km•h^{-1}) with no recording of a high-speed zone effort in the previous 0.5s. In contrast ‘leading sprints’ were categorised as those with an entry into the high-speed running thresholds (19.8 - 25.1km•h^{-1}) recorded within the preceding 0.5s. Alongside the increases in sprinting efforts, an increased proportion of these being categorised as explosive sprints was reported. During the 2006-07 season 34 ± 11% of sprints were explosive, whilst in the 2012-13 season 47 ± 9% of the sprints recorded were explosive, representing a large increase (ES = 1.31) (Barnes et al., 2014). It would appear that, at the elite level of soccer, the physical demands of the game, with specific reference to intensity, have increased substantially (Barnes et al., 2014).

Further analysis which assessed the effect of playing position on match performance parameters over the same 7-year period found noteworthy differences, particularly for wide players (Bush et al., 2015). In this study, positions were categorised as central defenders, full backs, central midfielders, wide midfielders, and attackers. For total distance covered, only small changes were reported across the timeframe for central midfielders (ES = 0.3) and central defenders (ES = 0.5) (Bush et al., 2015). All positions showed moderate increases in high-intensity running distances, with wide defenders showing the largest increase of 35% (ES = 1.3). Similarly, wide defenders showed a large (ES = 1.3) 62% increase in sprint distance covered. There were also very-large increases in explosive sprints, and moderate-large increases in leading sprints for all positions analysed. This analysis, alongside the results of Barnes et al. (2014), highlights that the physical demands of the game have increased, specifically for wide players.

2.2.2 - Match Analysis in Youth Soccer

The activity profile of adult soccer has been studied in depth and is relatively well understood due to advances in technology and increasing research interest. Similar research on activity profiles and match demands in youth soccer is growing (Buchheit et al., 2010, Stroyer et al., 2004, Helgerud et al., 2001, Castagna et al., 2009, Castagna et al., 2003, Mendez-Villanueva et al., 2013, Rebelo et al., 2014, Castagna et al., 2010). Castagna et al. (2003) showed that under-12 soccer players covered on average 6175 ± 318m during a 60-minute game, this is compared to adult players who have been reported to cover between 8680 to 11527m (Reilly and Williams, 2003). These findings support the belief that young soccer players should not be treated as 'mini-adults', as when this is extrapolated to 90mins the total distance covered of 8800m is less than what is typically observed in elite adult players (Castagna et al., 2003, Sarmento et al., 2014, Taylor et al., 2017). Castagna et al. (2003) also reported that U12 players spent 9% of total match time in HIA (> 13.1km•h^{-1}), however, due to difficulty standardising categories of activity between children and adults it is difficult to compare this to previous results reported by Bangsbo (1991), which showed that elite adult soccer players performed HIA for 8.6% of total playing time. The mean time spent sprinting (> 18.0km•h^{-1}), approximately 2 seconds, was however similar to those figures reported for adult players (Bangsbo et al., 1991, Reilly, 2003). Whereas, the mean time period between bouts of maximal sprinting was longer than what has previously been reported for elite adult players (Reilly, 2003). Further research by Castagna et al. (2009) showed that U15 soccer players covered similar distances to their U12 counterparts (6173 ± 734m). Of this, 741 ± 280m was spent running (> 13.1km•h^{-1} - 18km•h^{-1}) and 234 ± 137m was spent sprinting (> 18km•h^{-1}). They also reported a higher percentage (16%) of distance covered with HIA (> 13.1km•h^{-1}) than reported in younger players (9%) which may suggest an age or maturation effect on game intensity (Castagna et al., 2003). Further research by Castagna et al. (2010) in U15 soccer players showed similar results for total distance (6087 ± 582m), high-intensity running (713 ± 258m) and sprinting (217 ± 129m) with the same speed thresholds as used previously (Castagna et al., 2009).

Analysing the match activity profiles of older players (U-17), Rebelo et al. (2014) found similar findings, with players covering 6311 ± 948m during 80 minute matches. Of this, 529 ± 312m was in high-intensity running (13.0km•h^{-1} - 18.0km•h^{-1}) and 230 ± 135m was in sprinting (> 18.0km•h^{-1}). Finally, Helgerud et al. (2001) found that U19 elite soccer players covered higher distances, more in line with adult players. They found across groups that total distance covered ranged from 8619 ± 1237m to 10335 ± 1608m.

Table 2.2 - Match activity profiles in youth soccer

Author	Age Group	Participants (n)	Measurement Device	Match protocol	Measure and Distance Covered (Mean ± SD)
Castagna et al. (2003)	U12	11	CAVA	2 x 30min half 100 x 65m pitch 11-a-side	TD- 6175 ± 318m HIR (13.1 – 18km•h^{-1}) - 468 ± 89m Sprinting (>18km•h^{-1}) - 114 ± 73m
Castagna et al. (2009)	U15	21	GPS (1Hz) and accelerometer (100Hz) (GPS, SPElite, GPSports, Australia)	2 x 30min	TD- 6173 ± 734m HIR (13.1 – 18km•h^{-1}) - 741 ± 280m Sprinting (>18km•h^{-1}) - 234 ± 137m
Castagna et al. (2010)	U15	18	GPS (1Hz) and accelerometer (100Hz) (GPS, SPElite, GPSports, Australia)	2 x 30min	TD- 6087 ± 582m HIR (13.1 – 18km•h^{-1})- 713 ± 258m Sprinting (>18km•h^{-1}) - 217 ± 129m
Rebelo et al. (2014)	U17	30	CAVA	2 x 40min	TD - 6311 ± 948m HIR (13.1 – 18km•h^{-1})- 529 ± 312m Sprinting (>18km•h^{-1}) - 230 ± 135m
Helgerud et al. (2001)	U19	19	CAVA	2 x 45min	TG Distance Covered- 10335 ± 1608m Sprints 12.4 ± 4.3m CG Distance Covered- 9137 ± 1565m Sprints 7.5 ± 2.7

Key; CAVA – computer assisted video analysis, TD – total distance covered, HIR – high-intensity running, GPS – global positioning systems, TMA- time motion analysis, TG- Training group, CG- Control group

Perhaps the most comprehensive analyses of match play in youth soccer was performed in 2010 on 99 players (Buchheit et al., 2010) and in 2012 on 103 soccer players (Mendez-Villanueva et al., 2013) ranging from U13-U18 age groups (Table 2.2). Buchheit et al. (Buchheit et al., 2010) reported match activity profiles of young soccer players in relation to age, playing position and physical capacities. This research showed that match running performance was only slightly affected by age in the junior soccer players, with differences only clear between extreme age groups. The authors also showed that match running performance was position dependent. Match running performance was related to most physical capacities, however, this relationship varied in relation to physical capacity and playing position. The total distance covered in match play ranged from 6549 ± 597m in U13 players to 8867 ± 859m in U18 players (Buchheit et al., 2010). A key finding of this research was that when physical match performance was adjusted for individual playing time there was no statistically significant difference in running performance between U14, U15, U16 and U17 players. For total distance covered, when adjusted for playing time, there was a significant difference between U13 and U16,U17 and U18 players (Buchheit et al., 2010). There were minimal differences across all velocity defined locomotion, with U13 players covering significantly less distance at low intensity (< $13.0 km \cdot h^{-1}$) than U16 and U17 players. Additionally, U18 players covered significantly greater sprint (> $19.1 km \cdot h^{-1}$) distance than all other ages. Whilst more pronounced differences were recorded when considering actual playing time this was due largely to differences in activity time rather than any physiological differences between age groups. For example, U13 players (2 x 35mins) played 10minutes less than U15, U16, and U17 players (2 x 40mins), and 20minutes less than U18 players (2 x 45mins). These similarities in values could be due to several factors, the authors suggested that perhaps the overlapping of maturation levels across chronological age groups may explain the lack of between-age differences. Additionally, it could be argued that older, more experienced players are more capable of pacing, and as such do not cover unnecessary distance at low intensity but use their physical capacity to perform more high intensity movements.

Table 2.3 - Match activity profiles in youth soccer reported by Buchheit et al. (2010) from an elite soccer academy (All data collected via GPS devices).

Age Group	Participants (n)	Match Protocol	Activity Profile	Playing Time Adjusted Values
U13	7	2 x 35mins	TD - 6549m ± 597m[a,b,c,d,e] LIR - 5370m ± 470m[b,c,d,e] HIR- 671m ± 180m[b,c,d,e] VHIR- 323m ± 87m[b,c,d,e] Sprinting- 186m ± 92m[b,c,d,e] VHIA- 509m ± 156m[a,b,c,d,e] Max Velocity- 22.3km•h^{-1} ± 1.4km•h^{-1} [a,b,c,d,e]	TD - 7497m ± 196m[c,d,e] LIR - 6012m ± 142m[c,d] HIR - 837m ± 70m VHIR - 387m ± 40m Sprint - 260m ± 53m[e]
U14	17		TD - 7383m ± 640m[b,c,d,e] LIR - 5799m ± 454m[b,c,d,e] HIR- 821m ± 231m VHIR- 446m ± 162m[e] Sprinting- 318m ± 183m[e] VHIA- 763m ± 307m[d,e] Max Velocity- 24.4km•h^{-1} ± 1.8km•h^{-1} [b,c,d,e]	TD - 7956m ± 128m LIR - 6187m ± 93m HIR - 922m ± 46m VHIR - 484m ± 26m Sprint - 363m ± 35m[e]
U15	10	2 x 40mins	TD - 8129m ± 879m[e] LIR - 6288m ± 610m HIR- 954m ± 297m VHIR- 477m ± 156m Sprinting- 410m ± 204m[e] VHIA- 887m ± 311m[e] Max Velocity- 26.0km•h^{-1} ± 2.4km•h^{-1} [e]	TD - 8026m ± 143m LIR - 6218m ± 103m HIR - 936m ± 51m VHIR - 470m ± 29m Sprint - 402m ± 39m[e]
U16	12		TD - 8312m ± 1054m LIR - 6480m ± 845m HIR- 968m ± 258m VHIR- 479m ± 180m Sprinting- 384m ± 163m[e] VHIA- 864m ± 314me Max Velocity- 26.3km•h^{-1} ± 2.3km•h^{-1} [e]	TD - 8436m ± 156m LIR - 6565m ± 113m HIR - 991m ± 56m VHIR - 487m ± 32m Sprint - 394m ± 43m[e]
U17	17		TD - 8707m ± 1101m LIR - 6749m ± 768m HIR- 991m ± 370m VHIR- 519m ± 155m Sprinting- 449m ± 147m[e] VHIA- 967m ± 221m[e]	TD - 8448m ± 135m LIR - 6573m ± 98m HIR - 946m ± 48m VHIR - 501m ± 28m Sprint - 428m ± 37m[e]

			Max Velocity- 26.6km•h^{-1} ± 2.2km•h^{-1} e	
U18	14	2 x 45mins	TD - 8867m ± 859m LIR - 6650m ± 565m HIR- 976m ± 240m VHIR- 574m ± 164m Sprinting- 666m ± 256m VHIA- 1239m ± 337m Max Velocity- 28.3km•h^{-1} ± 2.2km•h^{-1}	TD - 8254m ± 118m LIR - 6235m ± 85m HIR - 869m ± 42m VHIR - 533m ± 24m Sprint - 617m ± 32m

Key; TD - Total Distance Covered; LIR - Low-Intensity Running Distance (<13.0km•h^{-1}); HIR - High-Intensity Running Distance (13.1 - 16.0km•h^{-1}); VHIR - Very-High Intensity Running Distance (16.1 - 19.0km•h^{-1}); Sprinting - Sprinting Distance (>19.1km•h^{-1}); VHIA - Very-High Intensity Actions - VHIR + Sprinting; a – significant difference (p<0.05) vs U14; b – significant difference (p<0.05) vs U15; c – significant difference (p<0.05) vs U16; d - significant difference (p<0.05) vs U17; e – significant difference (p<0.05) vs U18 (Adapted from Buchheit et al. (2010)).

Analysis carried out in English academy level players aimed to provide further understanding of the activity profile of youth soccer players (Harley et al., 2010). To do this they reported the demands of match play across U12 to U16 players (Table 2.3). To allow comparison between age groups, they used sprint performance to normalise thresholds and provide age-specific velocity bands (Harley et al., 2010). The physical capabilities of elite adult players in comparison to junior athletes suggests that applying commonly applied speed thresholds designed for adult players to juniors is inappropriate. To overcome this Harley et al. (2010) collected data from a flying 10m sprint test and obtained the mean velocity for each age group, which were then compared to mean values obtained from senior players. This was then used alongside the commonly used speed thresholds to create age-specific thresholds as a ratio. U15 and U16 players displayed significantly faster flying 10m sprint times than U12, U13 and U14 players. These results then lead to different speed thresholds, for example speed zone 6, the sprinting zone, for U16 players was 6.41m•s^{-1}, and 5.32m•s^{-1} U12 players.

In terms of comparisons between age groups, total distance covered was significantly higher in U16 players (7672 ± 2578m) than U12 (5967 ± 1277m), U13 (5813 ± 1160m), and U14 players (5715 ± 2060m). Comparing distances covered at various intensities, U16 players covered greater distance at high-intensity (2481 ± 1044m) than all other age groups. They covered significantly greater distance at very-high intensity (951 ± 479m) than U12 (662 ± 180m) and U13 players (644 ± 259m). They also covered significantly greater distance at sprinting velocities (302 ± 184m) than U12 (174 ± 64m) and U13 players (167 ± 96m). Interestingly however, when these values were normalised for time and expressed as per minute these significant differences were not as pronounced. Total distance covered per minute was significantly greater in U15 (118.7 ± 12.2m/min) and U16 (115.2 ± 15.8m/min) than U13 players (98.8 ± 23.5m/min) and significantly higher in U15 than U12 players (103.7 ± 5.8m/min). There were no significant differences between age groups in high-intensity distances. The only significant differences in very-high intensity distance and sprinting distance was between U14 and U13 players. This suggests that when movement characteristics are defined relative to the physical capacities of players, and when expressed per minute, there are little differences in the movement profiles of academy soccer players. In this regard these results are similar to the findings of Buchheit et al. (2010). However, Buchheit et al. (2010) did find significant differences for distance at sprinting velocities in U18 players compared to all other age groups. These differences are likely due to Buchheit et al. (2010) normalising for time, whereas Harley et al. (2010) considered both time and the physical capacities of young players.

Table 2.4 – Match activity profiles in youth soccer reported by Harley et al. (2010) from an elite soccer academy (All data collected via GPS devices).

Age Group	Participants (n)	Pitch Size	Match Configuration	Activity Profile (Relative distance)
U12	22	77 x 60m	3 x 25mins or 2 x 15mins plus 2 x 12.5mins	TD - 5967m (103.7m•min^{-1}) HID - 1713m (29.8m•min^{-1}) VHID - 662m (11.8m•min^{-1}) SPR - 174m (3.1m•min^{-1})
U13	20			TD - 5813m (98.8m•min^{-1}) HID - 1756m (29.4m•min^{-1}) VHID - 644m (11.1m•min^{-1}) SPR - 167m (2.9m•min^{-1})
U14	25	99 x 65m		TD - 5715m (106.5m•min^{-1}) HID - 1841m (35.1m•min^{-1}) VHID - 748m (14.3m•min^{-1} [b]) SPR - 248m (4.7m•min^{-1} [b])
U15	21			TD - 6016m (118.7m•min^{-1} [a,b]) HID - 1755m (34.8m•min^{-1}) VHID - 669m (13.3m•min^{-1}) SPR - 194m (4.3m•min^{-1})
U16	24		2 x 40mins	TD - 7672m [a,b,c] (115.2m•min^{-1} [a,b]) HID - 2481m[a,b,c,d] (36.3m•min^{-1}) VHID - 951m[a,b] (13.8m•min^{-1}) SPR - 302m [a,b] (4.3m•min^{-1})

Key; TD - total distance covered; HID - high-intensity distance; VHID - very-high intensity distance; SPR - sprinting distance; a – significant difference ($p<0.05$) vs U12; b – significant difference ($p<0.05$) vs U13; c – significant difference ($p<0.05$) vs U14; d – significant difference ($p<0.05$) vs U15; Note – Speed zone thresholds by age group calculated from 10m flying sprint times (Adapted from Harley et al. (2010))

Research investigating the physical demands of youth academy soccer has grown in recent years and, despite methodological concerns, there is a developing resource regarding the running based demands of match-play (Vieira et al., 2019). When using fixed speed thresholds there is an increase in match running performance as age and maturation of the player increases. When implementing some form of standardisation to account for the reduced playing time or physical capabilities of younger players, these differences between age groups are less apparent. Awareness of match running performance, alongside considerations of age and maturational development of youth players, can support practitioners in planning training programs. Several external factors should be considered when comparing research studies including match timing, pitch size, and rules, such as the use of rolling substitutions. As such practitioners should be wary when looking to apply or compare research concerning the running demands of youth soccer players.

2.3 - Training Load Monitoring in Soccer

Professional soccer clubs aiming to maximise performance and reduce injury risk employ practitioners to monitor loads experienced by their players (Akenhead and Nassis, 2016, McCall et al., 2015). It has been proposed that the main goal of training load monitoring is to identify whether athletes have been following a prescribed training plan, alongside monitoring how athletes are coping with the load prescribed (Impellizzeri et al., 2020). There are in essence two schools of thought when it comes to training load and its relationship with injury. One suggestion is that TL data can be monitored and manipulated to prevent injury (Bourdon et al., 2017). Another suggestion is that focusing on this relationship is an overly simplistic approach to a complex phenomenon (Impellizzeri et al., 2020). What is clear though is that access to technological devices such as GPS has provided opportunities for practitioners to collect and analyse data across groups of players. The perceived purpose of collecting training load data has been analysed with the main reasons highlight being ‘maximising performance’, ‘enhancing fitness’ and ‘reducing injury’ (Weston, 2018).

A survey carried out on professional clubs internationally found that 40 out of the 41 clubs analysed were collecting heart-rate and GPS data from every player during every training session, with the remaining club collecting data from a sub-group due to equipment limitations (Akenhead and Nassis, 2016). More than 50 variables were reported across the surveyed clubs to record training load, with clubs using an average of 7 ± 2 metrics to monitor training (Akenhead and Nassis, 2016). There appears to be no consistent method of load monitoring used across soccer teams, with some discrepancy between coaches and practitioners views on the usefulness of such measures (Weston, 2018, Akenhead and Nassis, 2016).

It has been highlighted that when youth players transition to a first team environment, they may be subject to an increase in training and match demands (Houtmeyers et al., 2021). In consideration of this, this section of the literature review will aim to describe training load profiles at youth and senior level soccer, with a further aim of providing some comparison between levels.

2.3.1 - Training Loads in Elite Senior Soccer Players

Whilst not including match data, Malone et al. (2015) quantified the weekly training load practices across a season. Taking measures from three individual weeks during the in-season phase, they reported mean values for total distance covered of 6182 ± 1841m, 6105 ± 1121m and 4714 ± 1581m. Alongside this they reported high-speed distance (>5.5m•s^{-1}) values of 243 ± 229m, 225 ± 213m and 146 ± 104m and weekly sRPE-TL values of 350 ± 191au, 340 ± 155au and 259 ± 129au. What is apparent from these values, in comparison to load values for youth players is the predominance of match play load in senior players in comparison to youth players across the training week.

Despite also not including match data, Manzi et al. (2009) reported the weekly training load values of an English Premier League team during the pre-season period. These values further highlight the predominance of match play load in senior soccer. In contrast, Malone et al. (2016) included match load when reporting weekly training loads in the pre-season and in-season period in elite soccer players. Collecting data from two elite professional teams, they reported significant differences for average weekly training loads between the pre-season (2984 ± 615au and in-season (2441 ± 215au). The pre-season is likely higher due to an increased focus on building physical fitness in comparison to a focus on technical and tactical elements during the in-season period (Malone et al., 2015).

Table 2.5 - Weekly Training load in senior elite soccer players.

Authors	Participants	Measures	Weekly Training Load
Malone et al. (2015)*	30 English Premier League Players	GPS & sRPE-TL	TD - 6182 ± 1841m 6105 ± 1121m 4714 ± 1581m HSD (>5.5m•s^{-1}) - 243 ± 229m 225 ± 213m 146 ± 104m sRPE-TL - 350 ± 191au 340 ± 155au 259 ± 129au

Manzi et al. (2013)†	Eighteen Italian Serie A Players	sRPE-TL	sRPE-TL - 644 ± 224au
Malone et al. (2016)	48 players across two elite European clubs	sRPE-TL	Pre-Season 2984 ± 615au In-Season 2441 ± 215au

Key; * - Results taken from 3 in-season weeks and not including match data; † - Does not include match data; TD – total distance covered; HSD – high-speed distance; au – arbitrary units

2.3.2 - Training Loads in Youth Soccer Players

Having an understanding of the training load generally experienced by youth soccer players may assist in optimising the long-term physical development of players by increasing positive training adaptations and reducing injury risk (Wrigley et al., 2012, Bowen et al., 2017). Considering the weekly external load profiles of elite youth soccer players, Bowen et al. (2017) recorded data from training sessions alongside estimated game data. They reported mean values for total distance covered of 19759m, with a range from 0 to 39426m. For high-speed distance (> 20km•h^{-1}) they reported a mean value of 856m with a range from 0 to 2048m.

Previous research has utilised sRPE-TL when measuring training load in youth soccer players. Wrigley et al. (2012) assessed the activity profiles of U14, U16 and U18 English Premier League academy players and found age-related increases in the volume and intensity of training. They showed that the greatest training load was undertaken by the U18 group, reflecting the increased number of field and gym-based sessions. The U18 group reported a statistically significant higher weekly load in field training (2464 ± 607au) and match play (759 ± 51au) than the U16 and U14 age groups. These values were similar to that reported by both Akubat et al. (2012) and Impellizzeri et al. (2006) in professional youth soccer players. Measuring differential RPE (dRPE), it was found that elite players reported higher perceived respiratory exertion (1460 ± 184au) than non-elite players (1223 ± 260au) and higher perceived muscular exertion (1548 ± 216au) than non-elite players (1318 ± 308au) (Gil-Rey et al., 2015).

Table 2.6 - Weekly Training load in elite youth soccer players.

Authors	**Participants**	**Measures**	**Weekly Training Load**
Wrigley et al. (2012)	24 U14-U18 English Premier League Academy Players	sRPE-TL	U18 - 3948 ± 222au U16 - 2919 ± 136au U14 - 2524 ± 128au
Bowen et al. (2017)	32 Youth English Premier League Academy Players (Age = 17.3 ± 0.9)	GPS	TD - 19759m (Range 0 to 39426) HSD (>20km•h^{-1}) - 856m (Range 0 to 2048m)
Gil-Rey et al. (2015)	14 Spanish 1st Division Youth Players (Age = 17.6 ± 0.6yrs)	dRPE	sRPEres - 1460 ± 184au sRPEmus - 1548 ± 216au
Akubat et al. (2012)	9 Professional Youth Players (Age = 17 ± 1yrs)	sRPE-TL, Banister's TRIMP, Team TRIMP, iTRIMP	sRPE - 2094 ± 466au Banister's TRIMP - 460 ± 98au Team TRIMP - 1538 ± 359au iTRIMP - 1830 ± 1805au
Impellizzeri et al. (2006)	29 Professional Youth Players (Age = 17.2 ± 0.8yrs)	sRPE-TL	Pre- to Mid- training Period GTG - 3605 ± 210au STG - 3475 ± 249au Mid- to Post training period GTG - 2875 ± 335au STG - 2798 ± 322au

Key; TD – total distance covered; HSD – high-speed distance; GTG – generic training group; STG – soccer-specific training group; au – arbitrary units

2.3.3 - Comparison of Training Load Values Between Elite Youth and Senior Soccer

The evolution of physical demands, particularly intensity, have been acknowledged anecdotally by coaches and evidenced through the work of Barnes et al. (2014) and Bush et al. (2015). The primary aim of youth academies is to prepare players for the demands of professional soccer (Buchheit et al., 2010). Despite this, little research has been done comparing the training and match play demands of youth and senior soccers players. Much of the research regarding transition from youth to senior sport has focused on demands and challenges faced by players and highlighted psychological coping strategies to aid athletes (Stambulova et al., 2009, Finn and McKenna, 2010). It is likely that alongside psychological difficulties during the transition to senior soccer, players will also experience an increase in training and match play intensity (Finn and McKenna, 2010). Recent research has assessed the differences in weekly load between U19 and 1st team players (Houtmeyers et al., 2021). Despite the U19 players performing 1 more field session than 1st team players, and a higher total distance, their sprint distance (> 25km•h^{-1}) was lower (Houtmeyers et al., 2021) . This study provides a useful insight into the weekly load structure of professional players at U19 and 1st team level, highlighting the differences in intensity at both levels. These differences can be interpreted in different ways, perhaps the 1st team players are more physically advanced than the younger players allowing them to perform more frequent bouts at high intensity. Similarly, it could be argued that the 1st team players are more technically advanced, allowing for higher intensities to be performed in training and match play. Importantly it would appear from this analysis that there is a clear distinction between load profiles when comparing youth and senior soccer players, and that this difference should be considered by practitioners when considering the transition of players. Given that this research was carried out on a single team, there is a need for further research to quantify differences between youth and senior soccer, and for this to be possible consistent training load measures should be used.

2.3.4 - Summary

A range of values for match play load have been presented in current literature. Practitioners should consider the influence of contextual factors such as playing position and formation when interpreting these. When considering the match play load of youth players, additional considerations such as physiological and biological development of the player and adapted playing formats should be accounted for. In senior players, match play load appears to be the primary focus within a training week, whereas larger respective training loads may be reported in development players, this is likely due to a need to promote technical, tactical, and physical adaptations in youth players. Elite senior soccer is evolving with regards to intensity, as such there is a need to consider this when developing future players. Comparison between levels is a developing area of research which warrants further attention.

2.4 - Methods of Training Load Monitoring

The physiological demands of soccer are complex, and as such multifactorial training plans are implemented by practitioners with the aim of improving performance and reducing injury risk (Morgans et al., 2014, Drew and Finch, 2016). If training were to be considered as a continuous loop (Figure 2.1), then training load could be considered as the input variable that ultimately results in a training outcome (Impellizzeri et al., 2020). Practitioners generally monitor physical work, characterised as external load, alongside physiological response that is characterised as the internal load (Gabbett, 2016). Both external and internal loads can provide practitioners with information to better tailor the stimulus and enhance adaptive response (Halson, 2014). Activities performed by athletes within training lead to a variety of modes of stress, such as biochemical stresses and mechanical stresses. With regards to physiological adaptations, these stresses ultimately lead to changes both centrally or peripherally (Vanrenterghem et al., 2017). Biomechanical adaptations take place through mechanical stresses to musculoskeletal tissues such as cartilage, bone, muscle and tendon tissue (Vanrenterghem et al., 2017). These adaptations, or training effects, can be grouped into four categories representing acute/chronic and positive/negative effects that can influence performance outcomes (Jeffries et al., 2021). Within their proposed conceptual framework of physical training, Jeffries et al (2021) utilised the terms acute and chronic with regards to the amount of training required to elicit an effect, and the time needed to return to baseline once training had stopped (Jeffries et al., 2021). More specifically, acute effects were considered to be outcomes which were induced by up to one week of training, thus only requiring a brief time to occur and to return to baseline once training has stopped (Jeffries et al., 2021). Chronic effects were considered to be those which required more microcycles of training, and required a longer time for the athlete to return to homeostasis (Jeffries et al., 2021). These acute or chronic effects can then either be classed as positive, those that directly improve a sport performance outcome, or negative, those that impair a sport performance outcome (Jeffries et al., 2021). Approaching training as a training-process framework (Figure 2.1) allows practitioners to appreciate and monitor the whole training process. In intermittent running-based sports, such as soccer, external load can be measured as total distance covered, total distance in specific speed thresholds, or by considering the frequency and duration of accelerations performed by the player. The internal load can be considered as the response to external load and is commonly measured via heart rate or subjective measures such as sRPE. Ultimately, it is the internal load that determines the training response or training effect. Additionally, this response is influenced by an individual’s characteristics such as age, weight, and nutrition, alongside external factors such as the training environment(Jeffries et al., 2021, Impellizzeri et al., 2019) Jeffries et al. (2021) proposed that positive and negative training effects could be categorised via performance measures, physiological measures, subjective measures or other measures. Performance measures refers to outcomes that specifically measure a task either related to competitive performance or measures a specific fitness component. For example, a countermovement jump could be used to monitor the effectiveness of a training programme to improve lower body power (Cormie et al., 2009), or to monitor acute negative effects of training via neuromuscular fatigue (Claudino et al., 2017). Various physiological measures have been validated within the literature which could be used to monitor positive effects or training, such as measures of maximal oxygen consumption to monitor effects of training interventions (Rosenblat et al., 2022). Conversely measures of creatine kinase levels following training could be used to monitor negative effects (Hagstrom and Shorter, 2018). Questionnaires such as the Recovery-Stress Questionnaire for Athletes could be used to provide subjective measures of training outcomes (Jones et al., 2017). Jeffries et al. (2021) proposed that other measures such as biomechanical or more area-specific measures could also be utilised within this conceptual model. Vanrenterghem (2017) proposed more generally that adaptions could be classified as being either physiological, be that central or peripheral, or biomechanical. These outcomes could then be classified related to underload, maintaining homeostasis, overload, or failure. For example, underload of an athlete with regards to physiological adaptation may lead to negative effects such as increases in adipose tissue, or muscle atrophy (Vanrenterghem et al., 2017). Similarly, with regards to biomechanical adaptations, underload may lead to decreased tendon stiffness or cartilage degeneration (Vanrenterghem et al., 2017). Overloading an athlete to the point of failure will induce negative physiological outcomes such as immune deficiency, and negative biomechanical outcomes such as damage to tissues for example muscle or tendon tear or bone fracture (Vanrenterghem et al., 2017, Kalkhoven et al., 2020). Appropriately planned load is more likely to lead to positive outcomes, such as cardiac or metabolic adaptation, or increased tendon stiffness or cartilage regeneration (Vanrenterghem et al., 2017). Therefore, the appropriate application, monitoring and modelling of load and athlete response is critical to support desired positive outcomes.

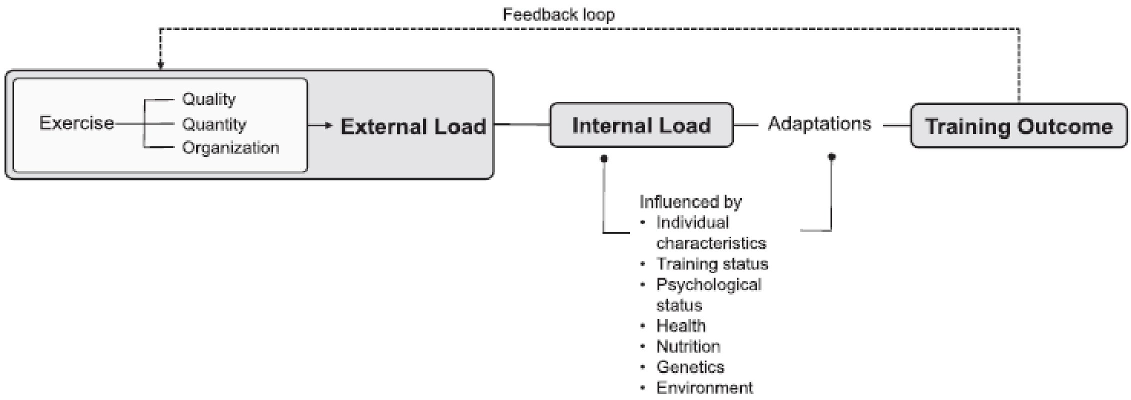

Figure 2.1 - Training process framework and measurable components for monitoring. Reproduced from Impellizzeri et al. (2020)

2.4.1 - Modelling Training Load Dose and Response

Practitioners working with elite athletes routinely collect and monitor training loads and athlete response to best prescribe training and ultimately improve performance. Within the literature there are a number of training theories that facilitate interpretation of training load data, the most prominent of these being the General Adaptation Syndrome, proposed by Selye (1956), suggests that all stressors result in similar responses. Initially, a system will enter an alarm stage where a negative response to the organism's physiological state is experienced. This stage is followed by the resistance phase, whereby an organism supercompensates, taking the system beyond homeostasis and into a higher state. The final stage of this theoretical model is the exhaustion phase, where the experienced stress is greater than the organisms ability to adapt (Chiu and Barnes, 2003). This basic theoretical model was the basis for Banister's Fitness-Fatigue model (Banister et al., 1975). The aim of the fitness-fatigue model was to assess biological responses to training by comparing the response to fatigue and fitness indicators modelled from the effects of training on performance (Busso et al., 1994). Originally proposed in 1975, Banister utilised systems theory to attempt to describe the biological response to physical training. The athlete or 'system' was viewed as a black box with a 'systems input', successive training loads, relating to an output, which was ultimately performance, a very simplistic method of contextualising a complex, physiological system. Profiles of fatigue and fitness could then be deciphered from model parameters by fitting the model performance to recorded performance. Model fatigue was then assumed to be the difference between a modelled level of performance and the recorded level.

Whilst Banister's model is a more realistic representation of training and response than general adaptation syndrome, it has been argued that this may still provide an imperfect description of training-induced fatigue (Busso, 2003). The basis of modelling for describing adaptations to training involves mathematically relating change in performance, to the amount of training (Busso, 2003). Banister's original model is defined by a transfer function composed of two first-order filters characterised by the two gain terms k1 and k2, and the two time constraints τ1 and τ2 (Equation 1).

$$: \hat{p}^n = p^* + k_1 \sum_{i=1}^{n-1} w^i e^{-(n-i)/\tau 1} - k_2 \sum_{i=1}^{n-1} w^i e^{-(n-i)/\tau 2}$$

Equation 1 – Original Fitness-Fatigue model proposed by Banister et al. (1975)

Whilst previously prescribing the training process relied largely on the experience of either the athlete or the coach, the aim of this model was to better prescribe training leading to an optimal performance at a given time. Calvert et al. (1976) then proposed a multicomponent model which encompassed four key training 'elements' and aimed to explain their effect on performance. The elements proposed were; endurance, strength, skill, and psychological factors (Figure 2.2). Calvert et al. (1976) admittedly stated that this initial model was a speculative attempt at assessing performance and should only be viewed as a 'skeleton' of what a complete model may eventually be. There is difficulty in using this model in quantifying values of the inputs and assessing the effects of the separate input components. At the time the limitations of this model were accepted, but it should be noted that these components account for the major determinants of performance, and ensuring these inputs are logical will lead to a more realistic output. Utilising a case study of a highly developed swimmer, Calvert et al. (1976) proposed that there was significant interplay between fatigue and fitness to determine performance (Equation 2). This updated model contained two negative components and one positive component to single out the fatigue effects on the time course of training adaptation (Equation 2). Whilst this fledgling model showed promise and laid the groundwork for further developments, there was a need to propose models with predictive abilities rather than assessing training and performance which had already taken place.

$$\hat{p}_n = p^* + k_1 \sum_{i=1}^{n-1} w^i[e^{-(n-i)/\tau 1} - e^{-(n-i)/\tau' 1}] - k_2 \sum_{i=1}^{n-1} w^{ie^{-(n-i)/\tau 2}}$$

Equation 2 – Updated model proposed by Calvert et al. (Calvert et al., 1976)

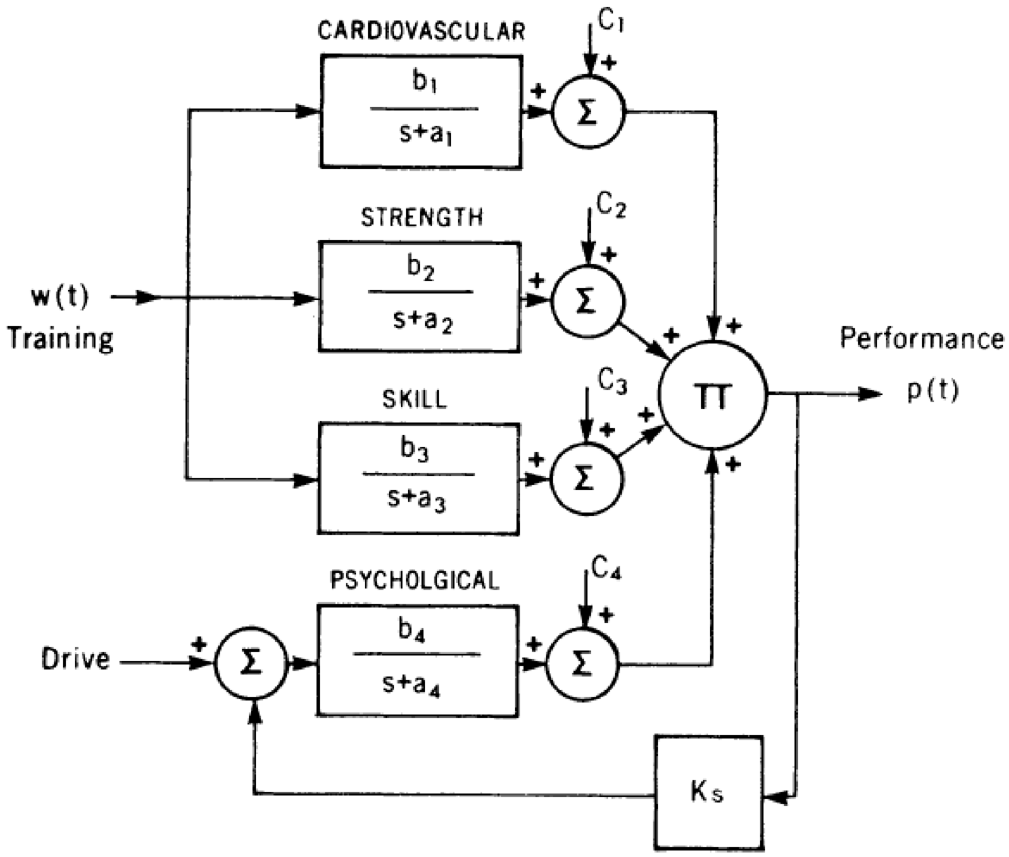

Figure 2.2- Calvert et al. (1976) Multicomponent model to explain effects of different forms of training on resultant performance.

Future models were developed over time in distance runners (Banister and Hamilton, 1985), elite weightlifters (Busso et al., 1990) and in recreational runners (Morton et al., 1990). Busso et al. (1994) then compared two differing methods of estimating fatigue and fitness to model resultant performance. Previous efforts had assigned negative and positive fatigue and fitness indicators as functions of the model (Banister et al., 1975, Banister and Hamilton, 1985, Morton et al., 1990, Busso et al., 1990) whilst some studies had computed fitness and fatigue indicators by combining the two components of the model (Busso et al., 1992). Utilising training data of a hammer thrower it was shown that both methods were valid however there was an effect of time and amount of training (Busso et al., 1994). Busso (Busso, 2003) then proposed a model which, potentially, describes the response to training more precisely. This model assumes that the gain term of the fatigue effect is mathematically related to the training dose using a first-order filter. Performance output can then be described as;

$$\hat{p}^n = p^* + k_1 \sum_{i=1}^{n-1} w^i e^{-(n-i)/\tau 1} - \sum_{i=1}^{n-1} k_2^i w^i e^{-(n-i)/\tau 2}$$

Equation 3– Busso (2003) proposed Fitness-Fatigue model. Where p is performance, w is training dose, k is gain in performance and t is a time constraint.

In which the value of k_2 at day *i* is estimated by mathematical recursion using a first-order filter with a gain terms of k_3 and a time constant τ3 (Equation 4).

$$k_2^i = k_3 \sum_{j=1}^{i} w^j e^{-(i-j)/\tau 3}$$

Equation 4- k2 calculation from Busso (2003) Fitness-Fatigue model

This model, appeared to improve the performance fit compared with previous models (Busso, 2003). A range of relationship from trivial to large have been found when using Busso's proposed model, largely dependent on the variable used to assess fitness or fatigue. Busso's model also suggested an inverted U shape relationship between daily amounts of training and performance, that is, athletes will reach an optimal training amount and further training would lead to a decline in performance. There are limitations that should be accounted for when comparing models. Busso (2003) used arbitrary training units to monitor training, based upon a percentage of peak power output, whereas other models used training impulse (TRIMP). Given improvements in technology there are a number of objective and subjective training monitoring measures which could be used as inputs, however practitioners should be cautious when generalising findings. The participants used in this study were also recreationally active volunteers, not athletes, and as such there training amounts appeared to be lower than in previous studies. This may have led to an over-simplification of training quantification and transfer to performance.

The developed model proposed by Busso (Busso, 2003) does appear to improve the performance fit compared with previous models (Banister et al., 1975, Calvert et al., 1976). However, it was highlighted that the shortcomings of the model, based on the training prescription and participants used, limits prediction to similar training practices. Different training strategies, or longer-term adaptations from advanced athletes could affect responses, and thus effect the model. Therefore, practitioners need to be cautious when applying models to their training data, particularly when selecting inputs from training data. Whilst these models have been proposed within the literature, their practical use is less clear. Anecdotally there may be several reasons for this including lack of resources to fit the models within athlete monitoring systems, and the underlying mathematics involved. To combat this more simplistic models such as the acute-chronic workload ratio have been proposed (Gabbett, 2016), and more recently challenged (Lolli et al., 2019). The commonality between these methods of load monitoring is the need for valid and reliable input measures, commonly assessed via internal or external load.

2.5 - Monitoring External Training Load via Global Positioning Systems (GPS)

2.5.1 - Overview

Use of GPS technology is now commonplace in society, with mobile phones and smart watches making this technology accessible to the general population. This technology, which was initially developed for military purposes, has also become of increasing interest to coaches and practitioners to monitor training and match-play activity (Akenhead and Nassis, 2016). GPS relies on satellite navigation to triangulate the position of the unit in space. Use of an atomic clock allows precise measurement of the length of time for a radio signal to travel from satellite to GPS receiver. This allows the distance from satellite to receiver to be collected, allowing accurate location of the receiver to be decoded (Aughey, 2011, Larsson, 2003). Once location is known, the change in position over given time periods can be used to calculate velocity. Commercially available microelectromechanical system devices house not just the GPS receiver, but also an accelerometer, gyroscope, magnetometers, microprocessor, and battery (Figure 2.3).

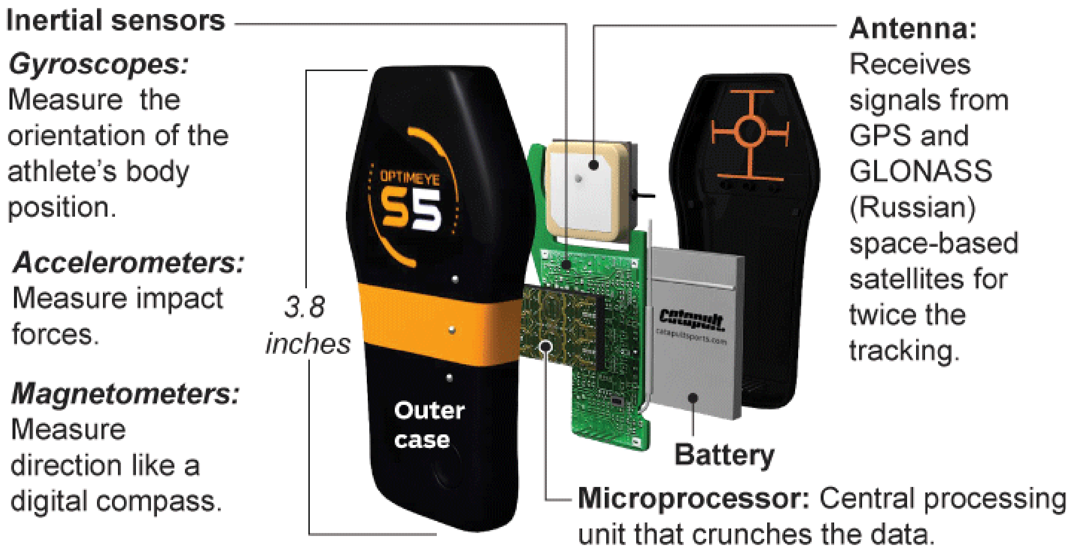

Figure 2.3 – Key features of a commonly available microelectromechanical system device

Since the first research study using GPS technology in sport was published in 2001 (Larsson and Henriksson-Larsén, 2001), the number has increased exponentially (Malone et al., 2017). The use of GPS technology in practical settings is now commonplace. GPS technologies are commercially available, and widely used across professional clubs. A survey analysis of 41 professional soccer teams found that 40 collected heart-rate and GPS data from every player during every pitch-based training session (Akenhead and Nassis, 2016). The remaining club performed data collection for every session on a sub-group of the team due to limitations with equipment (Akenhead and Nassis, 2016). The main purposes of monitoring training load in these athletes were identified as improving performance, management of training load distribution, and injury prevention (Akenhead and Nassis, 2016). In research settings, devices have been used to; investigate training and match load of athletes (Cummins et al., 2013), investigate relationships between load and injury (Gabbett and Domrow, 2007, Bowen et al., 2019), and monitor fatigue in athletes (Buchheit et al., 2015).

Given the wide and increasing use of GPS technology in team sports it is important for practitioners to understand; how data are produced, the validity and reliability of data produced, and what changes in hardware and software can affect factors such as filtering and smoothing data. The aim of this section is to provide greater understanding of the use of GPS technology applied in team sport settings.

2.5.2 - Validity and Reliability of GPS

The term validity is generally used to refer to how well a measure resembles what it is intended to measure (Currell and Jeukendrup, 2008). When discussing validity, this section will focus on logical, criterion and construct validity. Logical validity assesses whether a measure assesses what it intends to. There are two types of criterion validity; concurrent and predictive (Thomas et al., 2015). Concurrent validity means that the measure is correlated with a criterion measure (Thomas et al., 2015). For example, GPS derived total distance covered and the known distance of a measured track. Predictive validity involves using a measure to subsequently predict a future measure. Construct validity refers to the degree in which a measure assesses a hypothetical construct. In the context of GPS measurement, a metric which shows strong validity would be one which ultimately measures what it proports to. Reliability gives an indication of the variation of a measure, and the reproducibility of results from a given metric over repeated measures (Hopkins, 2000) . It is key to consider the reliability of GPS technology in team sport settings to allow consideration of the consistency between devices (inter-unit) and session-to-session variability (intra-unit) (Scott et al., 2016).

For this section of the thesis, concurrent validity was considered. The measures of validity reported are the standard estimate of error (SEE), standard error of measurement (SEM), coefficient of variation (CV), Standard Typical Error (STE), measurement bias, or the percentage of difference of the mean from the criterion measure. Measures for reliability are presented as CV, typical error of measurement (TEM) difference between units (DBU) and standardised mean bias (SMB). Intraclass correlation (ICC) has been reported where provided. In-line with a previous review, measures of validity and reliability were rated as good (<5%), moderate (5-10%) or poor (>10%) (Scott et al., 2016).

This section will aim to provide an assessment of studies which have tested the validity and /or reliability of GPS devices at various sampling rates. This section will specifically focus on studies which assessed movements related to team sports. To provide an assessment of the available literature a modified version of a previous strategy from a published review was used (Scott et al., 2016).

2.5.3 - 1Hz Global Positioning System – Validity

The first paper to assess validity of GPS technology in team sports settings was carried out by Edgecomb and Norton (2006) with the aim of assessing the validity and reliability of GPS and computer-based tracking (CBT) for measuring player distance in Australian Football (AFL). To determine the validity of the SPI 10 (GPSports), 59 trials were completed where an athlete moved around a circuit ranging from 128 – 1386 m, with the actual distance confirmed by trundle wheel. GPS derived distances and actual distances were highly correlated (r = 0.99), however there was a significant difference between distances measured via GPS and trundle wheel. On average the SPI-10 overestimated distance by 4.8 ± 7.2%, with an absolute error of 6.3 ± 6.0%. The authors attributed this to error provided by location from GPS technology, a visual location trace further evidenced this. The authors concluded that this was most likely due to the sampling rate available to the technology at the time.

Further analyses supported the use of 1Hz units in team sport settings. Petersen et al. (Petersen et al., 2009) reported good validity in walking (< 2m•s^{-1}), jogging (2 – 3.5m•s^{-1}), running (3.5 – 4m•s^{-1}) and striding (4 – 5m•s^{-1}) as they aimed to replicate distances and velocity of movement utilised in cricket. Assessing three different models of GPSports technology (SPI – 10, SPI Elite & WiSPI), Coutts and Duffield (2010) utilised a 128.5m team sport simulated circuit which included bouts of activity at various speeds. The SPI-10 and SPI Elite both underestimated total distance by 4.1 ± 4.6% and 2 ± 3.7% respectively, whilst the WiSPI overestimated total distance by 0.7 ± 0.6%. Whilst the three devices displayed good to moderate levels of validity, it should be noted that the three devices produced differing results, highlighting that practitioners should be wary of using different models interchangeably. This piece also showed that older models, specifically the SPI-10, underestimated total distance compared to newer models. The authors highlighted the use of accelerometer data which supported a corrective algorithm that was used at the time to overcome the limitations of the sampling frequency. Coutts and Duffield also highlighted the issue of velocity of movement when assessing distance covered by an athlete, with the three different models of units providing varying values for running distance at very high intensity (> 20km•h^{-1}), high intensity (> 14.4km•h^{-1}) and low intensity (< 14.4km•h^{-1}).

Whilst not using a team sport simulated circuit, Gray et al. (2010) further highlighted the issue of speed of movement when measuring distance covered via 1Hz units. They showed that during a linear running course, measured via an electronic transit theodolite integrated with electronic distance measurement, GPS distance was overestimated at all movement intensities with the walk (~1.6m•s^{-1}) and sprint (7-8m•s^{-1}) distances significantly greater that the jog (~3.5m•s^{-1}) and run (~5m•s^{-1}) distances. Interesting, whilst the distance was overestimated in the linear course, it was underestimated in the non-linear course. This underestimation increased with movement intensity, from 1.1m to 19.6m in walking and sprinting, respectively. In the non-linear course, all movement intensities were significantly different to each other, highlighting the effect which movement velocity may have on accuracy of this technology.

Contradictory to the findings above, Jennings et al. (2010a) found poor and moderate–to–poor validity of Catapult MinimaxX Team 2.5 devices. Using a combination of linear running, change of direction tasks and a team sport simulated circuit, they assessed validity of total distance measured against the criterion of a tape measure. Participants were required to walk, jog, stride, and sprint at self-selected speeds for distances of 10, 20, and 40m. For all conditions, the validity got progressively worse as velocity increased with the SEE ranging from 9.6 ± 2.0% in the 40m walk, to 32.4 ± 6.9% in the 10m sprint. It should also be noted that the validity improved with increasing distance across all movement velocities. Similarly, validity decreased as the movement velocity increased in all change of direction tasks apart from walking in the tight course. Interestingly, in a team sport simulated circuit, Jennings et al. (2010a) reported good validity for total distance covered 3.6 ± 0.6%. These findings are surprising when considering the team sport simulated circuit encompassed a combination of linear movement at different velocities, and prescribed changes of direction, given this research had previously reported moderate–to–poor validity for similar tasks. However, it has been proposed that this improved validity is likely due to the increased distance covered during the circuit, leading to greater accuracy of the GPS unit. This suggestion is supported by the increased validity shown across increasing distances in the previously performed linear tasks.

Another study to analyse the validity of the MinimaxX 2.5 device utilised a similar protocol. Using soccer field dimensions, Portas et al. (2010) assessed total distance validity in half-pitch linear running, three different short and long change of direction tasks, and a soccer specific course. The change of direction tasks were clarified as short or long, with turns of 180, 90 and 45 degrees assessed in both directions. The soccer specific course was based on English Premier League match data to characterise common positional movements and an additional high intensity bout of activity. Across the linear and change of direction tasks, they found good and good–to–moderate validity, whilst in the soccer specific course they revealed good validity across all position specific courses and for the high intensity bout of activity. Similar findings were shown in a circuit designed to simulate field hockey, with no significant difference found between GPS derived, and actual total distance (MacLeod et al., 2009). However, they did find significant differences between the criterion total distance and segments of the simulated sport circuit, similarly to the Jennings et al. (2010a) study discussed previously. To summarise these findings, whilst GPS technology with this initial sampling rate appeared to have limitations over short distances and be affected by increasing velocity, it appeared to display reasonable validity over sport specific movements in larger areas.

Two articles assessed the validity of movement velocity measured via GPS at 1Hz sampling rate (Barbero-Álvarez et al., 2010, MacLeod et al., 2009). The first, utilised a team sport simulated circuit to base movement patterns on National League hockey games (MacLeod et al., 2009). This circuit included various linear and non-linear tasks including a T-shaped shuttle, straight-line shuttle, straight-line sprint shuttle and a zigzag shuttle encompassing varying movement velocities. Electronic timing gates were used to assess time taken, and average velocity, across each of the four shuttle movements. A Pearson correlation of 0.99 was found between the mean speed recorded by the timing gates and that reported by the SPI – Elite hardware. The only shuttle task which displayed a significant difference between measures was the straight-line sprint shuttle, with the GPS technology overestimate speed by 0.2 ± 1.2km•h^{-1} (~1.5%). Barbero-Álvarez et al. (2010) found strong relationships between fastest recorded times (r^2 = -0.93) and total sprint time (r^2 = -0.96) from GPS derived measures and those recorded via infrared light sensors during a repeated sprint ability test. Whilst there was limited research at the time regarding the validity of assessing movement velocity in team sports, there did appear to be early promise in assessing mean velocity in linear and multi-directional tasks. However, there was no evidence to support the use of GPS technology sampling at 1Hz to assess instantaneous velocity in athletic populations.

Table 2.7 – Validity of Global Positioning System Devices (1Hz)

Reference	Device	Parameter	Task	Criterion Measure	Error Measurement	Int.
Gray et al. (2010)	WI SPI Elite	Total Distance	Linear & Non-Linear Running (200m)	Total Station EDM / Theodolite	Linear: – 1.8 to 5.8m Non-Linear: -1.1 to -19.6m	n/a
Coutts and Duffield (2010)	SPI – 10	Total Distance	Simulated Team Sport Running Track (6 x 128.5m)	Measuring Tape	TDE: -4.1%	G
	SPI Elite				TDE: -2.0%	G
	WiSPI				TDE: 0.7%	G
Jennings et al. (2010a)	MinimaxX Team 2.5	Total Distance	Sprint trials (10 – 40m, 20 – 40m split)	Measuring Tape	SEE: 9.6 – 32.4%	M-P
			Tight COD	Measuring Tape & Goniometer	SEE: 9 – 12.6%	M-P
			Gradual COD		SEE: 9.1 – 12.7%	M-P
			TSSC (5 x 140m)	Measuring Tape	SEE: 3.6%	G
Petersen et al. (2009)	SPI – 10	Total Distance	Cricket Specific Running (600 – 8800m)	Athletics Track	SEE – 0.5 – 2.1%	G
Barbero-Álvarez et al. (2010)	SPI – Elite	Velocity	RSAT (7 x 30m)	Infrared Light Sensors	Fastest time: r^2 = -0.93 (p<.001); Total Sprint Time: r^2 = -0.96 (p<.001)	n/a
MacLeod et al. (2009)	SPI – Elite	Total Distance	TSSC (14 x 487m)	Trundle Wheel	Mean Diff. for Total Circuit (± LOA): 2.5m ± 15.8m Sig. diff. (p<0.001) for subsections of TSSC	n/a
		Velocity		Timing Gates	Straight line sprint shuttle significantly different (p<0.01)	n/a
Portas et al. (2010)	MinimaxX v2.5	Total Distance	Linear Course (16 x 51m)	Trundle Wheel	SEE: 2.6 to 2.7%	G
			Multidirectional Course (2 x 8 x 51m – 180m)		SEE: 1.8 to 6.8%	G-M
			Soccer Specific Course (10 x 1min of 110m – 197m)		SEE: 1.3 to 3.0%	G
Edgecomb and Norton (2006)	SPI 10	Total Distance	Running Circuit (128 - 1386m)	Trundle Wheel	TDE (Mean ± SD) : 4.8% (p<.001)	G

Key; Int. - Interpretation; G- Good (<5%), M – Moderate (5 – 10%), P- Poor (>10%), n/a – not available; TDE – Total Distance Error; SEE – Standard Error of the Estimate; TSSC – Team-Sport Simulated Circuit; LOA – Limits of Agreement; Sig. Diff – Significant Difference; RSAT- Repeated Sprint Ability Test

2.5.4 - 1Hz Global Positioning System – Reliability

Edgecomb and Norton (2006) assessed intraunit reliability in SPI-10 units using a running circuit. Three repeated measures over a range of circuits demonstrated a technical error of measurement (TEM) of 5.5%, classified as moderate. The SPI-10 unit has demonstrated good intraunit reliability for measurements of total distance covered at various speeds to replicate the demands of cricket (Petersen et al., 2009). Petersen et al. (2009) recorded coefficients of variation (CV) ranging from 0.4 to 1.5%. Contrary to what some may expect there was not a systematic bias between CV increasing proportionally with activities performed at increasing velocity. Similarly to these studies, during linear and multi-directional movements, Portas et al. (2010) reported good-to-moderate interunit reliability at walking and running velocities. Reporting typical error as coefficient of variation, they found values ranging from 4.4 – 4.5% during linear walking and running respectively. Similar values were reported in a multi-directional, and soccer specific course suggesting that 1Hz GPS units can provide reliable total distance measures at varying locomotion in pre-planned linear and multi-directional movements.

Contrary to these findings, Jennings et al. (2010a) found predominantly poor and moderate intraunit reliability in MinimaxX Team 2.5 technology. During straight line running task ranging from 10 – 40m, at four different velocity bands, they found CV ranging from 7% to 77.2%. With this design, they did show that reliability reduced as the speed of movement increased. They also reported that the lowest recordings of reliability were seen at short distances. With CV of 30.8%, 34.7%, 58.8% and 77.2% recorded over a 10m distance for self-selected speeds of walking, jogging, striding, and sprinting respectively. These poor interpretations were found across the conditions, except for 40m walking (CV = 7%) and jogging (CV = 9.4%). Additionally, Jennings showed during change of direction tasks that only jogging through a gradual or tight pre-planned change of direction task displayed moderate reliability. However, the technology did display good reliability (CV = 3.6%) across a team-sport simulated circuit. These findings suggest that whilst the technology may report acceptable repeated measures of total distance over large-scale tasks, there are limitations in its ability to report short distance and high intensity movement velocities. Whilst the reliability of GPS measurement increased with increasing distance, it is important for practitioners to note it decreased with increasing velocity.

Coutts et al. (2010) assessed the interunit reliability of the SPI-10 model using a team-sport simulated circuit and found mixed results regarding total distance and distance covered at different speed thresholds. Assessing a single repetition of the circuit against continuous repetitions they found that the reliability improved with the increased number of circuits. When values from one lap of the circuit were assessed, they reported a CV of 6.4%, whilst six continuous laps of the circuit produced a CV of 4.5%. This would support previous findings regarding the reliability of this generation of technology over continuous movement. Again, supporting previous findings, they appeared to find a relationship between the speed at which movement is performed and reliability, with good-to-moderate reliability reported for total distance covered at low intensity (CV = 5.3%) whilst poor reliability was shown for high intensity (CV = 32.4%) and very high intensity running (CV = 30.4%). The only other study to assess interunit reliability in 1Hz GPS technology reported good reliability across a range of speeds in basic linear (CV = 1.46% – 3.38%) and good and moderate reliability in non-linear running (CV = 1.63% – 6.04%) (Gray et al., 2010).

These findings suggest that 1Hz GPS units can provide reliable data across longer distance in straight line and change of direction movements at various speeds. However, practitioners should be cautious of data reported from short distance movements or bouts of high intensity up to 40-m. This is of course problematic as many meaningful movements and those which demand a significant energy cost involve repeated, high-intensity, short actions These movements are those which practitioners are likely to wish to understand to better understand game and training intensities (Aughey, 2011).

Only two studies have assessed reliability of measuring velocity in 1Hz GPS technology. Measuring the SPI-Elite model, Barbero-Alvarez et al. (Barbero-Álvarez et al., 2010) recorded good intraunit reliability in both summated maximal speed (CV = 1.7%) and peak speed (CV = 1.2%) during a repeated sprint ability test. Coutts & Duffield (2010) reported moderate interunit reliability (CV = 5.8%) for peak speed measured in a 20-m sprint at the start of a team-sport simulated circuit. The limited amount of research performed in 1Hz technology makes stating conclusions difficult, however both studies suggest that the models assessed displayed sufficient inter- and intraunit reliability.

Table 2.8 – Reliability of Global Positioning System Devices (1Hz)

Reference	Device	No. of Units	Reliability	Parameter	Task	Error Measurement	Int.
Gray et al. (2010)	WI SPI Elite	8	Intraunit	Total Distance	Linear & Non-Linear Running (200m)	Linear (CV): 1.85 – 2.71% Non-Linear (CV): 1.98 – 4.8%	G
			Interunit			Linear (CV): 1.46 – 3.38% Non-Linear (CV): 1.63 – 6.04%	G-M
Coutts and Duffield (2010)	SPI-10, SPI Elite, WiSPI	2 each	Interunit	Total Distance	TSSC (1 x 128.5m)	CV: 3.6 – 7.2%	G-M
				LIA (<14.4km•h^{-1})		CV: 4.3 – 12.5%	G-P
				HIR (>14.4km•h^{-1})		CV: 11.2 to 32.4%	P
				VHIR (>20km•h^{-1})		CV: 11.5 to 30.4%	P
				Peak Speed		CV: 2.3 to 5.8%	G-M
Jennings et al. (2010a)	MinimaxX Team 2.5	1	Intraunit	Total Distance	Sprint trials (10 – 40m, 20 – 40m split)	CV: 7 – 77.2%	M-P
					Tight COD	CV: 8.6 – 17.5%	M-P
					Gradual COD	CV: 9 – 12.2%	M-P
					TSSC (5 x 140m)	CV: 3.6%	G
Portas et al. (2010)	MinimaxX v2.5	1	Intraunit	Total Distance	Linear Course (16 x 51m)	CV: 4.38 – 4.54%	G
					Multidirectional Course (2 x 8 x 51m – 180m)	CV: 3.08 – 7.71	G-M
					Soccer Specific Course (10 x 1min of 110m – 197m)	CV: 2.03 – 4.86%	
Edgecomb and Norton (2006)	SPI 10	1	Intraunit	Total Distance	Running Circuit (128 - 1386m)	TEM: 5.5%	M
Barbero-Álvarez et al. (2010)	SPI Elite	14	Intraunit	Summated Maximal Speed	RSAT (7 x 30m)	CV: 1.7%	G
				Peak Speed		CV: 1.2%	G
Petersen et al. (2009)	SPI 10	1	Intraunit	Total Distance	Cricket Specific Running (600 – 8800m)	CV: 0.4 – 1.5%	G

Key; Interpretation; G- Good (<5%), M – Moderate (5 - 10%), P- Poor (>10%); CV – Coefficient of Variation; TSSC – Team-Sport Simulated Circuit; VHIR – Very-High Intensity Running; HIR – High Intensity Running; LIA – Low Intensity Activity; RSAT - Repeated Sprint Ability Test

2.5.4 - 5Hz Global Positioning Systems – Device Overview

Nine studies assessed the validity of 5Hz GPS technology, whilst 10 assessed the reliability. A range of devices were used, predominantly those manufactured by Catapult Sports (n = 6) and GPSports (n = 3), whilst a more recent study invested the Wimu device (Muñoz-López et al., 2017). As seen in the 1Hz generation of technology, the most common parameters investigated were Total Distance (n = 8) and velocity in both an average (n = 4) and instantaneous (n = 2) form. However, practitioners also investigated metrics such as metabolic power (Rampinini et al., 2015), accelerations (Varley et al., 2012) and decelerations (Varley et al., 2012). Different movement tasks were used with the most common being formats of linear running (n = 9), adaptations of team-sport simulated circuits (n = 5) and pre-planned change of direction tasks (n = 3). The 5Hz units displayed predominantly good validity however as with 1Hz technology, practitioners may wish to proceed with caution as a large proportion of the outcome measures also met criteria for moderate-to-poor or poor validity. It is worth noting that of those outcome measures that did not meet the conditions of the interpretation criteria, the majority did not show significant differences between the criterion measure and the GPS derived measurement.

Of the ten studies that assessed the reliability of 5Hz technology, 5 assessed the intraunit reliability whilst 6 assessed interunit. The number of units used in assessments ranged from 1-8. A range of parameters were used to assess reliability, with the predominant metric being total distance (n = 9). The most common task used to assess reliability was linear running (n = 9) with team-sport simulated circuits (n = 6) and pre-planned change of direction drills (n = 4) also common. Findings regarding the reliability of 5Hz devices were conflicting, with the majority of 5Hz outcomes reporting poor or good reliability.

2.5.6 - 5Hz Global Positioning Systems – Validity

As was found with 1Hz technology, 5Hz global positioning systems display good validity in low-intensity, linear movements. Petersen et al. (2009), assessing the MinimaxX and SPI-PRO devices, recorded good validity for walking (SEE = 2% – 3.8%; 0.5% – 1%), jogging (SEE = 1.8% – 2.6%; 1.5 – 3.7%), running (SEE = 2.8% – 3%; 0.7% – 2.4%) and striding (SEE = 1.7% – 1.8%; 0.4% – 3%). They found similar error rates with the 1Hz SPI-10 device. Whilst these devices show good validity for low intensity, and longer distance movements, there appears to be some difference in measures of short-distance higher intensity efforts. Sprint efforts over 20m (SEE = 15.2% – 23.8%; 5.5% – 10.5%), 30m (SEE = 14.4% - 19.7%;4.2% - 7.6%), 40m (SEE = 14.9% - 16.1%; 2.9% - 7.7%) and ‘run-a-three’ (SEE = 5.3% - 12.7%; 2.6 – 6.7%) showed poor to moderate-to-poor validity for total distance measures using the MinimaxX device. Using the SPI-PRO device, the same measures showed good-to-moderate to moderate-to-poor validity. Similarly to 1Hz devices, 5Hz GPS technology shows promise in low intensity movements, however there are varying results in shorter distance, high-intensity efforts.

Portas et al. (2010) recorded good validity (SEE = 3.1 ± 1.37%; 2.9 ±1.27%) of MinimaxX v2.5 devices, in linear walking (1.79m•s^{-1}) and running (3.58m•s^{-1}) over a 51m distance. They showed similar results in various pre-planned change of direction tasks at both movement velocities. Good validity was also displayed in intermittent-linear shuttle runs over a 70m distance by Rampinini et al. (2015), whilst Waldron et al. (2011) recorded good and moderate validity for sprinting over distances of 10m (CV = 8.06%), 20m (CV = 8.09%), 30m (CV = 5%) and a moving 10m sprint (CV = 4.81%).

However, negative findings for linear running have been recorded. As previously found with the MinimaxX device sampling at 1Hz, Jennings et al. (2010a) reported poor validity for a range of outcome measures in the MinimaxX device. Again, this error measurement appeared to increase as locomotion progressed from self-selected walking to sprinting pace over a range of distance from 10m to 40m. As was shown in the 1Hz measurement, this error was worse over shorter distances with a SEE of 21.3 ± 5.8% and 9.8 ± 2.0% recorded for 10m and 40m walking respectively. Whilst there also seemed to be an effect of movement velocity, with an SEE of 21.3 ± 5.8% and 30.9 ± 5.8% recorded for 10m walking and 10m sprinting. This effect of movement velocity did however appear to be weaken as the distance increased, with SEE of 9.8 ± 2.0% and 11.9 ± 2.5% recorded for 40m walking and 40m sprinting. The effect of movement velocity on distance validity as also shown by Rampinini et al. (2015). Whilst they recorded good validity (CV = 2.8%) for total distance, moderate (CV = 7.5%) and poor (CV = 23.2%) interpretations were recorded for high (>4.17m•s^{-1}), and very high-speed running (>5.56m•s^{-1}) respectively. More recent studies also found significant differences between the Wimu model and criterion measures, however interpretation criteria were not assigned (Muñoz-López et al., 2017). They showed in 10m sprint trials that total distance was significantly under-estimated. Whilst total distance was overestimated in 30m sprint trials however this finding was not significant. Therefor it would appear practitioners should be cautious of measurements over short-distances, or those of high-intensity movement.

Whilst Jennings et al. (2010a) reported significant issues with the MinimaxX model, more recent research has recorded more favourable findings for various sport specific movements. Vickery et al. (2014) analysed total distance covered during various tasks specific to cricket and showed that 10 out of 12 GPS derived outcome measures were not significantly different to criterion measures taken from Vicon Motion Analysis. It has been suggested that these improved findings in the MinimaxX model may be due to improvements in software, with upgrades allowing the model to overcome previously identified issues (Scott et al., 2016).

Various analyses utilised forms of team-sport simulated circuit to assess the validity of total distance recordings. Johnston et al. (2012) found no significant difference between total distance measured via tape measure and recorded via MinimaxX Team 2.5 units. Portas et al. (2010), using the same methodology as for the 1Hz generation of technology found good validity in the MinimaxX 2.5 for soccer position specific movements (SEE = 1.5 - 2.2%) and high intensity bouts of activity (SEE = 1.5%). Jennings et al. (2010a), although recording poor and moderate-to-poor validity for linear movements and pre-planned change of direction tasks, reported good validity for a team-sport simulated circuit (CV = 3.8 ± 0.6%). This was again similar to their findings in 1Hz technology, suggesting the error recorded in short, high intensity movements evens out over longer distances. Vickery et al. (2014) utilised a field-based team sport circuit, similar to that used by Jennings et al. (2010a), involving pre-planned and random change of direction movements. They showed no significant difference between GPS derived total distance and that measured via Vicon.

Like the 1Hz technology, 5Hz GPS devices are capable of measuring total distance in team-sport simulated activities over long distances. Whilst MinimaxX units initially showed moderate-to-poor validity for measures of various speed over 10-40m (Jennings et al., 2010a), these limitations appear to have been resolved (Vickery et al., 2014), possibly because of software improvements. Studies using the SPI-PRO model appear to have shown good-to-moderate validity for measures of total distance, whilst the most recent study, using WIMU models shows significant differences to criterion measures over short distance sprints, which become non-significant over longer distances. However, in contrast to previous findings, they showed significant differences between criterion, and GPS derived, total distance over a team-sport simulated circuit.

The only article to assess velocity validity using SPI-Pro units, Waldron et al. (2011) recorded moderate validity (CV = 5.68 – 9.81%) in linear sprints ranging from 10m to 30m and including a moving 10m sprint. Assessing MinimaxX units, Varley et al. (2012) found that validity of constant velocity improved as the starting velocity increased from 1-3m•s^{-1} (CV = 11.1%) to 5-8m•s^{-1} (CV = 3.6%). This same phenomenon was found in acceleration, with validity improving from a starting velocity of 1-3m•s^{-1} (CV = 14.9%) to 5-8m•s^{-1} (CV = 7.1%). For constant velocity, the MinimaxX unit overestimated velocity at 1-3m•s^{-1} (Bias = 2.4%) and 3-5m•s^{-1} (Bias = 0.3%) starting velocity, whilst underestimating at 5-8m•s^{-1} (Bias = -0.5%) starting velocity. For acceleration, GPS derived measurements were underestimated at all starting velocities (Bias = -9.6% - -5.2%). Varley et al. (2012) also showed that validity was poor in decelerations at a rate of 5-8m•s^{-1} (CV = 33.2%). Also using the MinimaxX units, Johnston et al. (2012) showed no significant difference between GPS derived average speed and that measured via timing lights in a flying 50m. They also showed no significant difference in instantaneous speed when measured via a radar gun during the same test. Finally, Vickery et al. (2014) found conflicting results regarding average speed in various linear, agility and circuit based movements, with 5 out of 12 GPS derived measures not significantly different to criterion measures taken via Vicon Motion Analysis. Whilst all measures of peak velocity were not significantly different.

These findings would suggest that 5Hz GPS technology may be suitable for measuring average, and instantaneous, velocity in various linear and non-linear movements related to team sports. Some caution should be taken in slower accelerations and in decelerations (Varley et al., 2012). As with total distance measurements, validity appears to improve in specific team sport circuits, however practitioners should be wary of measurements over short-distance linear and agility tasks.

The ability to measure accelerations and decelerations in a practical setting has led to practitioners reporting measures such as energy cost and metabolic power using metrics derived from GPS technology (Rampinini et al., 2015). Using the SPI-PRO model, Rampinini et al. (2015) assessed the validity of GPS derived mean metabolic power, time at high metabolic power and time at very-high metabolic power. They showed good-to-moderate (CV = 4.5%) measures of validity for mean metabolic power, and moderate-to-poor measures for time at high metabolic power (CV = 9.0%) and time at very-high metabolic power (CV = 11.6%) respectively. These measures of metabolic power rely on measurements of forward acceleration and velocity (Di Prampero et al., 2005, Osgnach et al., 2010). Given that 5Hz models have been shown to have questionable validity for acceleration measurement (Varley et al., 2012), it is not surprising that moderate-to-poor findings have been shown for measures of metabolic power using 5Hz technology.

Improved ability of the technology to provide valid measures of acceleration and instantaneous velocity will improve its ability to provide values of metabolic power and energy cost to practitioners.

Table 2.9 - Validity of Global Positioning System Devices (5Hz)

Reference	Device	Parameter	Task	Criterion Measure	Error Measurement	Int.
Muñoz-López et al. (2017)	Wimu	Total Distance	Sprint Trials 10m	Tape Measure	Mean Bias (± SD): -0.8 ± 0.58m	n/a
			30m		Mean Bias: 0.42 ± 2.5m	n/a
			TSSC (1 x 146m)		Mean Bias: -2.73 ± 1.64m	n/a
Rampinini et al. (2015)	SPI-Pro	Total Distance	Intermittent Linear Shuttle Runs (3 x 70m & 4 x 70m)	Radar Gun	CV: 2.8%	G
		HSR Distance (>4.17m•s^{-1})			CV: 7.5%	M
		VHSR Distance (>5.56m•s^{-1})			CV: 23.2%	P
		Mean Metabolic Power			CV: 4.5%	G-M
		Time at HMP (>20W•kg^{-1})			CV: 9.0%	M-P
		Time at VHMP (>25W•kg^{-1})			CV: 11.6%	M-P
Varley et al. (2012)	MinimaxX v2.0	Constant Velocity	Linear Running	LAVEG Laser	CV: 3.6 – 11.1%	G-P
		Acceleration			CV: 7.1 – 14.9%	M-P
		Deceleration			CV: 33.2%	P
Jennings et al. (2010a)	MinimaxX Team 2.5	Total Distance	Sprint trials (10 – 40m, 20 – 40m split)	Measuring Tape	SEE: 9.0 – 30.9%	M-P
			Tight COD	Measuring Tape & Goniometer	SEE: 9.9 – 11.5%	M-P
			Gradual COD		SEE: 8.9 – 11.7%	M-P
			TSSC (5 x 140m)	Measuring Tape	SEE: 3.8%	G
Waldron et al. (2011)	SPI-Pro	Total Distance	Sprint (10 – 30m, moving 10m sprint)	Measuring Tape	CV: 4.81 – 8.09%	G-M
		Speed	Sprint (10 – 30m, moving 10m sprint)	Timing Gates	CV: 5.68 – 9.81%	M
Petersen et al. (2009)	MinimaxX	Total Distance	Cricket Specific Running (600 – 8800m)	Athletics Track	SEE: 1.7 – 3.8%	G
			Sprint Trials (20-40m sprint, run-a-three)	Timing Gates	SEE: 5.3 – 23.8%	M-P
	SPI-PRO	Total Distance	Cricket Specific Running (600 – 8800m)	Athletics Track	SEE:0.7 – 3.7%	G
			Sprint Trials (20-40m sprint, run-a-three)	Timing Gates	SEE: 2.6 – 10.5%	G-P
Portas et al. (2010)	MinimaxX v2.5	Total Distance	Linear Course (16 x 51m)	Trundle Wheel	SEE: 2.9 – 3.1%	G
			Multidirectional Course (2 x 8 x 51m – 180m)		SEE: 2.2 – 4.4%	G

			Soccer Specific Course (10 x 1min of 110m – 197m)		SEE: 1.5 – 2.2%	G
Johnston et al. (2012)	MinimaxX Team 2.5	Total Distance	TSSC	Tape Measure	No sig. diff. to criterion ($p<0.05$)	n/a
		Peak Speed (Average)	Flying 50m	Timing Lights	No sig. diff. to criterion ($p<0.05$)	n/a
		Peak Speed (Instantaneous)		Radar Gun	No sig. diff. to criterion ($p<0.05$)	n/a
Vickery et al. (2014)	MinimaxX v 2	Total Distance	Fast Bowling	Vicon Motion Analysis	2/2 measures sig. diff. ($p<0.05$)	n/a
			Fielding		2/2 measures not sig. diff. ($p<0.05$)	n/a
			90° COD		2/2 measures not sig. diff. ($p<0.05$)	n/a
			45° COD		2/2 measures not sig. diff. ($p<0.05$)	n/a
			Random FBTS		2/2 measures not sig. diff. ($p<0.05$)	n/a
			Run-a-three		2/2 measures not sig. diff. ($p<0.05$)	n/a
		Average Velocity	Fast Bowling		2/2 measures sig. diff. ($p<0.05$)	n/a
			Fielding		2/2 measures not sig. diff. ($p<0.05$)	n/a
			90° COD		2/2 measures sig. diff. ($p<0.05$)	n/a
			45° COD		2/2 measures sig. diff. ($p<0.05$)	n/a
			Random FBTS		1/2 measures sig. diff. ($p<0.05$)	n/a
			Run-a-three		2/2 measures not sig. diff. ($p<0.05$)	n/a
		Peak Velocity	Fast Bowling		2/2 measures not sig. diff. ($p<0.05$)	n/a
			Fielding		2/2 measures not sig. diff. ($p<0.05$)	n/a
			90° COD		2/2 measures not sig. diff. ($p<0.05$)	n/a
			45° COD		2/2 measures not sig. diff. ($p<0.05$)	n/a
			Random FBTS		2/2 measures not sig. diff. ($p<0.05$)	n/a

Key; Interpretation; G- Good (<5%), M – Moderate (5 – 10%), P- Poor (>10%), n/a – not available; TSSC – Team-Sport Simulated Circuit; SD – Standard Deviation; HSR – High Speed Running; VHSR – Very-High Speed Running; CV – Coefficient of Variation; HMP – High Metabolic Power; VHMP – Very-High Metabolic Power; COD – Change of Direction; SEE – Standard Error of the Estimate; FBTS – Field-Based Team Sport Circuit

2.5.7 - 5Hz Global Positioning Systems - Reliability

Investigating both the SPI-PRO and MinimaxX units, Petersen et al. (2009) showed good intraunit reliability across a range of velocities and longer distances specific to cricket match-play. However, they showed conflicting results for shorter distance, higher velocity efforts. The SPI-PRO appeared to show promising results, despite showing moderate-to-poor reliability in a 20m sprint. The MinimaxX device displayed poor intraunit reliability in 20m (CV = 19.7% - 30%), 30m (CV = 15.8% – 21.3%) and 40m (CV = 16.1% – 17.1%) sprint efforts and poor/good-to-moderate reliability in a “sprinting run-a-three” (CV = 5.3% – 13.6%). Jennings et al. (2010a) also showed poor intraunit reliability, with CV’s ranging from 15.6% to 39.5%, for distances of 10-40m at walking, jogging, striding and sprinting at self-selected pace. At the longer distance of 40m, the MinimaxX v2.5 device showed moderate reliability at all velocities ranging from 6.6% (Walk) to 9.2% (Sprinting). Waldron et al. (2011) however, reported good reliability for measurements of distance in a 10m (CV = 1.99%), 20m (CV = 2.06%) and 30m (CV = 1.84%) sprint and a moving 10m sprint (CV = 2.3%) in the SPI-PRO device. Similarly, Portas et al. (2010) showed good-to-moderate intraunit reliability in linear walking (CV = 5.31%) and running (CV = 4.55%) over a 51m course in the MinimaxX v2.5 device. Given these findings it is difficult to make a clear statement regarding the intraunit reliability of 5Hz GPS devices for measuring total distance in linear running.

Jennings et al. (2010a) also reported moderate and poor intraunit reliability for various pre-planned change of direction drills. Contradictory to that, Portas et al. (2010) found good and good-to-moderate intraunit reliability at various short and long change of direction drills. They did however also report good-to-poor reliability in a 180° long change of direction drill, that is a drill involving a 180° turn across the length of a soccer pitch 6-yard box. It appears that these measures even out over longer distance though, with good reliability reported in a team-sport simulated circuit (Jennings et al., 2010a) and in soccer forward specific circuits (Portas et al., 2010). Portas et al. (2010) also reported good-to-moderate reliability for all other position specific circuits and for a high-intensity bout circuit. Additionally, a more recent study investigating the WIMU device, found no difference during a team-sport simulated circuit.

It is hard to make conclusions on intraunit reliability of total distance measurements in 5Hz units, and this appears to be the case with interunit reliability also. Jennings et al. (2010b) recorded a broad range of differences between units. Utilising the protocol they had previously used to assess linear running at a range of velocities (Jennings et al., 2010a), they concluded that these differences should encourage practitioners to ensure players wore the same GPS unit consistently to enhance the reliability of results. They found similar results in various change of direction drills and in a team-sport simulated circuit. Whilst Jennings et al. (2010b) showed a range of results, Vickery et al. (2014) reported poor reliability for various cricket-specific movements ranging from CV's of 17.7% (90° COD) to 22.8% (Random Field Based Team Sport Protocol). Contrary to these findings, good reliability has been shown in team-sport simulated circuits (Johnston et al., 2012, Johnston et al., 2013). Investigating the MinimaxX Team 2.5 device, Johnston et al. (2012) showed a technical error of measurement of 2.0% when measuring total distance during 10 laps of a 130.5m circuit. Additionally, further investigations (Johnston et al., 2013) showed a technical error of measurement (TEM) of 1.2% between 2 MinimaxX S3 devices during 8 laps of a 165m circuit. It should be noted however that whilst good reliability was reported for overall total distance, the speed of the movement affected this, with moderate TEM's of 7.88% and 5.95% recorded for high-speed, and very high-speed running respectively (Johnston et al., 2013). Additionally, TEM's of 10.8% and 112% were recorded for high-speed running and sprinting when assessing the MinimaxX Team 2.5 device (Johnston et al., 2012). The MinimaxX Team 2.5 device also showed poor reliability during a flying 50m sprint for sprinting (CV = 59.3%) and very-high intensity running (CV = 20.1%).

As with previous generations, it appears that poor reliability may be overcome in longer distance team-sport simulations. However, practitioners should be wary of measurements of total distance over shorter distance and higher velocities. What can be concluded from these devices is that practitioners should aim to ensure athletes are wearing the same device consistently, and that practitioners should be wary of making comparisons between devices of distances covered at high intensity.

Only 2 studies have assessed intraunit reliability for velocity measurements in 5Hz devices. Waldron et al. (2011) showed good reliability in 10m (CV = 2.06%), 20m (CV = 1.92%), 30m (CV = 2.02%) sprint and a moving 10m sprint(CV = 1.62%) in the SPI-PRO device. Whilst a study by Munoz-Lopez et al. (2017) didn't meet interpretation criteria it also showed little difference in peak and average speed when assessing linear sprints and a circuit.

Varley et al. (2012) reported poor and moderate interunit reliability of the MinimaxX v2.0 device in assessing instantaneous velocity at different starting velocities. Whilst Vickery et al. (2014) reported poor reliability of mean and peak speed measurements across various cricket-specific change of direction tasks and circuits. Additionally, during a team-sport simulated circuit, Johnston et al. (2012) reported a TEM for average peak speed of 7.5%. These findings, alongside findings for total distance, enforce the need for practitioners to ensure that athletes are consistently wearing the same device. They also bring in to question the capability of these devices to allow comparison between athletes.

Enhanced sampling rate, and practitioner and researcher understanding of the capabilities of this technology instigated investigation into more advanced metrics which could be measured via GPS technology. "Exertion Index", a summated score of instantaneous velocity and velocity over previous 10 seconds and 60 seconds, showed good interunit reliability (TEM = 2.16%). Whilst a count measure of repeated high-intensity efforts showed poor interunit reliability, with a CV of 83.42%. Repeated high intensity efforts were recorded as three effort where speed was above $25km \cdot h^{-1}$ and/or accelerations above $2.78m \cdot s^{-2}$ over a 21 second period (Johnston et al., 2013, Gabbett et al., 2012, Spencer et al., 2004).

Table 2.10 - Reliability of Global Positioning System Devices (5Hz)

Reference	Device	No. of Units	Reliability	Parameter	Task	Error Measurement	Int.
Petersen et al. (2009)	SPI-PRO	2	Intraunit	Total Distance	Cricket Specific Running (600 – 8800m)	CV: 0.3 – 2.9%	G
					Sprint Trials (20-40m sprint, run-a-three)	CV: 2.0 – 9.3%	G-M
	MinimaxX	2			Cricket Specific Running (600 – 8800m)	CV: 1.2 – 2.6%	G
					Sprint Trials (20-40m sprint, run-a-three)	CV: 5.3 – 30%	G-P
Jennings et al. (2010a)	MinimaxX v2.5	1	Intraunit	Total Distance	Sprint trials (10 – 40m, 20 – 40m split)	CV: 6.6 – 39.5%	M-P
					Tight COD	CV: 8.6 – 15.2%	M-P
					Gradual COD	CV: 7.9 – 11.5%	M-P
					TSSC (5 x 140m)	CV: 3.6%	G
Varley et al. (2012)	MinimaxX v2.0	2	Interunit	Constant Velocity	Linear Running	CV: 6.3 - 12.4%	
				Acceleration		CV: 9.5 – 16.2%	
				Deceleration		CV: 31.8%	
Waldron et al. (2011)	SPI-PRO	1	Intraunit	Total Distance	Sprint (10 – 30m, moving 10m sprint)	CV: 1.84 – 2.3%	
				Mean Speed	Sprint (10 – 30m, moving 10m sprint)	CV: 1.62 – 2.06%	
Johnston et al. (2013)	MinimaxX S3	2	Interunit	Total Distance	TSSC (8 x 165m)	TEM: 1.2%, ICC: 0.65	G
				Exertion Index		TEM: 2.16%, ICC: 0.99	G
				RHIE		TEM: 83.42%, ICC: 0.33	P
				LSR (m; 0 – 13.99km•h^{-1})		TEM: 2.42%, ICC: 0.98	G
				HSR (m; 14.00 – 19.99km•h^{-1})		TEM: 7.88%, ICC: 0.98	M
				VHSR (m; >20.00km•h^{-1})		TEM: 5.95%, ICC: 0.95	M
Johnston et al. (2012)	MinimaxX Team 2.5	2	Interunit	Total Distance	TSSC (130.5 x 10)	TEM: 2.0%, ICC: 0.69	G
				Walking (m; <6.0km•h^{-1})		TEM: 7.5%, ICC: 0.96	M
				Jogging (m; 6.01 – 11.99km•h^{-1})		TEM: 8.2% ICC: 0.29	M
				Running (m; 12.0 – 18.0km•h^{-1})		TEM: 5.6%, ICC: 0.96	M
				HSR (m; 18.01 – 24.99km•h^{-1})		TEM: 10.8%, ICC: 0.9	P
				Sprinting (m; >25km•h^{-1})		TEM: 112%, ICC: 0.38	P
				Sprinting (m; >25km•h^{-1})	Flying 50m Sprint	TEM: 59.3%, ICC: 0.21	P
				VHIR (m; >20km•h^{-1})		TEM: 20.1%, ICC: 0.24	P
				Peak Speed (Average)		TEM: 7.5%	M
Jennings et al. (2010b)	MinimaxX Team 2.5	2	Interunit	Total Distance	Sprint trials (10 – 40m, 20 – 40m split)	DBU: 9.9 – 11.1%	
					Tight COD	DBU: 9.5 – 10.7%	
					Gradual COD	DBU: 9.7 – 10.4%	
					TSSC (5 x 140m)	DBU: 11.1%	
				High intensity Running		DBU: 11.6%	
				Total Distance	Match Play	DBU: 10.3%	
				High-Intensity Running		DBU: 10.2%	

Portas et al. (2010)	MinimaxX v2.5	1	Intraunit	Total Distance	Linear Course (16 x 51m)	CV: 4.55 – 5.31%	
					Multidirectional Course (2 x 8 x 51m – 180m)	CV: 3.42 – 6.72%	
					SSC (10 x 1min of 110m – 197m)	CV: 2.21 – 4.49%	
Vickery et al. (2014)	MinimaxX V2	2	Interunit	Total Distance	Run-a-three	CV: 22.1%, ICC: 0.06	P
					Fast Bowling	CV: 21.2%, ICC: 0.06	P
					Fielding	CV: 20.6%, ICC: 0.33	P
					90° COD	CV: 17.7%, ICC: 0.41	P
					45°COD	CV: 22.7%, ICC: 0.24	P
					Random FBTS	CV: 22.8%, ICC: 0.72	P
				Mean Speed	Run-a-three	CV: 27.1%, ICC: -0.5	P
					Fast Bowling	CV: 20.2%, ICC: 0.5	P
					Fielding	CV: 21.3%, ICC: 0.55	P
					90°COD	CV: 19.8%, ICC: -0.14	P
					45°COD	CV: 28.1%, ICC: -0.02	P
					Random FBTS	CV: 33.4%, ICC: 0.39	P
				Peak Speed	Run-a-three	CV: 14.2%, ICC: -0.16	P
					Fast Bowling	CV: 23.6%, ICC: 0.36	P
					Fielding	CV: 16.2%, ICC: 0.49	P
					90°COD	CV: 26.3%, ICC: 0.03	P
					45°COD	CV: 20.9%, ICC: 0.13	P
					Random FBTS	CV: 31.5%, ICC: 0.15	P
Muñoz-López et al. (2017)	WIMU	1	Intraunit	Total Distance	TSSC	BIAS: 0.00	N/A
					Sprint (10m & 30m)	BIAS: 0.00	N/A
				Peak Speed	Circuit	BIAS: 0.00	N/A
					Sprints (10m & 30m)	BIAS: 0.00	N/A
				Average Speed	Circuit	BIAS: 0.00	N/A
					Sprints (10m & 30m)	BIAS: 0.00	N/A
		8	Interunit	Average Speed	Circuit	ICC 0.976	N/A
					Sprints	ICC: 0.991	N/A

Key; Interpretation; G- Good (<5%), M – Moderate (5 – 10%), P- Poor (>10%), n/a – not available, Int - Interpretation; CV – Coefficient of Variation; COD – Change of Direction; TSSC – Team-Sport Simulated Circuit; RHIE – Repeated High Intensity Efforts; LSR – Low Speed Running; HSR – High Speed Running; VHSR – Very-High Speed Running; VHIR – Very-High Intensity Running ; FBTS – Field-Based Team Sport Circuit

2.5.8 - 10Hz Global Positioning Systems Overview

Twelve studies assessed the validity of 10Hz devices (Table 2.11), whilst 9 studies assessed the reliability (Table 2.12). This generation of GPS technology saw the first device developed by STATSport (Viper). Predominantly, the Catapult MinimaxX V4.0 device was assessed. As seen in previous generations, the most common parameter assessed was total distance (n = 8). In comparison to previous generations of GPS technology, it appears that 10Hz devices have positive interpretations of validity. Of the 9 studies which assessed reliability, 9 assessed interunit reliability and 3 assessed intraunit reliability. The predominant device assessed was the MinimaxX V4.0 and S4 device. It appears that 10Hz display good measures of interunit and intraunit reliability.

2.5.9 - 10Hz Global Positioning Systems – Validity

The first paper to assess the validity of total distance measured by 10Hz devices was published in 2011 by Castellano et al. (2011). Analysing the MinimaxX v4.0 device in short distance linear sprints of 15 and 30m, they showed a standard error of measurement (SEM) ranging from 3.4 – 9.6% and 1.7 – 6.7% respectively. Whilst they did report a mean SEM of 10.9% in the 15m sprint, 8 of the 9 devices recorded an SEM of ≤5.1%. Further analysis of linear running, revealed good validity (CV = 1.9%) in intermittent linear shuttle runs (Rampinini et al., 2015). As with previous devices, this was affected by the velocity of movement, with good-to-moderate (CV = 4.7%) and moderate-to-poor (CV = 10.5%) reported for high-speed running (>4.17m•s^{-1}) and very-high speed running (>5.56m•s^{-1}) distance respectively. Good and good-to-moderate validity was also displayed during a linear 20m shuttle run at speeds ranging from 8km•h^{-1} to 11.5km•h^{-1} with lower differences reported at faster speeds (Nikolaidis et al., 2018). Assessed against a measured athletics track, Nikolaidis et al. (2018) reported mean differences in a 200m run ranging from -0.06% – 1.06%. Beato et al. (2016) also showed no significant difference between total distance measured via tape measure or the Viper device, during linear shuttle runs.

Assessing the MinimaxX S4 device, Johnston et al. (2014) showed no significant difference between total distance measured via tape measure and GPS in a team-sport simulated circuit. Hoppe et al. (2018) also assessed the MinimaxX S4 device in a team-sport simulated circuit. They reported good validity for total distance measurements during 10m jogging (Bias = -3.3%), 10m jogging with a jump (Bias = 1.9%) and across the whole circuit (Bias = -2.1%). They also reported good-to-moderate validity for total distance measurements during lower intensity actions. For sprinting actions at 5m (Bias = -13.0%) and 10m (Bias = -11.9%) distance they reported poor validity, whilst for sprints over longer distances of 20m (Bias = -8.9%) and 30m (Bias = -6.8%) they reported moderate validity for measurements of total distance.

Using the same protocol as with 5Hz devices, Vickery et al. (2014) showed no significant difference in total distance measured via VICON or GPS during linear, cricket-specific movements. There was no significant difference during the run-a-three test, a test designed to mimic fast bowling, or a linear test to mimic fielding. Whilst there was no significant difference between measurements over a 45° change of direction course, there was significant differences recorded in a 90° change of direction course and in a cricket-specific circuit.

These findings would suggest that the increased 10Hz sampling rate of these devices has improved the validity of measures of total distance. There appears to be sufficient evidence to suggest 10Hz devices are valid in measurements of linear and non-linear running. Whilst Vickery et al. (2014) reported differences in measures during change of direction and circuit based activity, there is a majority of evidence to support the use of these devices during team-sport simulated circuits and linear running.

Assessing the MinimaxX V4.0, Vickery et al. (2014) showed no significant difference in peak velocity, using the criterion measure of VICON, across all 6 outcome measures, involving linear movements, change of direction, and a cricket-specific circuit. Whilst they showed no significant difference in the three linear outcomes, they did report significant differences in mean velocity for both change of direction tasks and the cricket-specific circuit. Further analysis of the MinimaxX V4.0 device, found good, good-to-moderate, and moderate measures of validity for instantaneous velocity at various constant velocities and accelerations (Varley et al., 2012). They did however report poor validity (CV = 11.3%) for decelerations with a starting velocity of 5-8m•s^{-1}. These findings are an improvement on the 5Hz MinimaxX 2.0 device which, when using the same methodology, showed poor validity for a range of these measures. Also utilising a short distance linear sprint, Akenhead et al. (2014) reported standard error of the estimates (SEE) ranging from 0.12 – 0.19 for smoothed instantaneous velocity measures. These measures did increase (SEE = 0.32) however when starting velocity increased to >4m•s^{-2}. Using a submaximal incremental linear speed task, Bataller-Cervero et al. (2019) found a near perfect relationship (r = 0.98, STE = 0.19) between the criterion measure of a radar gun and the Viper device for instantaneous velocity. They also found a near perfect relationship (r =

0.97, STE = 0.25) between the device and instantaneous velocity for a similar protocol involving a submaximal incremental speed followed by a submaximal decreasing speed. They also reported a near perfect relationship for mean velocity (r = 0.99, STE = 0.17). Also assessing the Viper device, Beato et al. (2016) found a range of differences between the Viper device and video assessed mean instantaneous velocity and average shuttle speed at various speeds.

Using a team-sport simulated circuit, Johnston et al. (2013) found a significant difference between mean peak speed measured via timing gates and that measured via the MinimaxX S4, however the percentage difference between the 2 units used for assessment was <2.5% and the relationship was nearly perfect (r = 0.89/r = 0.91) in both devices assessed. Also assessing the MinimaxX S4 unit using a team sport circuit, Hoppe et al. (2018) recorded good validity (Bias = 0%) for max velocity however it's worth noting they recorded poor validity (Bias = 24.7%) for acceleration measurements.

Whilst several the statistical methods used to assess outcome measures did not meet the interpretation criteria, it does appear that 10Hz devices generally display good validity for measures of instantaneous velocity for linear movements over long distance. However, caution should be taken for measures involving changes of direction or during team-sport specific movements. Additionally, the starting velocity appears to influence the measurement error involved, with error increased when very high accelerations ($>4m•s^{-2}$) are occurring, as happens in team-sport environments. However, 10Hz devices do appear to have improved validity than previous generations of the technology.

Table 2.11 - Validity of Global Positioning System Devices (10Hz)

Reference	Device	Parameter	Task	Criterion Measure	Error Measurement	Int.
Nikolaidis et al., 2018 (2018)	JOHAN	Total Distance	Curvilinear 5 x 200m run	Athletics Track	Mean Diff: -0.06 to 0.81%	G
			20m Shuttle Run		Mean Diff: -0.78 to 5.37%	G-M
Bastida-Castillo et al. (2019)	*Not identified*	Positional Coordinates	Linear running circuit	Geographic Information System	X (Mean Diff.); 2.69%	G
					Y (Mean Diff.); 2.31%	G
Rampinini et al. (2015)	MinimaxX v4.0	Total Distance	Intermittent Linear Shuttle Runs (3 x 70m & 4 x 70m)	Radar Gun	CV: 1.9%	G
		HSR Distance (>4.17m•s^{-1})			CV: 4.7%	G
		VHSR Distance (>5.56m•s^{-1})			CV: 10.5%	P
		Mean Metabolic Power			CV: 2.4%	G
		Time at HMP (>20W•kg^{-1})			CV: 4.5%	G
		Time at VHMP (>25W•kg^{-1})			CV: 6.2%	M
Varley et al. (2012)	MinimaxX V4.0	Instantaneous Velocity	Constant Velocity	LAVEG Laser	CV: 3.1 – 8.3%	G-M
			Accelerations		CV: 3.6 – 4.9%	G
			Decelerations		CV: 11.3%	P
Johnston et al. (2013)	MinimaxX S4	Total Distance	TSSC (8 x 165m)	Tape Measure	No sig. difference (p<.05)	n/a
		Peak Speed		Timing Lights	r = 0.89 (p<0.05), r = 0.91 (p<0.05)	n/a
Akenhead et al. (2014)	MinimaxX S4	Instantaneous Velocity	10m Sprint	Laser	SEE: 0.12 – 0.36m•s^{-1}	
Hoppe et al. (2018)	MinimaxX S4	Total Distance	TSSC (10 x 129.6) 25.1m sprinting with CODs	Measuring Tape	Bias: -11.7%	P
			10m walking with COD		Bias: -5.0%	G-M
			Linear Variations (5 – 30m)		Bias : -11.9% to 1.9%	
			129.6m entire circuit		Bias: -2.1%	G
		Acceleration	1.1 ± 0.0s for τ (6-9)	Timing Gates	Bias: +24.7%	P
		Max Velocity	8.2 ± 0.1m/s for V_{max} (6-9)		Bias: 0.0%	G
		Horizontal Force	7.7 ± 0.1 N/kg for F_{max}		Bias: -16.6%	P
		Horizontal Power	16.1 ± 0.4 W/kg for P_{max} (6-9)		Bias: -16.3%	P
Castellano et al. (2011)	MinimaxX v4.0	Total Distance	Linear Sprint (15 & 30m)	Tape Measure	SEM: 5.1 - 10.9%	M-P

Bataller-Cervero et al. (2019)	Viper	Instantaneous Velocity	ISV IncS (21 x 40m)	Radar Gun	STE: .19m•s^{-1}	n/a
			ISV Inc – DecS (21 x 50m)		STE: .25 m•s^{-1}	n/a
		Mean Velocity	MSV (21 x 40m)		STE: .17 m•s^{-1}	n/a
Vickery et al. (2014)	MinimaxX V4.0	Total Distance	Run-a-three	VICON	Not sig. diff	n/a
			Fast Bowling		Not sig. diff	n/a
			Fielding		Not sig. diff	n/a
			90° COD		Sig. diff. (p<0.05)	n/a
			45° COD		Not sig. diff	n/a
			Random FBTS		Sig. diff. (p<0.05)	n/a
		Average Velocity	Run-a-three		Not sig. diff	n/a
			Fast Bowling		Not sig. diff	n/a
			Fielding		Not sig. diff	n/a
			90° COD		Sig. diff. (p<0.05)	n/a
			45° COD		Sig. diff. (p<0.05)	n/a
			Random FBTS		Sig. diff. (p<0.05)	n/a
		Peak Velocity	Run-a-three		Not sig. diff	n/a
			Fast Bowling		Not sig. diff	n/a
			Fielding		Not sig. diff	n/a
			90° COD		Not sig. diff	n/a
			45° COD		Not sig. diff	n/a
			Random FBTS		Not sig. diff	n/a
Beato et al. (2016)	Viper	Total Distance	Linear Shuttle Runs	Tape Measure	No significant difference	n/a
		Mean Instantaneous Velocity (m•s^{-1})	Low Velocity Shuttles (5,10,15,20m)	Tape Measure/Video	3/4 Sig. diff. (p <0.01)	n/a
			Moderate Velocity Shuttles (5,10,15,20m)		All Sig. diff. (p<0.01)	n/a
			High Velocity (5,10,15,20m)		All Sig diff. (p<0.05)	n/a

Key; Interpretation; G- Good (<5%), M – Moderate (5 – 10%), P- Poor (>10%), n/a – not available, Int - Interpretation; HSR – High Speed Running; VHSR – Very-High Speed Running; HMP – High Metabolic Power; VHMP – Very-High Metabolic Power; CV – Coefficient of Variation; TSSC – Team-Sport Simulated Circuit; *sig at (p<0.05); τ = Acceleration time constant; Vmax = Theoretical maximal running velocity; Fmax = Theoretical maximal horizontal force; Pmax = Theoretical maximal horizontal power output; SEM – Standard Error of Measurement; ISV IncS – Instantaneous speed validation in submaximal increase speed conditions, ISV Inc-DecS – Instantaneous speed validation in submaximal increase and decrease speed conditions, MSV – Mean speed validation; STE – Standard Typical Error; COD – Change of Direction; FBTS - Field-Based Team Sport Circuit

2.5.10 - 10Hz Global Positioning Systems - Reliability

Four studies have assessed interunit reliability distance of 10Hz GPS devices for measuring total distance. Nikolaidis et al. (2018) showed that the JOHAN device had good reliability across all laps in a 200m run (CV = 1.31 – 2.2%), and across incrementally increasing speeds in a 20m shuttle (CV = 2.08 – 3.92%). Castellano et al. (2011) assessed reliability of the MinimaxX V4.0 device over shorter, linear sprints and also recorded good reliability. Using a 15m and 30m sprint protocol they recorded CV's of 1.3% and 0.7% respectively. Two studies have assessed interunit reliability of total distance in team-sport simulated circuits, both assessing the MinimaxX S4 device. Johnston et al. (2013), reported a typical error measurement (TEM) of 1.3%, similar to the TEM they reported in the 5Hz MinimaxX S3 device (1.2%). Hoppe et al. (2018) also recorded good levels of interunit reliability for the MinimaxX S4 device in a team sport simulated circuit (CV = 4.1%). Therefore, 10Hz devices show good reliability in linear and curvilinear runs over short and long distances and at various reported speeds. They also show good interunit reliability in team-sport simulated circuits.

However, Johnston et al. (2013) reported poor interunit reliability for very-high-speed running (>20km•h^{-1}) for distance covered (TEM = 11.5%), time at very-high speed (TEM = 11.7%), and a count of very-high speed running efforts (TEM = 13.7%). Therefore, whilst there are promising findings for the interunit reliability of 10Hz devices, practitioners should take some caution when interpreting higher speed efforts reported.

Only two studies have assessed intraunit reliability for assessing total distance in 10Hz devices. Nikolaidis et al. (2018) reported intraclass correlation coefficients of 0.833 over 200m running and 0.718 and 0.831 for various stages of intermittent, linear shuttle runs. Whilst Castellano et al. (2011) reported good CV's for both 15m (<4%) and 30m (<3%) linear sprints. These results, alongside the previous findings regarding interunit reliability, suggest 10Hz devices display good measures of reliability.

Predominantly good measures of reliability have also been found for measures of velocity in 10Hz GPS devices. Whilst the MinimaxX V2.0 (5Hz) device recorded moderate and poor interunit reliability (CV = 6.3 – 12.4%) for measures of instantaneous velocity during constant running velocity, the MinimaxX v4.0 showed good and moderate reliability over speeds of 1-3m•s^{-1} (CV = 5.3%), 3-5m•s^{-1} (CV = 3.5%) and 5-8m•s^{-1} (CV = 2.0%). Similarly, whilst the MinimaxX V2.0 showed poor and moderate-to-poor reliability (CV = 9.5 – 16.2%) for instantaneous velocity measured during accelerations, the MinimaxX

V4.0 showed good reliability over the three conditions (CV = 1.9 – 4.3%). The MinimaxX V4.0 also showed moderate reliability (CV = 6.0%) whilst the previous version reported poor reliability (CV = 31.8%). Similarly Akenhead et al. (2014) when assessing smoothed instantaneous velocity data from the MinimaxX V4.0 showed good and moderate interunit reliability (CV = 0.7 – 9.1%) during a 10m sprint with four acceleration categories. Good reliability was found for all conditions where acceleration less than $4 m \bullet s^{-2}$. It should also be noted that raw GPS data, that is only calculated with time and GPS positional data showed consistently poorer levels of reliability that smooth GPS data, that which included time, GPS positional data and a built-in manufacturer algorithm. Hoppe et al. (2018) also showed good levels of reliability for recordings of max velocity during a team-sport simulated circuit and Bataller-Cervero et al. (2019) reported positive findings regarding the reliability of the Viper device for measuring reliability during intermittent linear running. It appears that 10Hz devices display predominantly good interunit reliability for measures of instantaneous velocity in linear running and team-sport circuits. It appears that 10Hz units are superior in this regard to previously investigated 5Hz units. Practitioners should be aware of custom, manufacturer embedded algorithms which can improve measures of reliability.

Table 2.12 - Reliability of Global Positioning Systems (10Hz)

Reference	Device	No. of Units	Reliability	Parameter	Task	Error Measurement	Int.
Nikolaidis et al. (2018)	JOHAN	8	Interunit	Total Distance	5 x 200m Curvilinear run	CV: 1.31 – 2.2%	G
		20			20m Shuttle Run	CV: 2.08 – 3.92%	G
		8	Intraunit		5 x 200m Run	ICC: 0.833	n/a
		20			20m Shuttle Run	ICC: 0.718 – 0.831	n/a
Bastido-Castillo et al. (2019)	Not identified	2	Interunit	Position Coordinates	Linear Running Circuit	TEM: 1.98% – 2.12%	G
		14	Intraunit			CV: 2.54% – 3.48%	G
		2	Interunit		SSG	TEM: 1.54% - 1.99%	G
		14	Intraunit			CV: 1.89% – 2.24%	G
Varley et al. (2012)	MinimaxX V4.0	2	Interunit	Instantaneous Velocity	Linear Running - Constant Velocity	CV: 2.0 – 5.3%	M
					Accelerations	CV: 1.9 – 4.3%	G
					Decelerations	CV: 6.0%	M
Johnston et al. (2014), Johnston et al. (2013)	MinimaxX S4	2	Interunit	Total Distance	TSSC (8 x 165m)	TEM: 1.3%, ICC: 0.51	G
				Exertion Index		TEM: 1.02%, ICC: 1	G
				RHIE		TEM: 78.97%, ICC: -0.27	P
				LSR (m; 0 – 13.99km•h^{-1})		TEM: 1.67%, ICC: 0.97	G
				HSR (m; 14.00 – 19.99km•h^{-1})		TEM: 4.82%, ICC: 0.88	G
				VHSR (m; >20.00km•h^{-1})		TEM: 11.5%, ICC: 0.89	P
				LSR (s; 0 – 13.99km•h^{-1})		TEM: 0.78%, ICC: 0.99	G
				HSR (s; 14.00 – 19.99km•h^{-1})		TEM: 4.63%, ICC: 0.86	G
				VHSR (s; >20.00km•h^{-1})		TEM: 11.7%, ICC: 0.89	P
				HSR Efforts (14.00 – 19.99km•h^{-1})		TEM: 2%, ICC: 0.8	G
				VHSR Efforts (>20.00km•h^{-1})		TEM: 13.7%, ICC: 0.84	P
				Peak Speed		TEM: 1.6%, ICC: 0.97	G
Akenhead et al. (2014)	MinimaxX S4	2	Interunit	Instantaneous Velocity	10m Sprint	CV: 0.7 – 47.4%	G-P
Hoppe et al. (2018)	MinimaxX S4	2	Interunit	Total Distance	TSSC (10 x 129.6) 25.1m sprinting with CODs	CV: 4.1%	G
					10m walking with COD	CV: 7.2%	M
					Linear Variations (5 – 30m)	CV: 2.5 - 10.7%	P
					129.6m entire circuit	CV: 2.5%	G
				Max Velocity		CV: 3.3%	G
				Max Force		CV: 20.9%	P
				Max Power		CV 18.8%	P
Castellano et al. (2011)	MinimaxX V4.0	9	Intraunit	Total Distance	Linear Sprint (15 & 30m)	CV: <4%	G
			Interunit		Linear Sprint (15 & 30m)	CV: 0.7 - 1.3%	G

Bataller-Cervero et al. (2019)	Viper	2	Interunit	Instantaneous Velocity	Intermittent Linear Running	R = 0.97, SMB: 0.04, STE: 0.23	n/a
Beato et al. (2018)	Viper	20	Interunit	Total Distance	Curvilinear Running (400m)	CV: 1.6%	G
					TSSC – (128.5m x 1)	CV: 0.8%	G
					20m Linear Run (Jog)	CV: 0.4%	G
				Peak Speed	20m Linear Sprint	CV: 0.7%	G

Key; Interpretation; G- Good (<5%), M – Moderate (5 – 10%), P- Poor (>10%), n/a – not available, Int - Interpretation; CV – Coefficient of variation; SSG – Small-Sided Games; TEM – Typical Error of Measurement; TSSC – Team-Sport Simulated Circuit; RHIE – Repeated High Intensity Efforts; LSR – Low-Speed Running; HSR – High-Speed Running; VHSR – Very-High-Speed Running; SMB – Standardised Mean Bias; STE – Standard Typical Error

2.5.11 - ⩾15Hz Global Positioning Systems Overview

Recent analysis has assessed devices that sample at a rate of 15Hz and above. Of the 6 studies which assessed validity of these devices, 3 assessed devices which sampled at a rate of 15Hz, whilst 2 assessed 18Hz devices. The final device assessed sampled at a rate of 16Hz. As with previous generations, total distance was the most assessed metric (n = 4). These devices displayed predominantly good and good-to-moderate measures of validity. Seven articles assessed the reliability of these devices, with 6 assessing interunit reliability and 1 assessing intraunit reliability. Again, total distance was the commonly assessed parametric (n = 6). Studies presented conflicting findings regarding the reliability of these devices, with good reliability reported for most long-distance assessments, whilst poor and moderate interpretations reported for tasks involving shorter, higher intensity efforts.

2.5.12 - ⩾15Hz Global Positioning Systems – Validity

During a 13200m curvilinear and shuttle based course, Rawstorn et al. (2014) showed significant differences between total distance measured via a surveyors wheel and via the SPI-Pro X. Despite this, the measurement bias was good-to-moderate for total distance measured (Bias = -2.16%) and for total distance measured during walking (Bias = -2.18%), jogging (Bias = -2.2%), running (Bias = -2.16%), and sprinting (Bias = -1.92) during the shuttle test. Similarly, during the curvilinear protocol, good and good-to-moderate measurements of validity were recorded for total distance (Bias = 2.99%), walking (Bias = 2.99%), jogging (Bias = 2.95%), running (Bias = 2.95%) and sprinting (Bias = 3.16%). Hoppe et al. (2018), utilising the same protocol previously used to assess the 10Hz MinimaxX S4 device, assessed the validity of the 18Hz GPEXE PRO EXELIO. They showed good validity over the entire circuit with (Bias = -1.6%) and without (Bias = -4.5%) standing sections. However, they did show poor validity for measurements of total distance during a 5m sprint section (Bias = -11.8%), this appears to be consistent with previous issues of this technology at lower sampling rates. Longer distance sprinting efforts of 20m (Bias = -8.8%) and 30m (Bias = -6.7%) showed slightly improved validity. Johnston et al. (2014) showed no significant difference in total distance measured via tape measure and via the SPI-Pro X device. Vickery et al. (2014) also showed no significant difference between total distance measured via the SPI-Pro X device and via VICON.

Due to the recent nature of advancements in this technology, information regarding the validity of these devices for measures of velocity are limited. When assessing the SPI-Pro

X for measuring peak speed during a team-sport simulated circuit, Johnston et al. (2014) found significant differences in one device, but no significant difference in the other. Whilst the large (r = 0.64) and very-large (r = 0.76) Pearson correlation scores recorded were similar to the 10Hz device, the devices with the lower sampling rate displayed strong correlation scores. Vickery et al. (2014) showed no significant difference between criterion and the SPI-Pro X for measures of average and peak velocity for both linear protocols (run-a-three and fast bowling), and for fielding and circuit protocols. They recorded significant differences for average velocity in both the 90° and 45° COD course, and in the 45° COD course for peak velocity. More recent research by Lacome et al. (2019) with 16Hz devices showed that devices underestimated measures of maximal sprint speed during a 40m linear sprint, whilst Gimenez et al. (2020) recorded significant correlations for measures of maximum velocity of 0.943 and 0.971 between the WIMU and APEX devices and timing gates. Whilst the increased sampling rate has led to increased validity of devices for measuring distance parameters, this relationship appears less clear for velocity metrics. One explanation for this may be the method of achieving the increased sampling rate. Whilst more recent studies have, due to technological developments, reported a true GPS derived signal some have recorded 15Hz signals by an interpolation algorithm to increase sampling rate. In most instances the method of this interpolation is unclear, making it difficult for practitioners to make decisions upon.

Table 2.13 - Validity of Global Positioning Systems (≥15Hz)

Reference	Device	Sampling Rate	Parameter	Task	Criterion Measure	Error Measurement	Int.
Johnston et al. (2014)	SPI-Pro X	15Hz†	Total Distance	TSSC	Tape measure	No significant difference ($p<0.05$)	n/a
			Peak Speed		Timing Lights	r = 0.64, r = 0.76 ($p<0.05$)	n/a
Rawstorn et al. (2014)	SPI-Pro X	15Hz‡	Total Distance	LIST Shuttle – Total (13200m)	Surveyors Wheel	Bias:-1.92 to -2.2	G
				LIST Curvilinear – Total (13200m)		Bias: 2.95 to 2.99	G
Hoppe et al. (2018)	GPEXE PRO EXELIO	18Hz	Total Distance	TSSC (10 x 129.6) 25.1m sprinting with CODs	Measuring Tape	Bias: -9.2%	M
				10m walking with COD		Bias: -1.9 ± 0.3	G
				Linear Variations (5 – 30m)		Bias: -11.8 to +1.8	G
				129.6m entire circuit		Bias: -4.5 to -1.6%	G
			Acceleration	1.1 ± 0.0s for τ (6-9)	Timing Gates	Bias: +25.4 ± 3.1	P
			Max Velocity	8.2 ± 0.1m/s for V_{max} (6-9)		Bias: -0.2 ± 0.7	G
			Horizontal Force	7.7 ± 0.1 N/kg for F_{max}		Bias: -17.0 ± 1.7	P
			Horizontal Power	16.1 ± 0.4 W/kg for P_{max} (6-9)		Bias: -16.9 ± 1.5	P
Vickery et al. (2014)	SPI-Pro X	15Hz	Total Distance	Run-a-three	VICON	2/2 measures not sig. diff. ($p<0.05$)	n/a
				Fast Bowling		2/2 measures not sig. diff. ($p<0.05$)	n/a
				Fielding		2/2 measures not sig. diff. ($p<0.05$)	n/a
				90° COD		2/2 measures sig. diff. ($p<0.05$)	n/a
				45°COD		1/2 measures sig. diff. ($p<0.05$)	n/a
				Random FBTS		2/2 measures not sig. diff. ($p<0.05$)	n/a
			Average Velocity	Run-a-three		2/2 measures not sig. diff. ($p<0.05$)	n/a
				Fast Bowling		2/2 measures not sig. diff. ($p<0.05$)	n/a
				Fielding		2/2 measures not sig. diff. ($p<0.05$)	n/a
				90° COD		2/2 measures sig. diff. ($p<0.05$)	n/a
				45° COD		1/2 measures not sig. diff. ($p<0.05$)	n/a
				Random FBTS		2/2 measures not sig. diff. ($p<0.05$)	n/a
			Peak Velocity	Run-a-three		2/2 measures not sig. diff. ($p<0.05$)	n/a
				Fast Bowling		2/2 measures not sig. diff. ($p<0.05$)	n/a
				Fielding		2/2 measures not sig. diff. ($p<0.05$)	n/a
				90° COD		2/2 measures not sig. diff. ($p<0.05$)	n/a
				45° COD		1/2 measures not sig. diff. ($p<0.05$)	n/a
				Random FBTS		2/2 measures not sig. diff. ($p<0.05$)	n/a
Lacome et al. (2019)	Sensoreverywhere V2	16Hz	MSS	Linear Sprint (40m)	Radar Device	Bias: -3.0%	G
			MSS (Smoothed)			Bias: -1.61 ± 1.06	G
Gimenez et al. (2020)	Apex Pro	18Hz	Max Velocity	TSSC (165m x 8)	Speed Gates	R = .971, SEE = 0.25	n/a
	Realtrack WIMU Pro					R = .943, SEE – 0.35	n/a

Key; † - Additional 5Hz sampling rate obtained via accelerometer algorithm; ‡ - 5Hz GPS receiver and a proprietary interpolation algorithm that outputs positional data at 15Hz frequency; TSSC – Team-Sport Simulated Circuit; SD – Standard Deviation; * Sig difference to criterion; τ = Acceleration time constant; Vmax = Theoretical maximal running velocity; Fmax = Theoretical maximal horizontal force; Pmax = Theoretical maximal horizontal power output; FBTS – Field-Based Team Sport Circuit; COD – Change of Direction; MSS – Maximal Sprint Speed; SEE – Standard Error of the Estimate

2.5.13 - ⩾15Hz Global Positioning Systems – Reliability

As with validity, there is limited research on reliability of higher rate sampling devices. Initial studies seem promising, Rawstorn et al. (2014) reported good interunit reliability in both a curvilinear (CV = 2.16%) and shuttle (CV = 2.44%) circuit for the SPI-PRO X. Similarly Johnston et al. (2014) and Hoppe et al. (2018) both showed good interunit reliability for team sport simulated circuits assessing the SPI-PRO X (TEM = 1.9%) and GPEXE PRO EXELIO (CV = 1.4%) devices. As with previous devices, the speed of the movement appeared to affect the reliability measured. Johnston et al. (2014) recorded good validity for low-speed running distance (TEM = 2.0%), moderate validity for high-speed running distance (TEM = 7.6%), and poor validity for very-high speed running distance (TEM = 12.1%). Hoppe et al. (2018) did not observe this effect, however they did report moderate validity (CV = 5.1%) for short distance sprinting. Buchheit et al. (2014) also recorded good validity (CV = 3.0%) for a standardised running protocol and recorded the effect of speed of movement on reliability. They reported good validity for speeds less than 14.4km•h^{-1} (CV = 2.0%), and moderate validity (CV = 6%) for speeds greater than 25.1km•h^{-1}.

Utilising previously used protocols, Vickery et al. (2014) recorded moderate readings for interunit reliability during fast bowling (CV = 5.5%), 90° COD (CV = 6.2%) and a field-based team sport circuit protocol (CV = 8.2%). However, they recorded poor validity for run-a-three linear running test (CV = 17.9%), fielding (CV = 17.0%) and a 45° COD protocol (CV = 12.4%). More recently in more sport specific tasks, Bredt et al. (2016) reported moderate interunit validity during two small-sided game protocols (SEM = 5.2% / 7.2%). Again, there appeared to be an effect of speed of movement. Distance covered at <7.2km•h^{-1} showed moderate validity for both SSG conditions (SEM = 6.6%/7.9%), whilst distance covered at 14.4 – 25.1km•h^{-1} showed poor validity in both SSG conditions (SEM = 30% / 42%).

Whilst there are limited within-device reports, it does appear that devices of higher sampling rates can reliably measure total distance covered. Between-device measurements also appear to provide reliable measures of total distance covered however, practitioners should be cautious of comparing measurements of high-speed running between devices. Whilst a previous review has highlighted that higher sampling devices have performed worse than previous generations, it should be noted again that in some cases the increased sampling rate has been achieved by interpolation algorithms, and thus are not recording samples at a true rate.

One study assessed the interunit reliability of mean speed measurements measured via a 15Hz device. Vickery et al. (2014) reported poor validity for run-a-three (CV = 16.3%), fielding (CV = 15.2%) and a 45° COD test (CV = 12.4%). They also recorded moderate validity for fast bowling (CV = 8.8%), fielding (CV = 15.2%) and a field-based team sport circuit (CV = 7.5%). Using the same protocol, they reported poor validity for peak speed measurements during run-a-three (CV = 14.1%), fielding (CV = 16.9%), 90° COD (CV = 14.5%), 45° COD (CV = 20.0%) and the field-based team sport circuit (CV = 11.9%), and moderate validity for fast bowling (CV = 8.4%). Similarly, Johnston et al. (2014) recorded moderate validity (TEM = 8.1%) for measurements of peak speed during a team-sport simulated circuit. Bredt et al. (2016), when assessing two small-sided games protocols, reported poor validity of the SPI-PRO X device for measuring peak speed (SEM = 10.6% / 10.8%).

Conversely, Hoppe et al. (2018), assessing the GPEXE PRO EXELIO device, reported good validity (CV = 3.1%) for measures of peak speed during a team-sport simulated circuit. Buchheit and colleauges also reported good (CV = 1%) validity of the SPI-PRO X device for measuring peak speed during standardised running routines. Lacome et al. (2019) also reported good validity (CV = 0.5%) of devices to measure peak speed during linear running. Therefore, the findings regarding reliability of velocity measures made using devices which sample at a rate of 15Hz or greater are conflicting. Again, the issue of interpolation of data to achieve a higher sampling rate makes conclusions regarding these devices, and comparison between previous generations, difficult.

Table 2.14 - Validity of Global Positioning Systems (≥15Hz)

Reference	Device	Sampling Rate	No. of Units	Reliability	Parameter	Task	Error Measurement	Int.
Bredt et al. (2016)	SPI-PRO X	15Hz	18	Interunit	Total Distance	SSG	SEM: 5.2 – 7.2%, ICC: 0.68 – 0.71	M
					Distance <7.2km•h^{-1}		SEM: 6.6 – 7.9%, ICC: 0.38 – 0.42	M
					Distance 7.3-14.3km•h^{-1}		SEM: 11.2 – 15.1%, ICC: 0.56 – 0.74	P
					Distance 14.4 – 21.5km•h^{-1}		SEM: 30 - 42%, ICC: 0.28 - 0.54	P
					Peak Speed		SEM: 10.6 – 10.8%, ICC: -0.09 to 0.08	P
					Peak Accel		SEM: 12 - 12.5%, ICC: -0.29 to -0.24	P
					No. of Accels >2m•s^{-2}		SEM: 17.3 – 30.5%, ICC: -0.66 to -0.24	P
					Distance travelled in accels >2m•s^{-2}		SEM: 27.1 – 34.4%, ICC: 0.27 - 0.51	P
Johnston et al. (2014)	SPI-PRO X	15Hz†	2	Interunit	Total Distance	TSSC (8 x 165m)	TEM: 1.9%, ICC: -0.2	G
					LSR (m; 0 – 13.99km•h^{-1})		TEM: 2.0%, ICC: 0.98	G
					HSR (m; 14.00 – 19.99km•h^{-1})		TEM: 7.6%, ICC: 0.94	M
					VHSR (m; >20.00km•h^{-1})		TEM: 12.1%, ICC: 0.81	P
					Peak Speed		TEM: 8.1%, ICC: -0.14	M
Rawstorn et al. (2014)	SPI-PRO X	15Hz‡	1	Intraunit	Total Distance	LIST Shuttle (13200m)	CV: 2.44%	G
						LIST Curvilinear (13200m)	CV: 2.16%	G
Hoppe et al. (2018)	GPEXE PRO EXELIO	18Hz	2	Interunit	Total Distance	TSSC (10 x 129.6) 25.1m sprinting with CODs	CV: 1.4%	G
						10m walking with COD	CV: 1.5%	G
						10m jogging with jump	CV: 1.8%	G
						Linear Variations (5 – 30m) 10m jogging	CV: 2.3 – 5.1%	G
						129.6m entire circuit	CV: 1.1%	G
					Max Velocity		CV: 3.1%	G
					Max Force		CV: 7.5%	M
					Max Power		CV: 7.4%	M
Vickery et al. (2014)	SPI-PRO X	15Hz	2	Interunit	Total Distance	Run-a-three	CV: 17.9%, ICC: -0.17	P
						Fast Bowling	CV: 5.5%, ICC: 0.53	M
						Fielding	CV: 17.0%, ICC: -0.16	P
						90° COD	CV: 6.2%, ICC: 0.46	M
						45° COD	CV: 12.4%, ICC: 0.02	P
						Random FBTS	CV: 8.2%, ICC: 0.10	M
					Mean Speed	Run-a-three	CV: 16.3%, ICC: -0.10	P

						Fast Bowling	CV: 8.8%, ICC: -0.22	M
						Fielding	CV: 15.2%, ICC: -0.35	P
						90° COD	CV: 7.8%, ICC: 0.73	M
						45° COD	CV: 10.9%, ICC: 0.20	P
						Random FBTS	CV: 7.5%, ICC: 0.01	M
					Peak Speed	Run-a-three	CV: 14.1%, ICC: 0.05	P
						Fast Bowling	CV: 8.4%, ICC: 0.03	M
						Fielding	CV: 16.9%, ICC: -0.05	P
						90° COD	CV: 14.5%, ICC: 0.25	P
						45° COD	CV: 20.0%, ICC: 0.67	P
						Random FBTS	CV: 11.9%, ICC: -0.08	P
Lacome et al. (2019)	Sensoreverywhere V2	16Hz	6	Interunit	Max Velocity	40m Sprint	CV: 0.5%, ICC = 0.99	G
					Max Acceleration		CV: 6.4%, ICC = 0.74	M
Buchheit et al. (2014)	SPI-PRO X	15Hz	50	Interunit	Total Distance	Standardised Running Routine	CV: 3%	G
					Distance >14.4km•h^{-1}		CV: 2%	G
					Distance > 25.1km•h^{-1}		CV: 6%	M
					Peak Acc		CV: 10%	M
					Acc > 3m•s^{-2}		CV: 31%	P
					Acc >4m•s^{-2}		CV: 43%	P
					Peak Speed		CV: 1%	G
					Dec >3m•s^{-2}		CV: 42%	P
					Dec > 4m•s^{-2}		CV: 56%	P

Key; † - Additional 5Hz sampling rate obtained via accelerometer algorithm, ‡ - 5Hz GPS receiver and a proprietary interpolation algorithm that outputs positional data at 15Hz frequency; SSG – Small-Sided Games; SEM – Standard Error of the Measurement; ICC – Intraclass Correlation; CI – Confidence Intervals; LSR – Low Speed Running; HSR – High Speed Running; VHSR – Very-High Speed Running; TSSC – Team-Sport Simulated Circuit; TEM – Typical Error of Measurement; CV – Coefficient of Variation; Acc – Accelerations; Dec – Decelerations

2.5.14 - Data Generation, Software, and Hardware Considerations for GPS Technology

Signal quality received by GPS devices during data collection will influence the accuracy of information fed back to coaches by practitioners and also reported within scientific literature (Malone et al., 2017). Signal quality can be assessed based on the number of satellites interacting with the receiver at any one time. Thus, it can be affected depending on location and also environmental obstruction such as stadiums or tall buildings (Malone et al., 2017). Devices require a connection to a minimum of 4 satellites for adequate connection, however, in general, the greater the number of connected satellites, the greater coverage of the device (Malone et al., 2017). Whilst there is no gold standard for number of satellites connected to a receiver leading to improved data collection, Malone et al. (2017) suggested that devices connected to less than 6 satellites would tend to have reduced data quality. Practitioners should be mindful of satellite connection when reporting data back to coaches, particularly when competing or training in a stadium environment, as this will possibly impact the quality of data. Similarly, research projects should report the number of satellites connected during data collection to allow readers to understand the quality of data or exclude data if sampling points do not meet specific criteria.

Horizontal dilution of precision (HDOP) is a term regarding error relating to satellite position (Witte and Wilson, 2004). The HDOP provides a measure of the accuracy of the GPS horizontal positional signal determined by the geometrical organisation of the satellites (Malone et al., 2017). In basic terms, it is a measure of the ‘bunching’ of satellites connected to the receiver. If satellites are close together HDOP readings will be high and precision will be poor, whereas if satellites are spread HDOP is low and precision is considered good. Values of HDOP range from 0 to 50 (Witte and Wilson, 2004), with a value less than 1 considered ideal (Malone et al., 2017). As stated regarding the number of connected satellites, practitioners should be wary of HDOP values when reporting data, whilst HDOP readings should be reported in research projects.

Considering the number of satellites connected and HDOP values for any given data sample allow practitioners to consider implementing exclusion criteria in both practical and research settings. Anecdotally, practitioners will also visually inspect raw velocity traces recorded during an activity to inspect for irregularities (Malone et al., 2017). Malone et al. (2017) suggest these distortions may be due to sudden loss in satellite signal affecting the detection of movement. Anecdotally, there may be more practical causes of these flaws, such as a player removing their bib or an opponent tugging on the vest containing a receiver. Reporting of satellite connection, HDOP and a rigorous inspection of raw velocity traces should allow practitioners to increase confidence in their dataset, whilst ensuring coaches and academic readers can be assured of information reported.

2.5.15 - Considerations for Commonly Used GPS Metrics in Athlete Monitoring

Several metrics are available to practitioners when using GPS technology. The most common measure is total distance covered (Cardinale and Varley, 2017). A survey of professional soccer clubs by Akenhead and Nassis (2016) found that total distance covered was the most common variables used to quantify load in competitive matches, and the second most common variable used in training. The distance covered can be calculated using two methods; positional differentiation or as the integral of Doppler-shift velocity (Cardinale and Varley, 2017). To utilise positional differentiation, the device calculates position (latitude and longitude) using the distance of each satellite to the device, and triangulating the devices location (Malone et al., 2017). Measuring the change in location with each signal allows distance to then be calculated. Doppler-shift technology utilises the change in frequency of the periodic signal emitted by the satellite. To provide further context to the distance covered, it is general practice to report these values relative to specific speed thresholds (Cardinale and Varley, 2017). External load metrics occurring within specific speed thresholds are commonly reported as; distance covered, number of efforts or duration in a specific threshold. A range of thresholds are reported in the literature and can be generally categorised as absolute or relative. The use of absolute, or default, thresholds may lead to the over, or under-estimation of the running demands of sport players (Reardon et al., 2015). However, they are still commonly used both in practical settings and academia, likely due to the complexities surrounding their use, and the lack of consensus on selecting appropriate methods for determining these zones (Malone et al., 2017). Distance covered at $5.5m \cdot s^{-1}$ and $7.0m \cdot s^{-1}$ were the second and third most common reported metric during match play in surveyed professional soccer clubs (Akenhead and Nassis, 2016). To assess velocity, the device uses either the positional differentiation or Doppler-shift methods. Doppler-shift is more commonly used by manufacturers as this this method appears to be more accurate (Townshend et al., 2008). The most common variables used to asses training load in surveyed professional soccer teams were acceleration variables (Akenhead and Nassis, 2016). This is generally derived from Doppler-shift velocity (Malone et al., 2017). The time interval which is used to calculate an acceleration effort, minimum effort duration (MED) will alter the data recorded, and will depend on the model of device used (Malone et al., 2017). Assessment by Varley et al. (2017) showed that changes in MED as small as 0.1s affected the number of accelerations, high-speed running and sprint efforts detected during soccer matches. It is also critical that practitioners are aware that after acceleration is calculated, the data may be smoothed using filtering techniques, such as moving average, median, Butterworth and exponential filters (Malone et al., 2017). Additionally, acceleration and velocity data can be smooth by widening or shortening the MED (Varley et al., 2017). This is an important consideration when providers update software, as updates may influence the filtering technique used to calculate both acceleration and velocity efforts. Previous research has shown when comparing data before and after a software update, there was a substantial reduction in the number of accelerations reported following the update (Buchheit et al., 2014). This should be of concern to practitioners collecting longitudinal data, as it is often unclear what filtering technique has been used by manufacturers, and how software updates can affect data reported. It also makes collating historical datasets troublesome (Buchheit and Simpson, 2017).

2.6 – Accelerometery

Use of GPS technology to monitor training and match physical load has become common place (Akenhead and Nassis, 2016). Within commercially available devices, which house hardware for collection of positional data, technology such as accelerometers, gyroscopes and magnetometers are also typically encased. Accelerometers are able to measure the magnitude of acceleration, which leads to the ability to quantify the frequency, quality and intensity of movement (Hendelman et al., 2000). Tri-axial accelerometers are commonly used to assess movement in three dimension, anterior-posterior, mediolateral, and longitudinal (Krasnoff et al., 2008). Alongside this, the higher sampling rate of accelerometers is highlighted as a benefit of this technology. Sensors have an ability to sample at a rate of up to 500Hz, with most commonly used devices sampling at 100Hz (Chambers et al., 2015). This high sampling rate may give tri-axial accelerometers the ability to overcome limitations of GPS technology for measuring sport specific movements such as acceleration and deceleration (Boyd et al., 2011). Additionally the ability to collect measurements regarding player movement indoors, as well as outdoors, and more specific measurements regarding skill and contact-based aspects of sport have been highlighted as benefits of accelerometery (Boyd et al., 2011). The two most common accelerometer based workload quantifications cited in the literature are PlayerLoad (Catapult Sports, Melbourne, VIC, Australia) and BodyLoad (GPSports Systems, Canberra, Australian Capital Territory, Australia) (Chambers et al., 2015). PlayerLoad involves the use of vector magnitudes to accumulate accelerometery data (Boyd et al., 2011). This measure is expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the three vectors, divided by 100 (Eq. 1.).

$$PlayerLoad = \sqrt{\frac{(a_{y1} - a_{y-1})^2 + (a_{x1} - a_{x-1})^2 + (a_{z1} - a_{z-1})^2}{100}}$$

Equation 5 – The modified vector magnitude used to calculate PlayerLoad™ where:

a_y – anterior-posterior vector

a_x – medio-lateral vector

a_z – longitudinal vector

The BodyLoad measurement is described as an arbitrary measure of the total external mechanical stress as a result of accelerations, decelerations, changes of direction and impacts (Chambers et al., 2015, Weaving et al., 2014). It is calculated from the square root of the sum of the squared instantaneous rate of change in acceleration in the vertical, anterior-posterior, and medial-lateral vectors (Chambers et al., 2015). The following section aims to assess the validity and reliability of accelerometer use in team-sports.

2.6.1 – Validity of Accelerometery

Previous research has investigated the validity of accelerometers for measuring physical activity against outcome measures such as energy expenditure, heart rate and oxygen consumption to assess validity of tri-axial accelerometers (Levine et al., 2001, Rowlands et al., 2004). In studies focusing on the use of accelerometers for sporting actions, outcome measures such as video analysis, heart rate and oxygen consumption have been used (MacLeod et al., 2018, Barrett et al., 2014). Investigating the relationship between accelerometer outputs of a triaxial accelerometer (3dNX model, BioTel Ltd., Bristol, UK), speed, oxygen output and HR, Fudge et al. (2007) found nearly-perfect relationships between accelerometer output and treadmill speed during a continuous incremental continuous walking test ($r = 0.97$). They also showed a moderate positive association between instantaneous heart rate and accelerometer output (r = 0.59). During an incremental test involving continuous walking, and discontinuous running at speeds up to 18km•h^{-1} they reported very-large relationships between accelerometer outputs and speed (r = 0.89), VO_2 (r = 0.87), and instantaneous heart-rate (r = 0.72). During incremental walking, similar results were found for uniaxial accelerometers. The CSA7164 (Manufacturing Technology Inc., Fort Walton beach, FL), ActiGraph ((Manufacturing Technology, Inc., Fort Walton beach, FL) and ActiHeart (Cambridge Neurotechnology Ltd., Papworth, UK) devices, all of which measure in the vertical axis showed near-perfect relationships with speed of 0.96, 0.95 and 0.96, respectively. Additionally, during continuous walking, the CSA7164 (r = 0.54) and ActiHeart (r = 0.57) devices showed large correlations with heart-rate. Whilst the ActiGraph device showed moderate correlations (r = 0.49) with heart-rate. Crucially, during the incremental, discontinuous running phase of the test, the output on the ActiGraph, ActiHeart, and CSA7164 devices plateaued, whereas the triaxial 3dNX devices outputs rose in a linear fashion with speed up to and including 20km•h^{-1}. The ActiGraph and ActiHeart devices plateaued at running speeds corresponding to approximately 14-16km•h^{-1}, whilst the CSA7164 devices output also plateaued at approximately 10-12km•h^{-1}. Additionally, whilst the 3dNZ devices outputs rose linearly in line with VO2 and heart rate during running, the relationships between the uniaxial devices and VO2 and heart-rate increased in a non-linear fashion. These findings would suggest that the validity of uniaxial devices within running based activity is questionable at best however, would appear to endorse further investigation of triaxial devices.

Investigating the validity of PlayerLoad, using average HR as a criterion measure, Barrett et al. (2014) found between- and within-subject, correlations of -0.43 to 0.16 and -0.93 to 0.98 respectively. Compared to breath-by-breath VO_2 data they found between- and within-subject correlations of -0.28 to 0.16 and 0.92 to 0.96, respectively. Previous research has shown large and very-large between-subject correlations between PlayerLoad and total distance covered (r = 0.70), Edwards summated HR load (r = 0.72), and sRPE-TL (r = 0.76) (Casamichana et al., 2013). The differences in between-subject, correlations found by Barrett et al. (2014) would suggest that accelerometers should not be used as a surrogate measure for internal load when making comparisons between participants . However, the very-large to nearly perfect within-subject correlations shown by Barrett et al. (2014) would endorse the use of PlayerLoad when making individual specific considerations regarding athlete training. The authors suggested this is due to individual factors, specifically running kinematics such as stride rate and length, having a profound effect on the vector magnitude nature of the measure (Barrett et al., 2014).

Recent research has raised questions regarding the validity and application of PlayerLoad as a metric (Bredt et al., 2020). Firstly, the authors highlighted the varying definitions of the PlayerLoad measure provided within academic literature (Bredt et al., 2020). To do this they focused on the mathematical and literal definitions of PlayerLoad. It was argued that the mathematical and literal definitions of PlayerLoad do not reflect the rates of change in acceleration, but rather the sum of changes in acceleration. It was argued that, given this lack of relationship with the magnitude of acceleration, there is a limit to the measures applied use within sporting practice (Bredt et al., 2020). Additionally, the authors highlighted the variation within the academic literature of PlayerLoad equations and demonstrated that applying these varied methods resulted in different PlayerLoad results. Additionally, they highlighted varying practice with regards to the structure of the equation, particularly the division by 100. This further complicates comparisons between research findings and practical applications for practitioners. These highlighted limitations enforce the need for practitioners and academics to specifically describe how they have calculated the PlayerLoad metric within research, rather than challenging the validity and reliability of the measure.

Practitioners have also assessed the validity of accelerometer technology for quantifying the frequency and magnitude of collisions in sports such as rugby league, rugby union and American football (Gabbett, 2013, Gabbett et al., 2010). Comparing the MinimaxX device (Catapult Sports, Melbourne, VIC, Australia) against video recordings Gabbett et al. (2010) showed no significant differences between the two methods for measuring tackles, hit-ups, decoy runs and support runs in professional rugby league. Whilst near perfect ($r = 0.96$) correlations were found between collisions recorded via the MinimaxX devices and video coding (Gabbett et al., 2010). More recent research in rugby union found a near-perfect relationship between collisions quanitifed via StatSport devices and video coding ($r = 0.96$) (MacLeod et al., 2018). Additionally, further research in rugby league has has shown that Optimeye S5 devices (Catapult Sports, Melbourne, VIC, Australia), were able to capture 97.6% ± 1.5% of collision events identified via video coding (Hulin et al., 2017). Whilst these measurements have proved useful within collision-based team sports, their application to soccer is arguably limited. Recent research has investigated the validity and application of data provided by a foot-mounted inertial senor (PlayerMaker™, Tel Aviv, Israel) for monitoring technical actions within soccer (Marris et al., 2022) . Whilst this is a developing area within the research, when assessing proportions of agreement (P_A) between video coding and the device for measuring ball touches and releases within soccer activity, relationships of 95.1% and 97.6% were found. These findings may assist practitioners within soccer to better quantify technical demands, alongside established measures of physical load.

2.6.2 – Reliability of Accelerometery

Early assessments of the reliability of triaxial accelerometers have used a hydraulic shaker to provide highly repeatable dynamic movements (Boyd et al., 2011). Assessing static reliability, where only the effect of gravity of acceleration due to gravity should be measured, Boyd et al. 2011 found good within-device (CV = 1.01%) and between-device (CV = 1.10%) reliability (Table 2.15). Assessing dynamic within-device reliability they reported good measurements at 0.5 g (CV = 0.91%) and at 3.0 g (CV = 1.05%). Similarly, measuring between-device reliability they reported good measurements of reliability at 0.5 g (CV = 1.04%) and at 3.0 g (CV = 1.02%). These acceleration measures were selected based on typical values obtained during Australian football activity (Boyd et al., 2011), however it is worth noting that higher values of acceleration have been reported in professional soccer match play (Akenhead et al., 2013). Finally, the within-device reliability was assessed during semi-professional Australian football match play and was found to be good (CV = 1.94%). Using a flying 50m sprint to assed a newer version of the MinimaxX device, Johnston et al. (2012) showed good reliability when measuring PlayerLoad (CV = 4.9%). Further assessment of the MinimaxX S4 and S3 devices showed moderate (TEM = 5.87%) and good (TEM = 1.13) reliability during a team sport circuit (Johnston et al., 2013).

Using an incremental based treadmill test, Barrett et al. (2014) assessed the test-retest reliability of PlayerLoad and its contributing vector magnitudes. When assessing PlayerLoad they reported CV = 5.9%, whilst contributing vector magnitudes ranged from CV = 6.3% to CV = 12.0%. It is worth noting that a poor test-retest reliability was reported for the medio-lateral vector of PlayerLoad (CV = 12.0%). Additionally, poorer levels of reliability were reported at slowed speeds, with CV = 12.6% and CV = 13.1% at speeds of 1.94m•s^{-1} and 2.22m•s^{-1}. Conversely, improved reliability measures were reported at faster speeds, with CV = 4.8% and CV = 4.6% reported at speeds of 4.17m•s^{-1} and 4.44m•s^{-1}, respectively. Finally, when considering sport specific training, Luteberget et al. (2018)

reported good levels of reliability (CV = 0.9%) during handball training and MacLeod et al. (2018) reported large correlations and poor errors of measurement between units for various contact measures in professional rugby. However, the authors argued that these readings may have been influenced by the housing of two units between the scapulae of participants, possibly influencing the displacement readings of devices. Taken collectively these results would suggest that practitioners can have some confidence in the interunit and intraunit reliability of triaxial accelerometers for measuring PlayerLoad^{TM}. However, practitioners should be aware that the reliability of this microtechnology can be influenced by the speed of movement, and there is also questionable reliability when utilising these devices to identify collisions in certain team sports. As previously discussed, recent technological developments have enabled the quantification of technical demands within soccer environments (Marris et al., 2022) . The intra-unit reliability of these devices has been assessed, with good levels of agreement reported for ball touches (P_A = 96.9%) and ball releases (P_A = 95.9%). Whilst this is a developing area of research it is promising that early reports have shown both valid and reliable measurements of technical demands.

Table 2.15 - Reliability measures of accelerometer technology for measuring PlayerLoad and sport specific movements in team sports

Reference	Device	No. of Units	Reliability	Parameter	Task	Error Measurement
Boyd et al. (2011)	MinimaxX 2.0	10	Intraunit	PlayerLoad	Static Assessment	CV = 1.01%
			Interunit			CV = 1.10%
		8	Intraunit		Hydraulic Shaker – 0.5 g	CV = 0.91%
			Interunit		Hydraulic Shaker – 0.5 g	CV = 1.04%
			Intraunit		Hydraulic Shaker – 3.0 g	CV = 1.05%
			Interunit		Hydraulic Shaker – 3.0 g	CV = 1.02%
		2	Intraunit		Sport Specific	CV = 1.94%
Johnston et al. (2012)	MinimaxX 2.5	2	Interunit	PlayerLoad	Flying Sprint (50m)	CV = 4.9%
Johnston et al. (2013)	MinimaxX S3	2	Interunit	PlayerLoad	Team Sport Circuit	TEM = 1.13%
	MinimaxX S4	2	Interunit			TEM = 5.87%
Barrett et al. (2014)	MinimaxX	1	Test-Retest	PlayerLoad	Incremental Treadmill Test	CV = 5.9%, ICC = 0.93
				PL_{ap}		CV = 9.1%, ICC = 0.92
				PL_{ml}		CV = 12.0%, ICC = 0.80
				PL_{v}		CV = 6.3%, ICC = 0.93
MacLeod et al. (2018)	Viper	2	Interunit	Collision Load	Rugby Training Sessions	TE = 10.1%, ICC = 0.82
				Velocity		TE = 13.2%, ICC = 0.89
				Impact Force		TE = 19%, ICC = 0.70
				Momentum		TE = 13.2%, ICC = 0.92

Key; CV – coefficient of variation; TEM – typical error of measurement; PL_{ap} – Anterior-posterior vector of PlayerLoad™, PL_{ml} – Medio-lateral vector of PlayerLoad™, PL_{v} – Vertical vector of PlayerLoad™; ICC – intraclass correlation coefficient; TE – typical error

2.6.3 Summary – GPS and Accelerometer Technology

Validity and reliability of GPS devices for measuring metrics such as total distance and distance covered at specific thresholds has improved as the sampling rate has increased. Despite this further research is needed to establish the validity and reliability of newer devices with a sampling rate greater than or equal to 15Hz. Practitioners should be aware of a range of information when utilising GPS technology, such as number of satellites, HDOP, sampling rate, device brand and model, and data inclusion/exclusion criteria. Researchers should also report this information in published research to make their methodology replicable. Whilst it is difficult to report this information due to manufacturer discretion, efforts should also be made to understand filtering techniques used on acceleration and velocity data. Finally, practitioners should be aware that MED will affect the number of high intensity efforts reported during data collection. There is no consensus for MED however practitioners must understand the effect longer or shorter bands can have on data recorded. Limitations of GPS technology regarding sampling rate effect its ability to record sport specific actions and provide detailed high-frequency assessments of movement. Accelerometer based measurements overcome this with sampling rates generally occurring at 100Hz. Commercially developed measurements such as PlayerLoad have been shown to provide valid and reliable data regarding the locomotive demands of sport. There is also evidence regarding the use of accelerometers to quantify the frequency and magnitude of collisions within team sports however the applicability of this to soccer is limited. Recent technological advancements have developed valid and reliable measures of technical demands within soccer activity, which may supply practitioners with additional opportunities to report on both technical and physical demands of training and match-play.

2.7 - Measuring Internal Load

Internal load is predominantly measured in the field using HR monitors due to their simplicity and availability to practitioners. HR monitoring has been used to examine and characterise physiological load during training and match play in soccer since the 1960s (Seliger, 1968, Wilmore and Haskell, 1972). HR response was traditionally monitored using electrocardiogram (ECG) recording transmitted via short-range radio telemetry, however, the nature of soccer activities and sweat production during exercise compromised connection of electrodes to the skin (Alexandre et al., 2012). In the 1980s, wireless cardio monitoring technology was developed, which allowed for electronic transfer of data from a belt worn on the chest to a receiver worn as a wristwatch. This advancement allowed monitoring during actual training and match play without the previous limitations of ECG (Van Gool et al., 1983). In the 1990s, the integration of the HR monitor with a micro-computer and specific data analysis software. This system provides practitioners with a simple method of simultaneously monitoring players allowing post-event analysis. More recent developments have provided the opportunity of real-time HR monitoring, providing practitioners actionable data in the field (Alexandre et al., 2012).

HR data can be analysed various ways to produce outcomes such as training impulse (TRIMP) (Banister, 1991). TRIMP allows a training session to be quantified into a single unit ‘dose’ of physical effort. TRIMP is based on the extent to which a given bout of exercise raises heart rate between resting and maximal levels (Banister, 1991, Morton et al., 1990). TRIMP is calculated using training duration, maximal heart rate, resting heart rate and average heart rate during the bout of exercise.

$$w(t) = duration\ of\ training\ (mins) x\ \Delta HR\ ratio\ x\ Y$$

$$where\ \Delta HR\ ratio = \frac{HR_{ex} - HR_{rest}}{HR_{max} - HR_{rest}}$$

Equation 6 – Training impulse method originally proposed by Banister (1991) where w(t) = assessment of the amount of training undertaken during a training session, and Y is a weighting factor applied to increase the magnitude of quantity of training nonlinearly at higher training intensities. where Y = $0.64e^{1.92x}$ for males, Y = $0.86e^{1.67x}$ for females, e = 2.712 and x = ΔHR ratio.

Y is a weighting factor that emphasises high intensity exercise and is also applied to the equation to avoid giving disproportionate importance to long, low intensity exercise compared with intense, short duration exercise. The obvious advantage of this method of analysis is its ability to characterise training as one single figure. However, this method has been shown to require steady state heart rate measurements, this limiting the accuracy of this measure in exercise of an interval nature and field sport settings.

Busso et al. (1990) simplified the TRIMP equation by multiplying the average fraction of maximum aerobic power output during exercise to the session duration, thereby limiting the training stimulus to external loading. The equation of Busso et al. (1990) was adapted for use in resistance training by replacing heart rate reserve with %1RM and duration with number of lifts. This method allows quantification of non-aerobic modes of training such as resistance training. This systems model showed relationships between calculated fitness and fatigue levels and serum testosterone concentration, testosterone: cortisol and testosterone: sex hormone binding globulin ratios in six elite weightlifters (Busso et al., 1990). Further methods of adjusting TRIMP to characterise resistance training exercise have resulted in the inclusion of sRPE in the quantification of exercise intensity (Sweet et al., 2004, McGuigan and Foster, 2004, McGuigan et al., 2004, Egan et al., 2006).

Another commonly used practical method of characterising internal load is summated heart rate zone scoring, commonly referred to as Edwards TL (Borresen and Lambert, 2009) This involves calculating the total duration spent in each of five heart rate zones (e.g. 50-60%, 60-70%, 70-80%, 80-90% and 90-100% of maximal heart rate) is multiplied by a given weighting factor for each zone (e.g. 50-60% = 1, 60-70% = 2, 70-80% = 3, 80-90% = 4, 90-100% = 5). The weighted values are then summated to provide a single value to characterise a bout of training. A weakness of this method is that because a weighting factor is applied to zones, both ends of this zone will be treated the same, for example a period of work at 50% HR_{max} will produce the same value as the same period of work at 59% HR_{max}. Under certain circumstances, this could mean that a change of only 1beat/min will result in an increase in the weighting factor of the zone, thus increasing or decreasing the calculated load disproportionately (Borresen and Lambert, 2008). Borresen and Lambert (2009) suggest that there appears to be no evidence that this method of quantification has been validated, despite its use in practical settings. A method which modifies the summated heart rate zone equation has however been suggested. ‘Lucia’s TRIMP’ considers the duration spent in three heart rate zones and multiplies them by a coefficient relative to each zone (Lucía et al., 2003). Zone 1 is below the ventilator threshold, zone 2 is between the ventilator threshold and the respiratory compensation point, and zone 3 is above the respiratory compensation point. Each zone is then multiplied by its corresponding coefficient (k = 1 for zone 1, k = 2 for zone 2, k = 3 for zone 3) and the adjusted scores and then summated to again provide a single score. Clearly this method shares the same limitations as the summated heart rate zone scoring method as the weighting factor increases in a linear fashion, which does not reflect the physiological response to exercise.

2.7.1 - Rating of Perceived Exertion

Measuring ratings of perceived exertion has become a popular training load assessment tool in professional soccer (Akenhead and Nassis, 2016). The foundation of perceived exertion scales began in the 1950s and 1960s where range-models were proposed to allow a simple method of comparing physical exertion (Borg and Dahlström, 1960, Borg, 1962).

The original Borg scale (Borg, 1962) aimed to overcome previous difficulties with previously proposed ratio-scaling methods. The first scale, a 21-grade gauge with verbal anchors, was proposed in 1962 with the aim of overcoming difficulties association with previous ratio-scaling methods (Borg, 1962). The scale was a category model which, Borg proposed, allowed inter-individual comparisons. This category scale could be treated as a rank order scale, in that an increase in subjective intensity only suggests that there has been some increase in the intensity, not giving a specific magnitude of increase.

A new category scale was then developed, and designed to increase linearly in-line with the intensity for work on a cycle ergometer (Borg, 1970). The scale (Figure 2.4) comprises values range from 6 to 20 and was designed to mirror heart rate ranges from 60-200beats•min^{-1} (Borg, 1970). The aim of this scale was to allow values selected by the user to match with heart rate values. For example, if the scorer were to give a value of ‘14’, theoretically this would be equivalent to a heart rate value of 140beats•min^{-1}. This relationship however shouldn’t be taken to literally, and Borg (1982b) did highlight that heart rate values could be influenced by a range of factors. Another highlighted advantage of the 15-point scale is whilst historically scales were not designed to increase linearly with exercise intensity, due to the linear relationship this construction was designed to represent it may better represent magnitude of changes in intensity.

6	
7	Very, very light
8	
9	Very light
10	
11	Fairly light
12	
13	Somewhat hard
14	
15	Hard
16	
17	Very hard
18	
19	Very, very hard
20	

Figure 2.4 – 15 point scale for ratings of perceived exertion (Borg, 1970)

Borg himself clarified that there may not be one perfect scale to gather information on subjective intensities in different training environments (Borg, 1982b). To create a scale which was easy to understand they developed a new rating scale with both category and ratio properties (Borg, 1982a, Borg, 1982b). This 10-point scale (Figure 2.5) aimed to combine benefits of previously developed scales, whilst maintaining the ratio benefits of the 15-point ratio scale. The use of anchoring verbal expressions was intended to make the scale easily understood, whilst also retaining ratio properties. For example, if a score of ‘2’ is to be considered ‘Weak’, have of that value should be considered ‘Very weak’, furthermore half of the value of ‘1’, ‘0.5’. should then denote ‘Very, very weak’.

0	Nothing at all	
0.5	Very, very weak	(just noticeable)
1	Very weak	
2	Weak	(light)
3	Moderate	
4	Somewhat strong	
5	Strong	(heavy)
6		
7	Very strong	
8		
9		
10	Very, very strong	(almost max)
•	Maximal	

Figure 2.5 - Further developed scale proposed by Borg (Borg, 1970). This scale was designed as a category scale with ratio properties

This Borg CR10 scale was then modified in the late 80's by slightly changing the verbal anchors into idiomatic American-English. (Figure 2.5). For example, 'light' or 'Weak' became 'Easy', 'Strong' or 'heavy' became 'Hard'. Foster et al. (1988) then used the Borg CR10 scale to rate their perceived exertion across the entire session multiplied by the session duration to give sRPE-TL. Using the scale they found relationships between sRPE-TL and average % heart rate reserve during 30-min steady state running (r = 0.65). Foster et al. (1995) showed the sRPE-TL was capable of monitoring changes in training, and also showed a relationship between changes in training load and performance, and illness incidence (Foster, 1998). At this stage, many assessments had been carried out utilising clinical, steady state protocols to assess the relationship between different sRPE methods and other internal methods of assessing training load. Foster et al. (2001) assessed the relationship between sRPE-TL and HR based methods of monitoring load during various bike based steady state and interval protocols and also during basketball training and match-play. sRPE-TL scores, collected across all steady state and interval protocols, were significantly higher than summated HR zone scores. Despite this, regression analyses showed that the magnitude of change across bouts of exercise was similar in the summated HR zone method and the sRPE method. This pattern was also noted in the basketball training and match-play condition.

Foster et al. (2001) also made distinct changes to how they collected RPE data in comparison to previous Borg studies. The previously used clinical methodology required participating athletes to give RPE scores at particular moments. Foster et al. (2001) explained to participants that they required a global rating of the entire session. Critically, they also allowed a 30-minute delay at the end of a given training bout, so that any immediate segments wouldn't affect the global RPE score (Foster et al., 2001).

Rating	Descriptor
0	Rest
1	Very, Very Easy
2	Easy
3	Moderate
4	Somewhat Hard
5	Hard
6	.
7	Very Hard
8	.
9	.
10	Maximal

Figure 2.6 – Modification of the Borg CR10 scale (Foster, 1988, Foster et al., 1995)

The first recorded study to use this method in soccer was carried out by Impellizzeri et al. (2004). The authors used the Foster-modified version of the Borg CR10 scale (Figure 2.6) as to quantify training load in soccer players, using HR based methods as criterion measures. Using this method, they found individual correlations between sRPE-TL and Banister's TRIMP ranging from 0.5 to 0.77. They also reported correlations between sRPE-TL and Edwards' TL and Lucia's TRIMP of 0.54 to 0.78 and 0.61 to 0.85, respectively.

The CR10 scale has become popular in clinical and sport settings and appropriate for practical use. Despite this the scale is generally not treated as continuous, that is athletes rarely report decimal readings, therefore a more sensitive scale was desired (Borg, 2007). The CR100 scale (Figure 2.7) was developed, with an increased numerical range. The scale, starting at a minimum level of 1.5, ranges to a maximum level of "Maximal, Max X" which is anchored against a previously established maximal effort (Borg, 2007). Alongside the numerical and verbal categories within the CR100 scale there are triangles increasing in size and blackness to assist participants in interpreting the meaning of the verbal labels (Borg, 2007).

The CR100 scale appears to be a valid and reliable method for assessing perception of effort (Borg, 2007). An initial study comparing the CR100 scale with absolute magnitude estimation (AME) showed that the CR100 scale provided ratio data similar to the AME scale (Borg, 2007). In this assessment participants were required to complete an incremental bicycle ergometer test, with perceived exertion recorded at 3-minute intervals. The CR100 scale was also shown to be superior for detecting individual differences, with this scale able to discriminate perceived exertion by gender at their different physical work capacity, which the AME could not (Borg, 2007). Further analysis aimed to compare ratings taken using the 15-point Borg RPE scale, CR10 and CR100 scales. Against using a bicycle ergometer protocol, it was shown that the CR100 scale allowed a larger range in variability of numbers recorded, and participants were less likely to use numbers at the same location as verbal anchors than with the CR10 (Borg, 2007). These findings support the theory that the CR100 scale is more finely graded by participants than when using the CR10 scale.

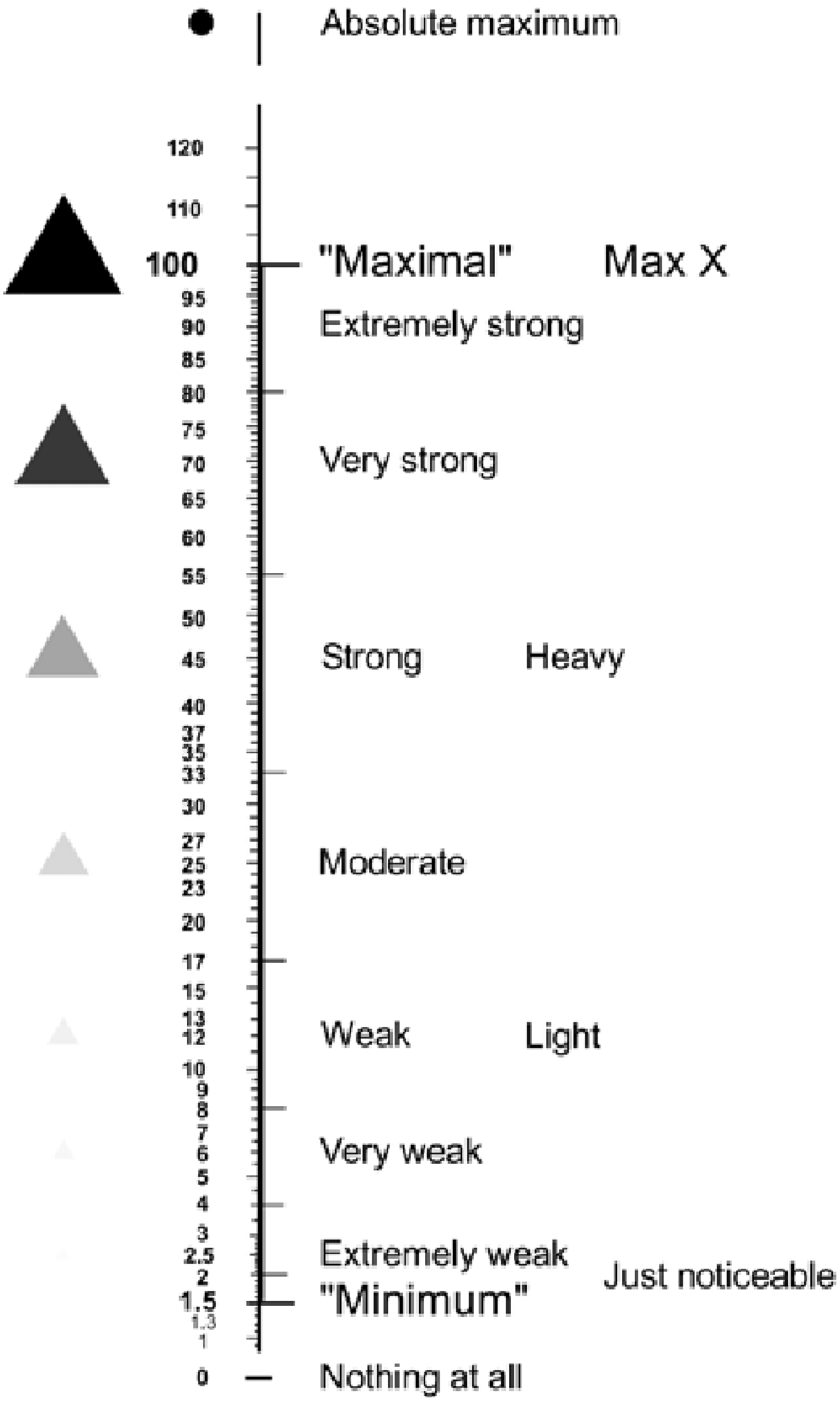

Figure 2.7 – CR100 scale (Borg and Borg, 2002)

Using data collected during Australian Football training, Scott et al. (2013b) reported significant within-individual correlations between sRPE-TL collected via the CR10 and CR100 scales and various HR-based, and external, training load measurements. Whilst these findings suggest training load assessed via the CR10 and CR100 scales are valid measures, poor levels of reliability were reported when assessing training load in a linear, intermittent running test (Scott et al., 2013b). Coefficients of variation of 31.9% and 38.6% were recorded for the CR10 scale and the CR100 scale respectively. However, previous research has highlighted difficulties in measuring the reliability of ordinal scales because of their multifactorial nature (Borg et al., 1987, Morgan, 1994, Scott et al., 2013b). Therefore, despite these poor reliability measures, which should be considered, sRPE has been suggested as a worthwhile measure. This is due to its strong validity alongside its simplistic, non-invasive and cost effective nature (Scott et al., 2013b).

Whilst assessment of player sRPE is relatively common in professional soccer training (Akenhead and Nassis, 2016), there have been concerns raised regarding its nature to oversimplify the training process (Weston et al., 2015). A potential solution for this is the assessment of dRPE, which allows assessment of separate sensory inputs, such as local and central exertion signals (McLaren et al., 2016a, Weston et al., 2015). Initial assessments by Borg et al. (2010) found strong correlations between ratings of leg fatigue and heart rate during an incremental bicycle ergometer test were found when using the CR10 ($r = 0.80$) and CR100 scales ($r = 0.77$). They also found strong correlations between heart rate and ratings of breathlessness using the CR10 ($r = 0.7$) and CR100 ($r = 0.67$) (Borg et al., 2010). Significantly, leg exertion rating was the dominant symptom at the final performed workload for the majority of participants when using both the CR10 and CR100 scales (Borg et al., 2010). Further studies assessed the potential of dRPE in both treadmill running (Green et al., 2009, McLaren et al., 2016a) and cycling (McLaren et al., 2016a) and there is now a growing body of literature regarding its use in team sport training.

McLaren et al. (2017) detailed dRPE values in English Championship rugby union players, specifically investigating the values recorded during training activities with differing external load profiles. Using the CR100 scale they collected sRPE scores, alongside values for breathlessness, leg muscle exertion, upper body muscle exertion, and technical demands (McLaren et al., 2017). Collecting data across a 6-week pre-season training period they found differences for training themes ranging from possibly trivial to most likely extremely large for both breathlessness and leg muscle exertion for between-session comparisons. They also found between-session differences of very likely trivial to very likely moderate for technical ratings. With respect to the different training themes, they showed that dRPE-TL explained 66% to 91% of variance within global sRPE-TL. Further analysis revealed unclear, to near perfect partial correlations between differential sRPE-TL and gestalt sRPE-TL for different training themes. For example, within training categorised as Repeated High-Intensity Efforts, they found that 91% of the variance in sRPE-TL was explained by dRPE-TL. Whilst for sessions categorised as Speed, they found that 66% of the variance in sRPE-TL was explained by dRPE-TL. The strongest relationship between any of the dRPE-TL measures and global sRPE-TL, across all training categories, was with sRPETL-L ($r = 0.55 \pm 0.32$ (90%CI)). Specifically, to individual training modes, a very likely, Very Large relationship was recorded between sRPETL-B and sRPE-TL ($r = 0.89 \pm 0.08$ (90%CI)) during the repeated high-intensity effort training mode. Also, a possibly, Near Perfect relationship was recorded between sRPETL-U and sRPE-TL ($r = 0.92 \pm 0.07$ (90%CI)) during upper body resistance training. Conversely, an unclear relationship was reported between sRPETL-B and sRPE-TL during upper body resistance training, and an unclear relationship was reported between sRPETL-L and sRPE-TL ($r = 0.19 \pm 0.35$ (90%CI) during the repeated high-intensity effort training mode. This would therefore suggest that when distinct training modes are used, dRPE-TL can be utilised to better understand the perceived effort of the athlete.

Use of measurement scales to assess an athlete’s perceived exertion allows practitioners to monitor the training load in a cost-effective manner. Theoretically, using this method will allow practitioners to monitor the volume and intensity of the training session. The aim of this section therefor is to provide a greater understanding of the using of sRPE in team-sports. Firstly, this will focus on the validity and reliability of this measure, before going on to discuss more practical application within the team sport setting.

2.7.2 - Validity of sRPE-TL Method using Borg CR10 Scale

This section aims to assess the criterion validity, and reliability, of the rating of perceived exertion method for measuring load in team sport players. As with previous sections, to provide an assessment of the available literature a scoping strategy was used. Only studies which involved data collection in pitch-based training were used, accordingly studies with lab-based protocols or in non-field-based team sports were excluded from this review. Interpretations of correlation magnitudes were classified as trivial ($r < 0.1$), small (0.1 -

0.3), moderate (0.3 - 0.5), large (0.5 - 0.7), very large (0.7 - 0.9) and almost perfect (> .9) (Hopkins et al., 2009).

There is no single gold standard metric for measuring internal load, and as such previous research has quantified load validity against other measures of load (Lovell et al., 2013, Scott et al., 2013a, Weaving et al., 2014) or with the response of fitness measures (Manzi et al., 2013, Akubat et al., 2012). A range of correlations have been shown between sRPE-TL and various internal and external training load measures (Table 2.16). Measuring internal training load via three HR-based measures, Impellizeri et al. (Impellizzeri et al., 2004) reported large to almost perfect correlations. Across a 7-week training period they reported relationships between sRPE-TL and Edward's TL (r = 0.54 to 0.78), Banister's TRIMP (r = 0.5 to 0.77) and Lucia's TRIMP (r = 0.61 to 0.85). The correlations reported in this study were lower than those reported in endurance athletes (r = 0.75 to 0.90) (Foster, 1998). The authors suggested that this may be due to the intermittent nature of soccer and the increased anaerobic contribution. This increased anaerobic contribution would then lead to participants reporting an increased exertion rating in comparison to steady-state exercise (Impellizzeri et al., 2004, Drust et al., 2000). Alexiou and Coutts (2008), Campos-Vasquez et al. (2015) and Clarke et al. (2013) reported similar values in female soccer players, professional men's players and Canadian football players, respectively.

In Australian Footballers, Scott et al. (2013b) recorded sRPE-TL alongside measures of internal and external training load, reporting large to very-large correlations. Similarly, to previous research they reported very-large correlations between sRPE-TL and Edwards TRIMP (r = 0.83), Banister's TRIMP (r = 0.83) and %HR peak (r = 0.66). Alongside this they also reported correlations between sRPE-TL and total distance covered (r = 0.81), PlayerLoad (r = 0.83) and high-speed running distance (r = 0.71). Across 2400 individual rugby league training sessions, Lovell et al. (2013) also considered the relationships between sRPE-TL and internal and external measures of training load. They reported significant correlations between sRPE-TL and total distance covered (r = 0.83), high-speed running (r = 0.6), BodyLoad (r = 0.56), Impacts (r = 0.55) and Banister's TRIMP (r = 0.75). Similarly, Gaudino et al. (2015) reported large correlations between sRPE-TL and high-speed distance (r = 0.61), impacts (r = 0.729) and accelerations (r = 0.631) in professional soccer players. In semi-professional soccer players, Casamichana et al. (2013) also reported large to very-large correlations between sRPE-TL and total distance covered (r = 0.74), PlayerLoad (r = 0.76), HSR efforts (r = 0.64) and Edward's TL (r = 0.57).

Weaker correlations were reported between sRPE-TL and measures of very-high speed running distance (r = 0.43) and time at very-high speed running (r = 0.46) in professional soccer players (Scott et al., 2013a). The authors suggested that an explanation for this may be that the use of speed thresholds to assess physiological demands of intermittent activity may be limited as it does not account for high-intensity bouts such as jumps, turns and physical contacts (Scott et al., 2013a). Therefore, whilst these movements may be classed under a lower locomotive threshold, they may influence the perceived exertion of players. As such this would increase the relationship between sRPE-TL and lower locomotive categories.

Conversely, Rodriguez-Marroyo and Antoñan (2015) reported small correlations between sRPE-TL and Edwards TRIMP in youth soccer players (Age = 11.4 ± 0.5yrs). The authors suggested that this relatively low correlation was likely due to the sessions being largely technical and tactical in nature whereas previous research which had validated the use of sRPE in younger players had been done using steady-state ergometer protocols. This perhaps highlights the use of sRPE as a global measure of training load, including both the physical and psychological components of training stress.

In senior athletes, it is likely that the mode of training will affect the relationship between perceived exertion and internal or external workload performed. In professional rugby league players, Weaving et al. (2014) reported correlations between various training load measures during small-sided games, conditioning, skills, speed and strongman based sessions. The mode of training did appear to affect the relationship between measures and there also appears to be a significant amount of individual variability. For example, during SSG there was a large-to-very large relationship between sRPE-TL and 'Impacts' (r = 0.70), whilst during session categorised as 'Wrestle' there was a trivial-to-large relationship (r = 0.35). Across the five modes of training, they reported a range of relationships for iTRIMP (r = 0.47 to 0.81), BodyLoad (r = 0.24 to 0.48), high-speed distance (r = 0.04 to 0.75) and impacts (r = 0.29 to 0.7). Analysis by Weaving et al. (2017) further evidenced these findings with Championship rugby league players. Correlations ranging from small to very-large were found between sRPE-TL and HREI (r = 0.3 (95%CI 0.23 – 0.4)), PlayerLoad (r = 0.47) and HSD (r = 0.27). There findings, combined with principal component analysis to assess the underlying structure of these relationship suggest that the mode of training should be considered when deciding on the training load measure used and when assessing the relationships between training load measures.

Finally, assessing the relationship between sRPE-TL and various training load metrics in three different small-sided games protocols, Casamichina et al. (2015) reported weaker and also negative correlations. The authors concluded that there were no clear differences between the three small-sided games protocols (3v3, 5v5 and 7v7). The finding of this study suggest that when considering drills within a session, rather than the session as a whole, and during SSGs, a global measure of training load such as sRPE may not be sensitive enough to detect small changes in high intensity activity (Casamichana and Castellano, 2015). As such, this global measure of training load will not best represent the intermittent nature of activity during drills such as SSGs.

When assessing a short time-frame of AFL training, Gallo et al. (2015) found moderate to very-large correlations for average speed (r = 0.45), total distance (r = 0.88), high-speed running (r = 0.51), PlayerLoad^{TM} (r = 0.86), and PL_{slow} (r = 0.8). Following this assessment Gallo et al. (2015) carried out a principal component analysis to better understanding the relationship between external measures and sRPE-TL. They found that, when combined with measures of experience, position and performance in a time-trial, external training load explained 70%, 69% and 71% of the variance in sRPE-TL training load, respectively. These findings suggest that a player's individual characteristics will have some impact when measuring sRPE-TL highlighting the need for individual assessment.

This evidence would suggest that measures of sRPE-TL collected using the Borg CR10 scale relate with several measures of internal and external training load when used in field-based team sports. However, there appears to be evidence that whilst there is a relationship between measures, sRPE-TL should not be treated as a replacement for internal measures such as Banister's TRIMP, Edwards TL or Lucia's TRIMP. Individual characteristics such as experience or position player appear to affect the relationship, additionally the theme of training appears to affect the relationship between sRPE-TL and other objective measures in a range of field-based team sports.

Table 2.16 - Relationship between subjective and objective training load measures using the CR10 Borg Scale (Borg et al., 1987)

Reference	Task	Criterion Measure	Error Measurement
Rodríguez-Marroyo and Antoñan (2015)	20 sessions	Edwards TRIMP	r = 0.17 (p = 0.335)
Clarke et al. (2013)	713 individual sessions (11-weeks)	Polar TRIMP	r = 0.65 – 0.9 (p<.01)
Impellizzeri et al (2004)	476 individual sessions (7-weeks)	Edward's TL	r = 0.54 – 0.78
		Banister's TRIMP	r = 0.5 – 0.77
		Lucia's TRIMP	r = 0.61 – 0.85
		Banister's TRIMP	r = 0.67 - 0.95 (p<.01)

Alexiou and Coutts (2008)	Soccer Training (16-weeks)	LT_{zone}	r = 0.56 - 0.97 (p<.01)
		Edward's TL	r = 0.5 - 0.96 (p<.01)
Gomez-Piriz et al. (2011)	Soccer (SSG - 13 sessions)	TBL (GPS)	β = 0.23 (p<.05)
Gaudino et al. (2015)	1892 individual soccer sessions	High-Speed Running (>14.4km•h^{-1})	r = 0.61 (p<.001)
		Impacts	r = .729 (p < 0.001
		Accelerations	r = .631 (p < 0.001)
		Distance and number of impacts	r = 0.45 (p < 0.001)
		Accelerations >3m•s^{-2}	r = 0.37
Lovell et al. (2013)	2400 individual sessions	Distance	r = 0.83 (p<.05)
		HSR (>15km•h^{-1})	r = 0.6 (p<.05)
		BodyLoad	r = 0.56 (p<.05)
		Impacts	r = 0.55 (p<.05)
		TRIMP	r = 0.75 (p<.05)
Akubat et al. (2012)	6-weeks	Banister's TRIMP	r = 0.75 (p=0.02)
		% ΔvLT	r = 0.13
		%ΔvOBLA	r = 0.4
		%ΔLThr	r = 0.2
		%ΔOBLAhr	r = 0.15
Casamichana et al. (2013)	44 sessions	TD Covered	r = 0.74 (p<.01)
		PlayerLoad	r = 0.76 (p<.01)
		HSR (≥18km•h^{-1}) Efforts	r = 0.64
		W:R Ratio	r = 0.29
		Edwards TL	r = 0.57 (p<.01)
Campos-Vazquez et al (2015)	Soccer Drills & SSG (Full Competitive Season)	Average HR	r = -0.06
		>80%HR_{max}	r = 0.23
		>90%HR_{max}	r = 0.11
		Edwards TRIMP	r = 0.55
Gabbett and Domrow (2007)	Rugby League Training	HR	r = 0.89
		Blood Lactate	r = 0.86
Vahia et al. (2019)	160 soccer training sessions	HRTL	r = 0.54 - 0.88 (p<.05)
Casamichana and Castellano (2015)	8 -Weeks of SSG Protocol (7v7/5v5/3v3)	%HRmean	r = 0.381 - 0.601
		TD Covered	r = 0.194 -0 371
		PL	r = 0.053 - 0.444
		DSS (>21km•h^{-1})	r = -0.94 - 0.236
		DHS (>18km•h^{-1})	r = -0.73 - 0.129
		FSS (>21km•h^{-1})	r = -0.45 - 0.65
		FHS (>18km•h^{-1})	r = -0.008 - 0.76
Gallo et al. (2015)	14 skill-based AFL training sessions	Total Distance	r = 0.88 (95%CI 0.85 - 0.9)
		Average Speed	r = 0.45 (95%CI 0.35 - 0.54)
		HSR (individualised)	r = 0.51 (95%CI 0.42 - 0.59)
		PL	r = 0.86 (95%CI 0.83 - 0.89)
		PLslow	r = 0.8 (95%CI 0.75 - 0.84)
Pustina et al. (2017)	Two Competitive Seasons	TD	r = 0.573 - 0.808
		PL (Minutes Played)	r = 0.544 - 0.774
		HSR (14.4km•h^{-1}) (Minutes Played)	r = 0.477 - 0.570
Scott et al. (2013a)	29 pitch-based soccer sessions	Total Distance	r = 0.80 (95%CI 0.72 - 0.86)
		LSA (<14.4km•h^{-1}) Distance	r = 0.80 (95%CI 0.71 - 0.86)
		LSA (<14.4km•h^{-1}) Time	r = 0.78 (95%CI 0.69 - 0.85)
		HSR (>14.4km•h^{-1}) Distance	r = 0.65 (95%CI 0.51 - 0.75)
		HSR (>14.4km•h^{-1}) Time	r = 0.67 (95%CI 0.54 - 0.77)
		VHSR (>19.8km•h^{-1}) Distance	r = 0.43 (95%CI 0.26 - 0.58)
		VHSR (>19.8km•h^{-1}) Time	r = 0.46 (95%CI 0.29 - 0.60)
		PlayerLoad	r = 0.84 (95%CI 0.77 - 0.89)
Weaving et al. (2014)	2 x 12-week pre-seasons	iTRIMP	r = 0.47 - 0.81
		BodyLoad	r = 0.24 - 0.48
		HSD (>15km•h^{-1})	r = 0.04 - 0.75
		Impacts	r = 0.29 - 0.70
Weaving et al. (2017)	1 x 12-week pre-season	HREI (Skills)	r = .30 (95%CI 0.23 - 0.4)
		PlayerLoad (Skills)	r = 0.47 (95%CI 0.39 - 0.54)
		HSD (Skills)	r = 0.27 (95%CI 0.18 - 0.35)
		HREI (Conditioning)	r = 0.73 (95%CI 0.66 - 0.79)

		PlayerLoad (Conditioning)	r = 0.56 (95%CI 0.45 - 0.65)
		HSD (Cond.)	r = -0.21 (95%CI -0.34 to -0.07)
Scott et al. (2013b)	38 sessions over 13-weeks	Edwards TRIMP	r = 0.83
		Banisters TRIMP	r = 0.83
		%HR peak	r = 0.66
		TD Covered	r = 0.81
		PL	r = 0.83
		HSR	r = 0.71

Key; TRIMP – training impulse; LT – lactate threshold; TBL – total body load; HSR – high-speed running; vLT – velocity at 2mmol•L^{-1}, LT_{HR} – heart rate at 2mmol•L^{-1}; vOBLA – velocity at 4mmol•L^{-1}; $OBLA_{HR}$ - heart rate at 4mmol•L^{-1}; TD – total distance; HRTL – heart rate training load; PL – PlayerLoad; DSS – distance covered at sprint speed; DHS – Distance covered at high-speed; FSS – Frequency of efforts at sprint speed; Frequency of efforts at high-speed; LSA – low-speed activity; VHSR – very-high speed running; iTRIMP – individualised training impulse; HSD- high-speed distance; HREI – heart rate exertion index

2.7.3 - Validity of sRPE-TL Method using Borg CR100 Scale

The relationships between sessional ratings of perceived exertion, collected using the CR100 scale, and objective measures of training load are summarised in Table 2.17. There is less evidence supporting the use of the CR100 scale, however several internal and external measures correlate with this method of assessing training load. Fanchini et al. (2016) assessed the relationship between Edward's TL and sRPE-TL collected via CR100. They found correlations ranging from 0.52 to 0.85, with 37% of correlations considered Large, and 63% considered very large. Fanchini et al. (2016) also assessed the relationship between sRPE collected via CR10 and CR100 to determine whether these respective scales were interchangeable. They found a near perfect correlation between the two scales (r = 0.95). Whilst there was a strong relationship between the two scales, and the authors suggested these could be used interchangeably, they argued that the CR100 scale may be preferable to the CR10. This is due to the CR100 showing less 'clustering' of ratings around verbal anchors, suggesting it is more finely graded possibly making it a more sensitive measure of exertion.

Weston et al. (2015) used the CR100 scale to collect measures of dRPE over 9 AFL matches in professional players. They found relatively weak correlations for measures of local (sRPETL-M), central (sRPETL-B) and overall match exertion (sRPETL-M). Stronger relationships were found between RPE-L and relative total distance (r = 0.37). They also found that a combination of RPE-L, RPE-B and technical demand (RPE-T) combined to explain 76% of the total variance in overall match exertion (RPE-M).

Scott et al. (2013b) assessed the relationship between sRPE-TL and various measures of internal and external training load across 13-weeks of AFL training. They reported large and very large correlations between measures with the strongest relationship recorded for Edward's TRIMP. Whilst these findings supported the use of both the CR10 and CR100 scales for measuring training load, they reported poor reliability scores for both scales. The authors suggest that whilst previous research has advocated the use of CR100 above CR10 due to increased sensitivity of the CR100, their findings suggest that these scales provide similar information.

Table 2.17 - Relationship between subjective and objective training load measures using the CR100 centiMax scale (Borg and Borg, 2002);

Reference	Task	Criterion Measure	Correlation
Scott et al. (2013b)	38 sessions over 13-weeks	Edwards TRIMP	r = 0.81
		Banisters TRIMP	r = 0.8
		%HR peak	r = 0.59
		TD Covered	r = 0.78
		PlayerLoad	r = 0.8
		HSR	r = 0.69
Weston et al. (2015)	9 AFL matches	PlayerLoad (sRPE-M)	r (±90%CL) = .16 ± 0.16
		PlayerLoad 2D (sRPE-M)	r (±90%CL) = 0.2 ± 0.16
		LSR (<14.4km•h^{-1}) (sRPE-M)	r (±90%CL) = 0.14 ± 0.16
		HSR (≥14.4km•h^{-1}) (sRPE-M)	r (±90%CL) = 0.25 ± 0.15
		TD Covered (sRPE-M)	r (±90%CL) = 0.25 ± 0.15
		Rel. HSR (sRPE-M)	r (±90%CL) = 0.21 ± 0.16
		Rel. TD (sRPE-M)	r (±90%CL) = 0.28 ± 0.15
		HP Distance (sRPE-M)	r (±90%CL) = 0.24 ± 0.15
		EEE (sRPE-M)	r (±90%CL) = 0.24 ± 0.15
		Pmet (RPE-M)	r (±90%CL) = 0.26 ± 0.15
		Equiv. Distance (sRPE-M)	r (±90%CL) = 0.24 ± 0.15
		Rel. HP Dis. (sRPE-M)	r (±90%CL) = 0.2 ± 0.16
		PlayerLoad (sRPE-B)	r (±90%CL) = 0.06 ± 0.16
		PlayerLoad 2D (sRPE-B)	r (±90%CL) = 0.1 ± 0.16
		LSR (<14.4km•h^{-1}) (sRPE-B)	r (±90%CL) = 0.06 ± 0.16
		HSR (≥14.4km•h^{-1}) (sRPE-B)	r (±90%CL) = 0.17 ± 0.16
		TD Covered (sRPE-B)	r (±90%CL) = 0.14 ± 0.16
		Rel. HSR (sRPE-B)	r (±90%CL) = 0.19 ± 0.16
		Rel. TD (sRPE-B)	r (±90%CL) = 0.24 ± 0.15
		HP Distance (sRPE-B)	r (±90%CL) = 0.15 ± 0.16
		EEE (sRPE-B)	r (±90%CL) = 0.12 ± 0.16
		Pmet (sRPE-B)	r (±90%CL) = 0.22 ± 0.15
		Equiv. Distance (sRPE-B)	r (±90%CL) = 0.12 ± 0.16
		Rel. HP Dis. (sRPE-B)	r (±90%CL) = 0.17 ± 0.16
		PlayerLoad (sRPE-L)	r (±90%CL) = 0.06 ± 0.16
		PlayerLoad 2D (sRPE-L)	r (±90%CL) = 0.08 ± 0.16
		LSR (<14.4km•h^{-1}) (sRPE-L)	r (±90%CL) = 0.03 ± 0.15
		HSR (≥14.4km•h^{-1}) (sRPE-L)	r (±90%CL) = 0.31 ± 0.15
		TD Covered (sRPE-L)	r (±90%CL) = 0.19 ± 0.16
		Rel. HSR (sRPE-L)	r (±90%CL) = 0.34 ± 0.14
		Rel. TD (sRPE-L)	r (±90%CL) = 0.37 ± 0.14
		HP Distance (sRPE-L)	r (±90%CL) = 0.29 ± 0.15
		EEE (sRPE-L)	r (±90%CL) = 0.18 ± 0.16
		Pmet (sRPE-L)	r (±90%CL) = 0.36 ± 0.14
		Equiv. Distance (sRPE-L)	r (±90%CL) = 0.18 ± 0.16
		Rel. HP Dis. (sRPE-L)	r (±90%CL) = 0.34 ± 0.14
Fanchini et al. (2016)	Training data collected within Serie A soccer players	Edward's TL	r = 0.52 – 0.85

Key; TRIMP – Training Impulse; TD – total distance; HSR – high-speed running; RPE-M -overall match perceived exertion; LSR – low-speed running; HP – high power distance; EEE – estimated energy expenditure; Pmet – average metabolic power; RPE-B – central rating of exertion (breathlessness); RPE-L – local rating of exertion (legs); TL – training load

2.7.4 - Reliability of RPE Method using Borg CR10 and Borg CR100 Scales

Using a standardised intermittent running test, Scott et al. (2013b) assessed the reliability of RPE measured via the Borg CR10 and CR100 scales. Athletes were required to perform a submaximal yo-yo test at speeds of 10km•h^{-1}, 11.5km•h^{-1} and 13km•h^{-1}. Typical error was assessed via coefficient of variation and interclass correlation of coefficient with both showing poor levels when using the CR10 scale (31.9% CV, 0.66 ICC). Whilst a poor level of reliability was shown for the slowest speed protocol (34.8% CV, 0.55 ICC), improved reliability measures were shown at the 13km•h^{-1} protocol (21.2% CV, 0.66 ICC). When using the CR100 they reported poor levels of reliability over all speed categories (38.6% CV, 0.70 ICC). Again, a poor level was reported at the lowest speed level (52.4% CV, 0.55 ICC) with improved reliability at the highest speed level (25.5% CV, 0.79 ICC). These findings do indicate that the use of sRPE-TL may be limited in intermittent bouts of exercise. However, the authors do highlight that use of CV may be a poor method for determining reliability of ordinal scales (Scott et al., 2013b).

2.7.5 Internal Load Monitoring Summary

Internal training load ultimately determines the outcome of training and can be measured via objective and subjective means. Understanding the internal load experienced by players will provide practitioners with a greater understanding as to how players have responded to the external load imposed upon them. When measures of external load are not available, then understanding the internal load experienced by players can provide practitioners with valuable information regarding the player’s response to training. Understanding both the objective internal load, and the player’s perceived experience of this is key. The validity and reliability of sRPE and sRPE-TL has been evidenced through a range of studies using both the CR10 and CR100 scales. In the absence of gold-standard measures of internal load, practitioners have generally inferred validity using various other measures of internal or external load. Measures of subjective load provide a valid, reliable, and cost-effective method of monitoring load experienced by players, and thus warrants further investigation.

Chapter 3 Experimental Approach to the Thesis

3.1 – Literature Review Conclusion and Perspective and Thesis Rationale

This literature review aimed to provide an assessment of the current practices regarding the monitoring of training and match-play load in soccer players. To do this it has explained the match demands of both youth and senior soccer, methods of collecting and analysing training load data, and the training load profiles of youth and senior soccer players. Whilst there is growing evidence at both youth and senior levels of the load experienced by players, there is little evidence of quantifying load across transitions from youth to senior soccer. Whilst sRPE, and sRPE-TL, have been proposed as suitable methods for measuring training load it has been suggested that, due to it being a global measure of load, it may lack the sensitivity to appreciate changes in load profiles. However, sRPE may be an attractive option to practitioners who do not have the financial budget to invest in technologies which allow the assessment of objective measures of load (Foster et al., 2021). Therefore, the broad aim of the subsequent experimental portion of this thesis is to better understand the relationships between objective and subjective measures of load in professional youth soccer players within the specific context of a professional soccer club. This final stage of the academy transition to senior soccer is key and can be viewed as the final step before senior professional soccer for many players.

The review of literature has highlighted the number of measures used to quantify both internal and external load. Recent research has highlighted that adopting a single training load measure is suboptimal, and measures should be used interchangeably depending on the training mode (Weaving et al., 2014, Weaving et al., 2017). This research has been carried out in rugby league, and there is little information regarding these relationships in soccer. As such, a robust understanding of the relationships between training load measures is required to provide practitioners with confidence when utilising training load measures in youth and senior players in differing training modes. Having a better understanding of these relationships may also assist in monitoring players through the transition from youth to senior professional soccer.

Utilising subjective methods of load, such as sRPE, may provide practitioners with valid, simplistic, and cost-effective methods for monitoring load in soccer players. Whilst load monitoring technologies such as GPS and HR systems are now commonplace in senior environments (Akenhead and Nassis, 2016), financial restraints may limit their use in an academy or amateur infrastructure. As such, subjective methods may be the single consistent load monitoring strategy used across both populations. Whilst previous research has highlighted the validity of sRPE-TL as a monitoring tool (Scott et al., 2013b), it's lack of sensitivity has previously been highlighted (Weston, 2013, McLaren et al., 2016b). As such practitioners have utilised dRPE to greater account for distinctive insights into the perceived loads of players (McLaren et al., 2016a). Further understanding of dRPE, and its ability to provide greater sensitivity of load monitoring in soccer players, will also be of benefit to practitioners.

Qualitative research has highlighted the perspectives of coaches and practitioners that players transitioning from youth to senior soccer are subject to increases in intensity of training. Despite this, little quantitative research has been carried out comparing youth and senior load profiles. Whilst sRPE-TL has been shown to be a valid, reliable, and cost-effective measure of monitoring training load (Foster et al., 2021, Impellizzeri et al., 2004), its ability to detect changes in load across transitions is unclear. Considering this, the aim of this thesis is firstly to quantify and describe the relationships between subjective and objective training load measures to assess their suitability for monitoring load. Secondly, to quantify and describe the load profiles of an elite professional youth time, considering contextual factors such as the stage of the season and the training theme. Before going on to investigate potential methods for modifying subjective measures of load to improve monitoring methods available to practitioners. Whilst these analyses will be case specific, it is an additional aim of the thesis to develop robust analysis tools to support other practitioners in validating these tools in their own context.

To summarise, it appears that multiple valid and reliable measures are taken to assess load experienced by players (Akenhead and Nassis, 2016). Despite this, and despite the complex nature of load monitoring and the physiological and biomechanical response, studies have previously used univariate strategies to relate load performed with outcomes such as injury incidence (Hulin et al., 2016). Not only is it likely that univariate analysis will be insufficient when attempting to understand complex structures such as load, but there is also evidence that training mode (Weaving et al., 2014, Weaving et al., 2017) will influence the relationships between measures. Previous findings in rugby league would suggest that, whilst for some modes of training load measures can be used interchangeably, other modes may be better represented by the application of multivariate measures (Weaving et al., 2014). Additionally it would appear that following PCA, the resultant component loadings align themselves with either external or internal load measures (Weaving et al., 2014). This phenomenon of aligning, and the resulting relationships between measures, was also influenced by the mode of training (Weaving et al., 2014). Previous research has assessed the use of PCA to better understand the relationship between variables (Weaving et al., 2017, Weaving et al., 2014). The use of this method will allow multiple training load measures to be reduced to non-correlated factors representing much of the variance provided by the original measures (Rojas-Valverde et al., 2020). This method will allow the understanding of some key applications for applied practitioners. Firstly, if the majority of variance can be explained by a single component, then this would suggest that load metrics can be used interchangeably. This has significant implications for this thesis as it would suggest that, in settings where technology such as HR monitoring or GPS assessment cannot be carried out, an inexpensive, subjective measurement such as sRPE-TL may be sufficient to monitor load in players. Secondly, if in line with previous research multiple components are identified (Weaving et al., 2017, Weaving et al., 2014), it will provide more information for practitioners regarding the use of sRPE-TL as a measure of training and match-play load. Additionally, the discovery of multiple principal components would also evidence that use of univariate analyses might underrepresent the actual load imposed on players. Whilst findings regarding relationships between variables, and the components produced following PCA, will be case specific, introducing the process of PCA in a soccer context may support practitioners allowing this process to be utilised in their own context.

By understanding the multivariate relationships between objective and subjective measures of load this thesis will aim to identify whether multiple subjective measures are suitable for use in the applied practice of load, it will also investigate whether these relationships are influenced by mitigating factors (e.g. training theme or phase of season) and will propose alternative subjective methods of monitoring training load before collectively applying them across the transition from youth to senior soccer.

3.2 - Specific Aims of the Thesis

Chapter 4: Relationship Between Subjective, and External, Training Load Variables in Youth Soccer Players

The specific aims of this chapter were to:

- Assess and describe the relationship between commonly used objective and subjective measures of load in professional youth soccer players using multivariate methods of analysis
- To determine the requirement for dRPE when assessing subjective load measures

Chapter 5: The Impact of Training Theme on Training Load Measures in Youth Soccer Players

The specific aims of this chapter were to:

- Further investigate the relationship between objective and subjective variables using multivariate methods, with specific reference to the training mode defined by proximity to MD

Chapter 6: The Impact of Stage of Season on Training Load Measures in Youth Soccer Players

The specific aims of this chapter were to:

- Further investigate the relationship between objective and subjective variables with specific reference to the phase of the season. To do this phase of season was categorised as three levels: pre-season, competitive phase 1 and competitive phase 2.

Chapter 7: Does Transforming Subjective Measures of Load Better Represent Training and Match Play Intensity in Youth Soccer Players?

The specific aims of this chapter were to:

- Collectively considering the results of Chapters 4, 5, and 6, to propose alternative methods of subjectively monitoring load utilising previously validated methods of transformation.
- Compare relationships between objective measures of load, and traditional and proposed methods of subjective measures of load.

Chapter 8: Monitoring the Load Experienced by Players During the Transition from Academy to Youth Professional Soccer

The specific aims of this chapter were to:

- Describe and quantify the load experienced by players undergoing a transition from youth to senior professional soccer.
- Utilise and assess previously proposed alternative subjective load measures within this transition

3.3 – Participants

Soccer players who were all contracted to an SPFL club's development squad were recruited as participants for all studies. The characteristics of all participants are summarised in the table below (Table 3.1).

Table 3.1 - Overview of participant characteristics for Chapters 4 – 8. Descriptive characteristics are presented as mean ± SD

Chapter (Group)	N	Age (years)	Height (cm)	Weight (kg)
4 to 7 (Development Squad)	20	17.4 ± 1.3	178.0 ± 8.1	71.8 ± 7.2
8 (Academy)	4	15.9 ± 0.2	175.8 ± 3.5	68.8 ± 7.9
8 (Transition)	4	16.2 ± 0.2	178.4 ± 5.2	71.0 ± 8.6
8 (Development Squad)	19	17.9 ± 1.1	179.1 ± 6.7	75.7 ± 8.7

3.4 – Research Design

3.4.1 Chapters 4 to 7

A longitudinal retrospective research design was used throughout this thesis. Data collected via GPS devices, which were worn during training and match play, were used to assess external load. Measures of sRPE were used to assess subjective internal load. Data were collected across an entire 47-week season which consisted of a 6-week pre-season phase, and two competitive phases lasting 20- and 19-weeks respectively, separated by a 2-week break.

In Chapter 5 each training session was categorised based on its proximity to MD (MD-1, MD-2 etc.). This is a commonly used method in soccer, with traditional stages of recovery for the two days succeeding a match, followed by a two- or three-day loading period before a one- or two-day taper period before a match. The exact periodisation strategy employed by teams appears to be coach dependent (Kelly et al., 2020, Malone et al., 2015). However regardless of the training strategy of teams it appears that some form of tapering load on the day preceding a game is common practice (Kelly et al., 2020, Malone et al., 2015).

In Chapter 6 stages of season were categorised based on their involvement of competitive match play. This allowed comparisons to be made between the pre-season phase and two competitive phases, which were split by a winter break.

Prior to the start of data collection, each participant was familiarised with the objective and subjective methods of collecting load. Description of each external and internal load monitoring technique is discussed in section 3.5 and 3.6. The training sessions were designed by the clubs coaching staff, whilst the competitive matches were designated by the sport's governing body. A summary of competitions which matches took place in is presented in Table 3.2. All matches undertaken during this period were over a typical period of 90 minutes. A typical training week would involve a match on a Tuesday followed by a day off, then three subsequent training days followed by a further day off before a further session the day before the subsequent match.

Table 3.2 -Description of various competitions undertaken by Development Squad players in season 18/19

Competition Category	Competition
National Competitions	SPFL Reserve League SFA Youth Cup
Regional Competitions	Aberdeenshire Cup Aberdeenshire Shield
Loan Player Competitions	SPFL Championship SPFL League One SPFL League Two

Key; SPFL – Scottish Professional Football League; SFA – Scottish Football Association

3.5 – Methods of Measuring External Load

The external load variables described in chapter 5 to 9 were collected via Catapult X4 devices (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware Version 7.27). These devices have a 10Hz GPS sampling rate alongside a 100Hz accelerometer sampling rate. This specific sampling rate of GPS unit has been shown to have acceptable levels of validity and reliability when taking measures of distance and velocity (Chapter 2). Similarly, this accelerometer technology has also shown acceptable levels of validity and reliability (Chapter 2). The velocity and acceleration dwell times were set at 0.6s and 0.4s, respectively. All data were downloaded using Catapult Openfield software (Version 1.19, Catapult Sports, Melbourne, Australia). Devices were worn as per manufacturer instruction, contained within a neoprene vest which holds the unit between the shoulder blades. Players included in the analysis were required to wear this equipment during training and match play by club protocols. The satellite count and horizontal dilution of precision (HDOP) are included in the methods section of each investigation within this thesis. Following each training session or match-play observation, recordings were inspected to ensure a minimum of 6 satellites were connected to devices, and a HDOP of < 2.0 (Malone et al., 2017, Weston et al., 2015). Additionally, raw traces of velocity for each participant were visually inspected to identify, and remove, any irregularities in recordings (Malone et al., 2017).

3.5.2 – GPS Analysis of Match Play

GPS data were collected using a time on pitch analysis, with no bench time or half-time period included. Match play was reported as "1st Half", the time between beginning of the match and the beginning of the half-time period, and "2nd Half", the time between the end of the half-time period and the end of regulation time. Any extra-time periods were treated in the same manner. In the event which match-play was decided via a penalty shoot-out, this period was not included in the analysis. All data were downloaded immediately following match-play and speed zones were set as km•h^{-1}.

3.5.3 – GPS Analysis of Training

GPS devices were worn from the start of the warm-up. Training sessions were split into 9 categories: Warm-Up, Conditioning, Technical, Tactical, Possession Games, Small-Sided Games, Medium Sided Games, Large Sided Games, and Individual Practice. All training categories are summarised in Table 3.3.

Rest periods within each drill were retained within the data, however periods between drills were omitted. It was believed this procedure would give a better replication of match play demands as the half-time period is omitted from match play analysis however periods of ball out of play are included.

Table 3.3 – Training Drills Classification Criteria used throughout the data collection process of Chapters 4 – 8.

Training Category	Description
Warm-Up	Any pre-training preparation drills. Warm-up was included in the analyses as part of training.
Conditioning	Any drills with a specific goal of improving physical qualities. These included speed drills, aerobic conditioning, or repeated sprints for example.
Technical/Tactical	Any drills which were based around skill work or tactical outcomes.
Possession Games	Any size of game, which did not include goalkeepers.
SSG	Any game with player numbers of 1 v 1 to 4 v 4 which included goalkeepers. Pitch dimensions generally ranged from approx. 10 x 6m to 30 x 18m.
MSG	Any game of with player numbers of 5 v 5 to 8 v 8 which included goalkeepers. Pitch dimensions generally ranged from approx. 40 x 24m to 70 x 42m.
LSG	Any game with player numbers of 9 v 9 to 11 v 11 which included goalkeepers. Pitch dimensions generally ranged from approx. 80 x 48m to 100 x 60m.
Individual Practice	Any drill completed by an individual player. These usually took place at the end of training and included passing drills, or tactical-based drills

Key; SSG – small-sided games; MSG – medium-sided games; LSG – large-sided games

3.5.4 – Arbitrary Velocity Thresholds

Due to the observational nature of this research, velocity zones used to categorise the distance covered within various thresholds were determined by the club providing the data. These zones are similar to those used commonly in practice (Chapter 2). Threshold were used to determine low-intensity running (<14.4km•h^{-1}), high-speed running (19.8 - 24.98 km•h^{-1}) and sprinting (>24.98km•h^{-1}). As discussed in Chapter 2, arbitrary velocity thresholds have commonly been used in soccer and other running-based team sports to describe and assess the physiological demands of match play. There are suggestions in the literature that an individualised approach to velocity thresholds may provide a greater understanding of the load imposed upon an athlete, and provide a proxy measurement to better represent dose-response (Hunter et al., 2015, Lovell and Abt, 2013). However, findings regarding this appear to be conflicting, with more recent research showing similar relationships between arbitrary and individualised velocity thresholds and various objective and subjective internal load measures (Scott and Lovell, 2018). Additionally, methods used to anchor velocity thresholds to physiological characteristics has been shown to provide varying levels of success, with single fitness attributes such as maximal aerobic speed or maximal sprint speed resulting in misleading interpretations of intensity distribution in U18 soccer players (Hunter et al., 2015). Additionally, arbitrary velocity thresholds allow both within-, and between-player and team comparisons, as well as longitudinal comparisons of match and training demands (Hunter et al., 2015).

3.5.5 - PlayerLoad^{TM}

The devices used to monitor external load allow PlayerLoad^{TM} to be collected during each recording via a 100Hz tri-axial accelerometer. Briefly, PlayerLoad^{TM} is a vector magnitude which allows data to be summated across three planes of movement (X, Y and Z). More specifically, PlayerLoad^{TM} is expressed as the sum of the squared instantaneous rate of change of acceleration in three axes. These three axes are generally defined as vertical (Y), medial-lateral (X) and anterior posterior (Z). Data provided via PlayerLoad^{TM} are expressed as arbitrary units (au). The validity and reliability of accelerometers, and more specifically PlayerLoad^{TM}, are discussed in Chapter 2 of this thesis. To support validity and reliability of data, all athletes wore correctly fitted vests which were implemented at the beginning of pre-season.

3.5.6 – High Intensity Accelerations and Decelerations

Accelerations and decelerations are a key, and frequent, part of most team sports. The increase in sampling rate to 10Hz has improved the validity and reliability of these devices for measuring discrete, intense, movements over shorter distances. The threshold for high-intensity accelerations was set at 2m•s^{-2}, whilst the threshold for high-intensity decelerations was set at -2m•s^{-2}. The validity and reliability of 10Hz devices for measuring acceleration and deceleration are discussed in section 2.6.2 of this thesis. Throughout experimental chapters of the thesis, frequency of efforts which entered the relevant threshold were included for analyses.

3.6 – Methods of Measuring Internal Load

3.6.1 – Session Rating of Perceived Exertion

Ratings of perceived exertion were collected from each player following all training and match-play events using the Borg CR10 scale (Borg et al., 1985). The exact scale used is a modified version of the Borg CR10 which has previously been used in professional soccer and is commonly applied in this environment (Figure 2.6) (Impellizzeri et al., 2004). All players included in the analysis had previous experience using the scale as part of their training monitoring as this scale was consistent with what is used in their regular training and match-play routine throughout the academy and professional squads. Each sRPE score was multiplied by session duration, provided via the GPS devices, to provide sRPE-TL (au) as a measure of subjective, internal load. The validity and reliability of sRPE and sRPE-TL are discussed in section 2.7 of this thesis.

3.7 – Statistical Analysis

All external load data was downloaded and reported via Catapult Openfield software (Version 1.19, Catapult Sports, Melbourne, Australia), before being analysed through the statistical environment R. The statistical approaches utilised within each analysis is described in greater detail within each experimental chapter. For validity of assessments to be understood it is necessary to describe the frequency of missing data within a dataset (Schafer and Graham, 2002). A review of 136 studies carried out specifically in soccer published in 2019 found that 11% acknowledged the influence of, and approach to, missing data (Borg et al., 2022). Not addressing the approach to missing values can negatively influence the ability of practitioners and researchers to interpret research findings, and also to replicate studies (Borg et al., 2022). Therefore, throughout the practical element of this thesis, the approach to handling missing data is reported. Due to the repeated measures nature and observational design of each experimental chapter, data may be missing for numerous reasons, such as participant adherence to reporting subjective load data, or technical faults such as battery failure affecting the collection of external load data via GPS. Therefore the missing data can be considered implicit as these were not recorded in the dataset (Borg et al., 2022). It has been suggested that there is no ‘rule of thumb’ when deliberating on the amount of missing data to be replaced, or when to remove a variable from an analysis completely (Borg et al., 2022). However, it would appear logical to remove a variable if most data were missing. Whilst there is no gold-standard method of imputation, multiple imputation, where multiple values are imputed for each missing value and then combined, is often considered to reflect the uncertainty in missing values (Borg et al., 2022, Little and Rubin, 2019). Following recommendations from Borg, Nguyen and Tierney (Borg et al., 2022), multiple imputation using the *mice* package (Buuren and Groothuis-Oudshoorn, 2010) in R was utilised to impute missing variables. As separate conditions were placed upon the datasets for each chapter, such as the inclusion of individual sessions, imputation was carried out for each experimental chapter.

Chapter 4 - Relationship Between Subjective and External Training Load Variables in Youth Soccer Players

4.1 Prelude

To assess the suitability of use of dRPE, identified in Chapters two and three, greater understanding regarding the relationships between subjective and objective measures of training load requires investigation. Therefore, the purpose of this chapter was to quantify and describe relationships between subjective and external measures of training load in professional youth soccer players. Whilst previous literature has evidenced the relationships between subjective measures and external load measures via bivariate analyses, it is likely that more sophisticated multivariate techniques will provide more meaningful and useful insights. Greater understanding of these relationships will firstly benefit practitioners who do not have the resources to allow external load monitoring, with a greater appreciation of the constructs of dRPE. Additionally greater understanding of the relationships between variables may allow practitioners to effectively reduce the number of variables that require monitoring to influence decisions regarding loading.

4.2 Introduction

Training load monitoring is common practice in elite sport to develop and prepare athletes (Malone et al., 2017, Coutts and Duffield, 2010). Data collected via technology such as GPS can be transformed to create metrics to monitor external training load. The ability to collect valid and reliable field based data has also generated a large amount of applied research that can be used by practitioners to collect and analyse training load data, and also to predict and prescribe future training (Malone et al., 2017). Monitoring positional measures of training load such as total distance, velocity, and distance covered at specific speed thresholds are now common in professional team sports (Coutts and Duffield, 2010, Akenhead and Nassis, 2016, Johnston et al., 2014) as well as accelerometer based metrics such as PlayerLoad^{TM} (Akenhead and Nassis, 2016).

In contrast to external measures of training load, sRPE has been shown to be useful as a tool to measure load (Impellizzeri et al., 2004) . It has been suggested that a global measure of internal training load such as sRPE-TL may lack sensitivity due to large variations in intensity between and within individuals during training and competition

(Weston, 2013). Differential ratings of perceived exertion (dRPE) have been proposed to distinguish between muscular and cardiovascular exertion, thereby providing additional and more detailed information to monitor load (McLaren et al., 2018b, Jaspers et al., 2017, McLaren et al., 2016a). Previously, clear between-protocol differences, in relation to dRPE scores have been found during cycling and treadmill based activity (McLaren et al., 2016a). For example, a difference of 13.8% ± 7.3 and 37% ± 17 was found in sRPETL-B, and sRPETL-L during incremental cycle and treadmill test, respectively. These findings were also supported by between-protocol differences in objective measures of physiological load. Weekly scores of sRPETL-B has been shown to be higher in players who improved Yo-Yo Intermittent Recovery Test Level 1 and countermovement jump, with 18 ± 11% and 15 ± 16% difference between 'responders' and 'non-responders' respectively (McLaren et al., 2018b). McLaren et al. (McLaren et al., 2017) showed that dRPE could isolate specific demands of training. The results showed that sRPETL-B was greatest during field based repeated high-intensity effort training, skills and speed-based sessions, whilst sRPETL-U was highest in resistance training-based sessions. Overall, dRPE explained 77% of the variance within sRPE-TL training load and the strongest association between the differential markers and sRPE-TL was with measures of sRPETL-L. These findings support the notion that different modalities of training will elicit unique training responses, encouraging the use of dRPE in team sports.

Recent research has provided further evidence to support the use of TL in team sports and as a cost-effective alternative to methods such as GPS monitoring and heart rate analysis. A recent meta-analysis across team sports reported positive linear associations between sRPE-TL and various external training load measures (McLaren et al., 2018a). In soccer specifically, whilst sRPE-TL correlates well with external training load measures (Gaudino et al., 2015), correlations tend to be weaker with measures of intensity such as distance covered at high-speeds (Gaudino et al., 2015, McLaren et al., 2018a). These lower correlations may reflect the difficulty in obtaining a single measure of intensity to represent the intermittent demands of field sports (McLaren et al., 2018a). Previous research has tended to focus on bivariate correlations that provided limited insight into underlying structure between groups of variables. In contrast, more advanced analyses such as PCA and exploratory factor analysis (EFA) may identify structure of relationships between perceived measures of training load and objective measures. Weaving et al. (Weaving et al., 2014) included PCA analysis when exploring the relationships between internal and external measures of load in rugby league players. The authors concluded that across the five variables collected, PCA analysis identified that the structure was different across training methodologies and could often be well explained by two principal components aligning to either internal or external load measures. For example, during skills training the highest loading for the first principal component, which explained almost half the variance was best represented by body load and total impacts. The highest loadings for the second principal component, which explained a further 20.7% of the variance, was best represented by iTRIMP and sRPE-TL, with component loadings of 0.88 and 0.77 respectively. Additional insights may be obtained employing EFA which provides opportunity to rotate solutions and uncover groupings of measures.

The aim of the current investigation was to quantify and describe relationships across multiple RPE variables and commonly used measures of external training load in soccer players. Statistical approaches were adopted to provide the most meaningful and useful summary of these relationships. Such understanding would benefit practitioners that only have access to simple RPE measures and provide information to effectively reduce the number of variables that require monitoring to influence decisions on loading.

4.3 Methods

4.3.1 Experimental Approach to the Problem

The study design for this chapter featured a prospective longitudinal design across an entire 47-week season with professional youth soccer players. The data collection period consisted of a 6-week pre-season and two competitive phases (20-weeks and 19-weeks) split by a 2-week break. Subjective measures of training load were collected via a range of RPE measures, whereas objective measures of training load were collected via GPS units worn during training and match play. The primary aim of the investigation was to assess the relationship between subjective and objective measures of training load using a range of statistical techniques.

4.3.2 Participants

Twenty male professional youth soccer players (age: 17.4 ± 1.3 yrs, height: 178.0 ± 8.1 cm and weight: 71.8 ± 7.2 kg) were recruited to take part in this study. A total of 3324 individual recordings were taken across the season, consisting of 153.3 ± 48.5 and a range of 5 to 200 recordings per player. These 3324 recordings consisted of 696 match play recordings and 2628 training recordings. . Mean durations (± SD) of training and match play are presented in Table 4.1. The group comprised multiple positions, with data collected from goalkeepers removed. Rehabilitation sessions were also removed from the analysis leaving a total of 3221 sets of observations. Data collected and the prospective nature of the study conformed to the University of Glasgow research policies in accordance with the declaration of Helsinki.

Table 4.1 - Load and Intensity measures categorised for match play and training for 20 male professional youth soccer players

Variable	Match values	Training Values
Time (mins)	72.7 ± 28.5	58.5 ± 17.5
sRPE-TL (au)	540.6 ± 291	306 ± 154.2
sRPETL-L (au)	550.1 ± 304	295.2 ± 173.2
sRPETL-B (au)	528.8 ± 294.8	284.2 ± 167.4
Total Distance (m)	8198.4 ± 3287.6	4413.3 ± 1563.1
PlayerLoad (au)	843.5 ± 345.8	496.4 ± 170.4
LI.Running (m)	6430.5 ± 2585	3769.4 ± 1235.9
High-Speed Running (m)	393.9 ± 198.8	136.9 ± 156.5
Sprinting (m)	104.2 ± 92	30.1 ± 50.9
Accelerations (f)	27.9 ± 15	21 ± 10.1
Decelerations (f)	25.3 ± 12.6	13.6 ± 7.8
sRPE (au)	7.2 ± 1.8	5.2 ± 1.7
sRPE-L (au)	7.5 ± 1.9	5.4 ± 1.8
sRPE-B (au)	7.2 ± 1.9	5.2 ± 1.8
Total Distance•min^{-1} (m)	113.7 ± 12.4	76 ± 19
PlayerLoad•min^{-1} (au)	11.7 ± 1.7	8.6 ± 2
LI.Running•min^{-1} (m)	88.7 ± 9.3	64.1 ± 12.4
High-Speed Running•min^{-1} (m)	5.6 ± 2.2	2.7 ± 4.7
Sprinting•min^{-1} (m)	1.6 ± 1.5	.7 ± 2
Accelerations•min^{-1} (f)	.4 ± .2	.4 ± .2
Decelerations•min^{-1} (f)	.4 ± .1	.2 ± .1

Key; mins – minutes; sRPE-TL – sessional RPE training load; SRPETL-L - sessional RPE training load (leg muscle exertion); sRPETL-B – sessional RPE training load (breathlessness); au – arbitrary units; m – metres; f -frequency; sRPE – ratings of perceived exertion; sRPE-L – ratings of perceived exertion (leg muscle exertion); sRPE-B – ratings of perceived exertion (breathlessness)

4.3.3 Procedures

Each player's sRPE, sRPE-B, and sRPE-L were collected, in isolation, approximately 30 minutes after each training session using a standardised scale which has previously been used in soccer (Borg CR10) (Impellizzeri et al., 2004). All players had previous experience using the scale as part of their training monitoring. Each sRPE score was multiplied by session duration to calculate session loads (sRPE-TL) (Foster et al., 2001). During training and match-play, players wore commercially available GPS units (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27).These units have been utilised previously in analyses involving team sports (Weaving et al., 2018, Weaving et al., 2017, Jones et al., 2019). Velocity and acceleration dwell times were set at 0.6s and 0.4s respectively. The units include a GPS receiver and a triaxial accelerometer which collect data at 10Hz and 100Hz respectively. To avoid interunit error, each player wore the same GPS device for each session. After recording, data were downloaded to a computer and analysed via the software package Openfield (Software version 1.19, Catapult Sports, Melbourne, Australia). To minimise differences in data processing, the same software version was used to export training load data (Malone et al., 2017). The average satellite count was 10.73 ± 1.71, the average horizonal distribution of position was 0.78 ± 0.2. The variables selected to quantify external load were total distance (TD, m), PlayerLoad™ (PL, au), low intensity running (LIR, < 14.4km•h^{-1}, m), high-speed running (HSR, 19.8 - 24.98km•h^{-1}, m), sprinting (SPR, > 24.98km•h^{-1}, m), accelerations (ACC, > 2m•s^{-2} frequency) and decelerations (DEC < -2m•s^{-2}, frequency) expressed in their absolute units and per minute. PlayerLoad™ is derived from the 100Hz tri-axial stored within the receiver and is a measure of external load experienced by players (Barrett et al., 2014). Running based variables, and accelerations and decelerations were included due to their general use practically (Akenhead and Nassis, 2016) and are all measured at 10Hz.

4.3.4 Statistical Analysis

Complete data were obtained for almost 90% of sessions. Where data were missing, these were treated as missing at random and were primarily due to technical errors such as battery failure. Whilst use of correlation is a popular statistical method to quantify association between two variables, use of common measures, such as Pearson correlation, assume independence of error between observations (Bakdash and Marusich, 2017). However, assumptions of independence are contravened in repeated measures data, therefore initial assessment of relationships between variables was made using repeated measures correlation to reduce bias (Bakdash and Marusich, 2017, Gaudino et al., 2015). The thresholds <0.10 (trivial), 0.1 - 0.3 (small), 0.3 - 0.5 (moderate), 0.5 - 0.7 (large), 0.7 - 0.9 (very large) and > .9 (almost perfect) were used (Hopkins et al., 2009). Comprehensive assessments of relationships across all variables were made using PCA and EFA. PCA is a data reduction technique used to reduce the dimensionality of a dataset whilst maintaining variability (Weaving et al., 2014, Kaiser, 1960, Federolf et al., 2014). PCA is an explorative technique that is effective in describing structure among highly correlated variables. PCA produces a set of principal components (linear combinations of the original variables), each containing a set of variables that are correlated with each other; however, the principal components themselves are not correlated. Based on the assumption that data were missing at random, imputation of missing data was made using the imputePCA function from the missMDA package (Josse and Husson, 2016) in the statistical environment R. Suitability of data to perform PCA was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett test of sphericity (Bartlett, 1954). Prior to carrying out PCA, data within each variable were centred and scaled (Bro and Smilde, 2003). Number of components retained in the analysis was determined by visual inspection of the scree plot and the ‘elbow’ of the data. Final assessment of underlying structure of relationships between variables was made with EFA. EFA is also a data reduction technique, however whilst PCA simply creates linear combinations of the variables, EFA assumes that the measures observed are manifested by latent variables which can be allowed to correlate with each other. Additionally, solutions can be rotated to assist with useful interpretation of latent variables and as a result the underlying structure. EFA with oblimin rotation was carried out using lavaan version 0.5-23 (Rosseel et al., 2017) in the statistical environment R. To assess model adequacy, the Tucker-Lewis Index and root mean square error of approximation (RMSEA) were used. TLI and RMSEA are measures of model fit, with a TLI value of equal to or greater than 0.95 considered very good, and an RMSEA between 0.08 to 0.1 considered marginal (Dodd et al., 2010). Sensitivity analyses were conducted using the complete cases data set and did not provide any substantive changes, and so all results presented include those generated with the imputed data.

4.4 Results

Within-individual correlations across dRPE and external load measures are presented in Table 4.2. All variables measured were positively related to each other ($p < 0.001$), with correlations from 0.44 to 0.99 ($\bar{r} = 0.71 \pm 0.16$). Correlations were quantified between perceptual and external variables with measures expressed either per session or per minute

(Table 4.3). Correlations were similar for each of the sRPE measures and values were consistently lower when measures were expressed per minute.

Table 4.2 - Pearson correlations (r) for each training load measure for data collected from 20 male professional youth soccer players across a season

	sRPEL-TL	**sRPETL-B**	**Total Distance**	**PL**	**LIR**	**HSR**	**Sprinting**	**Accelerations**	**Decelerations**
	r	r	r	r	r	r	R	r	r
sRPE-TL	.93	.94	.86	.86	.85	.62	.44	.62	.7
sRPETL-L		.97	.82	.82	.82	.59	.44	.58	.68
sRPETL-B		-	.82	.82	.82	.59	.44	.58	.67
Total Distance			-	.98	.99	.74	.54	.65	.8
PL				-	.98	.71	.52	.67	.8
LIR					-	.65	.48	.64	.78
HSR						-	.68	.57	.65
Sprinting							-	.47	.58
Accelerations								-	.73

Key; sRPE-TL - sessional RPE training load; sRPETL-L - sessional RPE training load (leg muscle exertion); sRPETL-B – sessional RPE training load (breathlessness); PL - PlayerLoad ;LIR – Low-intensity running; HSR – High-speed running; All correlations were significant ($p<0.001$) and 95% Confidence Intervals less than ± 3 units.

Table 4.3 - Between-Individual correlations (95% CI) Between sRPE and sRPE-TL and the External Measures of Training Load.

Variable	**sRPE/sRPE-TL Corr. (Magnitude)**	**95% CI**	**sRPE-L/sRPEL-TL Corr. (Magnitude)**	**95% CI**	**sRPE-B/sRPEB-TL Corr. (Magnitude)**	**95% CI**
sRPE-TL (Absolute)						
Total Distance	.86 (VL)	.85 - .87	.82 (VL)	.81 - .83	.82 (VL)	.81 - .83
PlayerLoad	.86 (VL)	.85 - .87	.82 (VL)	.81 - .83	.82 (VL)	.81 - .83
LIR	.85 (VL)	.84 - .86	.82 (VL)	.80 - .83	.815 (VL)	.80 - .83
HSR	.62 (L)	.60 - .65	.59 (L)	.57 - .62	.59 (L)	.565 - .61
Sprinting	.44 (M)	.41 - .47	.44 (M)	.41 - .47	.44 (M)	.41 - .47
Accelerations	.62 (L)	.59 - .64	.58 (L)	.56 - .61	.58 (L)	.555 - .605
Decelerations	.70 (VL)	.68 - .72	.68 (L)	.66 - .7	.67 (L)	.65 - .69
sRPE (per min)						
Total Distance per min	.56 (L)	.54 - .59	.55 (L)	.52 - .57	.55 (L)	.53 - .58
PlayerLoad per min	.52 (L)	.5 - .55	.50 (L)	.48 - .53	.51 (L)	.48 - .54
LIR	.67 (L)	.65 - .69	.67 (L)	.64 - .69	.65 (L)	.63 - .67
HSR per min	.295 (S)	.26 - .33	.29 (S)	.25 - .33	.3 (M)	.27 - .34
Sprinting per min	.14 (S)	.11 - .18	.14 (S)	.1-.18	.15 (S)	.12 - .19
Accelerations per min	.14 (S)	.11 - .18	.13 (S)	.1 - .17	.15 (S)	.11 - .19
Decelerations per min	.38 (M)	.35 - .41	.37 (M)	.34 - .41	.37 (M)	.34 - .41

Key; sRPE-TL – sessional RPE training load; SRPEL-TL sessional RPE training load (leg muscle exertion); sRPEB-TL – sessional RPE training load (breathlessness); sRPE – ratings of perceived exertion; sRPE-L – ratings of perceived exertion (leg muscle exertion); sRPE-B – ratings of perceived exertion (breathlessness); LIR – low-intensity running; HSR – high-speed running; min – minute; Magnitude of the Correlation: T = Trivial, S = Small, M = Moderate, L = Large, VL = Very Large, NP = Near Perfect

PCA provided two readily interpretable principal components with eigenvalues greater than, or equal to, 1 ($PCA1_{eig}$ = 7.3, $PCA2_{eig}$ = 1.0) and cumulatively described 83.3% of the variance within the dataset (Table 4.4). The first principal component, which explained 72.9% of variance, demonstrated substantive contributions from all subjective and objective load variables. The second principal component, which explained 10.4% of variance, was best represented by contrasting sRPE measures and LIR with high intensity activities such as HSR, SPR and ACC (Figure 4.1).

Table 4.4 - Results of Principal Component Analysis showing the eigenvalue, percentage of variance explained, and cumulative percentage of variance explained by each principal component for all variables. As well as the component loadings for the principal components maintained (PC1 & PC2).

	Component	
	1	2
Eigenvalue	7.29	1.04
% of Variance	72.9	10.4
Cumulative Variance %	72.9	83.3
Component Loadings		
sRPE-TL	0.91	-0.3
sRPETL-L	0.89	-0.34
sRPETL-B	0.88	-0.33
Total Distance	0.95	-0.07
PlayerLoad	0.94	-0.04
LIR	0.93	-0.15
HSR	0.78	0.39
Sprinting	0.62	0.64
Accelerations	0.74	0.31
Decelerations	0.85	0.21

Key; ; sRPE-TL – sessional RPE training load; SRPETL-L sessional RPE training load (leg muscle exertion); sRPETL-B - sessional RPE training load (breathlessness); LIR – low-intensity running; HSR – high-speed running

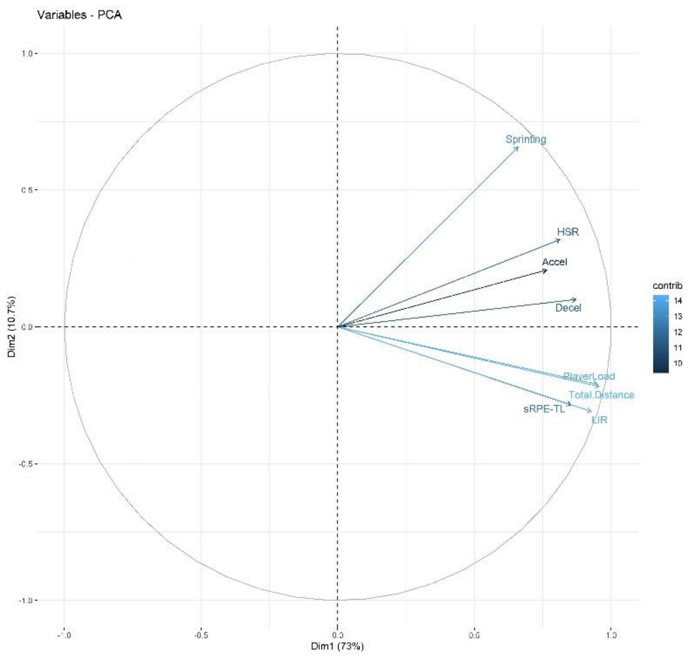

Figure 4.1 – PCA biplot showing scaled eigenvector arrows for each objective and subjective training load variable. Key; sRPE-TL – sessional RPE training load; LIR – low-intensity running; HSR – high-speed running Accel – accelerations; Decel – decelerations; Dim1 – Dimension 1 (1st principal component); Dim2 – Dimension 2 (2nd principal component) Contrib – scale of contribution value of each individual variable to relevant principal components.

EFA was conducted, the most appropriate model produced four latent factors (Table 4.5) with correlations between 0.5 and 0.8. The correlations between factors ranged from 0.5 to 0.8. The model had a Tucker-Lewis Index (TLI) of 0.97 and RMSEA of .10 (90% CI 0.10 – 0.11). Four factors produced were identified as: 1) Objective volume (TD, PL, LIR); Objective running (HSR and SPR); Subjective measures (sRPE-TL, sRPETL-L and sRPETL-B); and 4) Objective high intensity (SPR, ACC, DEC) based on loadings. EFA was carried out with only sRPE-TL from the subjective measures and the most appropriate model included three latent factors (TLI = 0.967 and RMSEA 0.12 [90%CI 0.11 - 0.13]) identified as: 1) Volume (sRPE-TL, TD, PL and LIR); 2) Intense running (HIR and SPR); and 3) Intense actions (ACC and DEC) (Table 6).

Table 4.5 - Results of Exploratory Factor Analysis showing the loadings of each factor identified with a cut-off of 0.3. Each factor has been given a representative heading based on the variables with the heaviest loadings

	Factor 3 (Subjective Measures)	Factor 1 (Objective Volume)	Factor 4 (High Intensity Objective)	Factor 2 (Objective Running)
sRPE-TL	.791			
sRPETL-L	.991			
sRPETL-B	1.016			
Total Distance		.91		
PlayerLoad		.83		
LIR		1.008		
HSR				.922
Sprinting			.396	.504
Accelerations			.720	
Decelerations			.799	

Key; sRPE-TL – sessional RPE training load; SRPETL-L sessional RPE training load (leg muscle exertion); sRPETL-B – sessional RPE training load (breathlessness); LIR – low-intensity running; HSR – high-speed running

Table 4.6 - Results of Exploratory Factor Analysis only including sRPE from subjective measures. Each factor has been given a representative heading based on the variables with the heaviest loadings

	MR1 (Volume)	MR3 (Intense Actions)	MR2 (Intense Running)
sRPE-TL	.741		
Total Distance	.947		
PlayerLoad	.852		
LIR	1.041		
HSR			.892
Sprinting			.557
Accelerations		.743	
Decelerations		.805	

Key; sRPE-TL – sessional RPE training load; LIR – low-intensity running; HSR – high-speed running

4.5 Discussion

Understanding the relationships between subjective training load measures and external training load measures can provide practitioners with information to better understand training and match play load. This study aimed to assess the relationship between subjective measures of training load and commonly used objective metrics measured via GPS. Whilst the various measures are positively correlated with each other PCA and EFA provided distinctions between characteristics of metrics. Therefore, there is potential to obtain more useful information by collecting data on multiple variables. However, for the population and physical loads investigated in the present study, the results suggested that RPE measures (sRPE-TL, sRPETL-L, and sRPETL-B) are not distinct and that they are more closely related to objective volume measures of training load than measures of intensity.

The results from the repeated measures correlation suggest that dRPE was related to all measures of external training load and , in line with previous findings (Gaudino et al., 2015), this relationship was weaker when expressed as ‘per minute’. Gaudino et al. (2015) previously investigated the relationship between sRPE-TL and external measures of training load in professional soccer players. They found that sRPE-TL was significantly related to high-speed distance (r = .61 (95%CI .58 - .64)), impacts, a combination of collisions and step impacts whilst running, (r = .73 (95%CI .71 – .75)) and accelerations (r = .63 (95%CI .60 - .66)). This relationship was weaker than when variables were expressed as ‘per minute’ for sRPE and high-speed distance per minute (r = 0.26 (95%CI 0.21 - 0.30)), impacts per minute (r = 0.23 (95%CI 0.19 - 0.27)) and accelerations per minute (r = 0.30 (95%CI 0.26 - 0.34)). These results are similar to our findings where we showed moderate to very large correlations, ranging from 0.44 to 0.86, between each dRPE reading and external measures of training load, which were then lower, 0.13 to 0.67, when expressed per minute. Previous research has suggested that this may be due to the multifactorial nature of precepting session intensity (Gaudino et al., 2015). However, we would suggest it is also likely due to the large component of duration in sRPE-TL calculation, and the ‘frequency’ nature of the GPS metrics commonly included in studies.

Stronger relationships (Very Large) were measured for sRPE-TL, sRPETL-L, and sRPETL-B, with TD, PL and LIR. These findings are similar to results published by McLaren et al. (McLaren et al., 2018a) in team sports which showed “Likely Large” to “Possibly Very Large” inferences between sRPE-TL and accelerometer load and TD respectively. They also showed “Likely Moderate” and “Unclear” relationships between sRPE-TL and high-speed running distance (≥13.1 - 15.0km•h^{-1}) and very high-speed running distance (16.9 - 19.8km•h^{-1}) respectively. McLaren et al. (2018a) surmised that these differences may be due to a number of factors including; measurement error of GPS devices (Rampinini et al., 2015, Johnston et al., 2014), individual differences in the velocity at which physiologically high intensities are attained (Buchheit and Laursen, 2013, Abt and Lovell, 2009) or the non-linear relationship between running velocity and internal exercise intensity (Faude et al., 2009).

Attempts to move beyond bivariate relationships and assess more in-depth relationships were initiated with PCA. The analysis has been suggested to provide useful information to practitioners as it more clearly indicates the uniqueness between sets of variables (Weaving et al., 2014, Williams et al., 2017). PCA provided two readily interpretable components that cumulatively described 83.3% of the variance within the dataset. The PCA biplot (Figure 4.1) displays the eigenvector arrows for each training load variable. The first principal component accounted for 72.9% of the total variance in the data and represented a relatively simple and equal weighted sum of all the measures. This was expected due to the large positive correlations obtained between all measures and identified that whilst there were aspects of uniqueness, the variables tended to provide similar information and thereby represented a measure of total training load. The second principal component accounted for 10.4% of the total variance and contrasted sRPE-TL measures and LIR with SPR and HIR. This second component could be interpreted as providing differential information between volume and high intensity, or high intensity and perceptions of effort. These findings are similar to those reported by Weaving et al. (2014) with professional rugby league players. The authors also identified more than one principal component for various modes of training with an initial component representing a balanced sum and that subsequent components tended to contrast internal and external load measures.

Weaving et al. (2014) proposed that the intermittent nature of small-sided games results in a prolonged external-load component, ultimately leading to a high internal load response. As small-sided games were used frequently in the training of the players investigated in the present study, possibly explaining the similarity in results obtained. Conversely, previous research in soccer showed no correlation between sRPE-TL and external load variables, except for a small correlation with PlayerLoad™ (Casamichana and Castellano, 2015). The findings of Weaving et al. (2014) suggest that during small-sided games, the load measures account for a similar amount of the variance explained by the single principal component suggesting a single measure of training load may be sufficient to monitor training load. Conversely the findings of Casamichana and Castellano (2015) suggest that, due to low correlations between measures, a range of indicators are required to best understand training load. Our findings appear to support both arguments for global training. The large amount of variance explained by the first principal component support the findings of

Weaving et al. (2014), however if practitioners wish to further understand the volume and intensity of training then complementary measures may be required.

The initial EFA identified four latent factors that were interpreted as: 1) objective volume; 2) objective running based; 3) subjective measures; and 4) objective high-intensity measures. Combined with the very high correlations amongst the three sRPE-TL measures ($r > 0.93$), these grouping suggest that there was minimal distinction between different sRPE-TL measures and that for the population and physical loads investigated there would be limited benefit measuring all three. Removing sRPETL-B and sRPETL-L from the analysis and only using sRPE-TL as a subjective measure changed the structure of the factor analysis, reducing the model to three-factors, with sRPE-TL aligning with objective measures of volume. Collectively, these findings indicate that for the population and physical loads investigated sRPETL-L and sRPETL-B providing essentially the same information as sRPE-TL and that this information reflects primarily the training volume completed. Findings regarding dRPE across the literature have been contradictory. McLaren et al. (2018b) reported moderate (10% ± 90%CL 8.4) differences between weekly sRPETL-B and sRPETL-L in Championship Rugby Union players. Whereas, Los Arcos et al. (2016) found only trivial differences (ES = -0.17 ± SD 0.63) between sRPETL-B and sRPETL-L in young professional soccer players during full match-play. However, further research by McLaren et al. (2016a) found clear and large differences between sRPETL-B and sRPETL-L at all time points during incremental treadmill and cycling laboratory based tests. These differences may be due to a number of factors, including the activity assessed, participant demographic and participant familiarity with test protocols. The results from the present findings indicate that in a cohort of youth soccer players, dRPE is unnecessary and does not provide unique information compared with sRPE.

There are limitations to our study which should be considered. Firstly, we did not include rehabilitation or gym sessions within the analysis. Whilst this does provide an incomplete view of training load across a season, it won’t affect the relationship between variables. However, use of different training modalities, such as those used in rehabilitation, may affect the relationship between dRPE measures and support its use. The lack of HR data also didn’t allow comparisons between sRPE-TL and an objective measure of internal training load, which may provide a better relationship with sRPETL-B. It could also be argued that sRPE-TL is too simplistic a measure to assess diverse physiological goals, however due to its ease of use and relationship with internal load it is commonly used in team sports. A recent paper has also suggested its use to monitor biochemical and mechanical stresses, thus again supporting the use of dRPE (Vanrenterghem et al., 2017). This should be considered by practitioners looking to assess global training load, or more specific load to assess resultant adaptations.

4.6 Conclusion

There are strong correlations between sRPE-TL, sRPETL-L and sRPETL-B, and external training load variables. Variables which could be considered as measures of volume had the strongest correlations. Further analysis showed that 2 principal components explained 83.4% of the variance in the dataset. The first principal component had large component loadings from all variables, whilst the second had contributions from variables related to high intensity. The large component loadings in the first principal component suggest that these metrics may be providing practitioners with similar information regarding load. Exploratory factor analysis provided four themes, one of which was represented by all dRPE measures. When only including sRPE-TL in the analysis the structure of the factors changed, with sRPE-TL aligning to objective measures of volume.

Chapter 5 – The Impact of Training Theme on Training Load Measures in Youth Soccer Players

5.1 Prelude

A range of internal and external load metrics are collected and analysed within professional soccer. Understanding the relationships between metrics can aid practitioner understanding when designing and planning training alongside match load. Following multivariate analyses, it would appear that whilst all measures are correlated with each other there are distinct relationships between metrics. Whilst previous research has suggested that there is potential to collect more specific and detailed subjective information via dRPE, this analysis would suggest that differential measures are not distinct, questioning the use of multiple subjective measures in an applied environment. Additionally, it would appear that subjective measures of load are closely related to objective measures of volume, rather than intensity. This analysis provides information on a general level, however given potential variations in training and match theme further research is required to ascertain the stability of these relationships and will be investigated in chapter 5.

For practitioners to have confidence regarding the relationships between subjective and external load measures, greater understanding regarding the contextual factors which influence these is required. Having greater understanding of the influence of training theme or impact of competition on relationships will provide further understanding regarding the stability of relationships between measures. Traditionally, soccer training sessions are categorised based on their proximity to match-day (e.g., MD-1, MD-2, etc.). Theoretically, the aims and objectives of these sessions will be varied, with specific technical, tactical, and physical qualities targeted within specific sessions. Therefore, the aim of this chapter is to further investigate the relationships between subjective and external measures of load in professional youth soccer players, whilst accounting for the effect of training theme, or competition.

5.2 Introduction

Load monitoring is common practice in elite sport where coaches and practitioners prescribe and adjust training to maximise performance and reduce injury risk (Drew and Finch, 2016). Load monitoring is seen as a complex and vital aspect of preparing team sport athletes that engage in a wide range of training activities and are required to perform near maximum capacity frequently during the competitive season. Survey research conducted in professional soccer identified that load monitoring is widely used and identified that a wide range of load measures were collected (Akenhead and Nassis, 2016). Monitoring practices generally track physical work completed by the player, characterised as external load, alongside monitoring of the physiological response, characterised as internal load (Halson, 2014).

Due to the lack of a criterion measure of load, the majority of research studies have simply investigated the validity of measures of load against other available measures (Scott et al., 2013a). However, there are many complexities that have been identified with regards to load measurement including the multifactorial nature of the physiological response, and divergent individual response in terms of absolute values and the relationship between external and internal values. Additionally, the relationship between internal and external load metrics has been shown to alter based on the mode of training, providing an additional consideration for practitioners (Weaving et al., 2014). Alexiou and Coutts (2008) with women soccer players reported a range of correlation coefficients between sRPE-TL and Banister's TRIMP of 0.74, 0.49, 0.61, 0.68 and 0.25 for sessions classified as conditioning, matches, speed, technical and resistance, respectively. A similar range of correlation coefficients demonstrating different relationships with training types were also presented for Lucia's TRIMP (0.34 - 0.75) and Edward's summated HR scores method (0.52 - 0.82) (Alexiou and Coutts, 2008).

Given findings of previous research demonstrating divergence of metrics across different training contexts, it has been suggested that training load measures used individually or in combination, should be analysed based on the training theme (Weaving et al., 2014). Using five variables to quantify load, the authors' first assessed the underlying structure of relationships between measures during rugby league training via correlation analysis and PCA (Weaving et al., 2014). Sessions were categorised as small-sided games, conditioning, skills, speed, strongman, and wrestle, PCA was performed to reduce the dimensionality of the dataset. Using this technique, more than one principal component for four of the six training themes (skills, speed, wrestle, and strongman training) was identified. They also found that for these modes of training, the component loadings for each of the load variables appeared to order themselves into groups of internal or external measures (Weaving et al., 2014). Furthermore, the mode of training appeared to affect whether the first principal component, that explains the most variance, loaded towards internal or external measures.

Further assessment of training practices in professional rugby league revealed the potential for multiple and contrasting components for different training types (Weaving et al., 2017). Using the same PCA techniques as implemented in their previous study (Weaving et al., 2014), the authors assessed the underlying structure of load measures for sessions categorised as skills and conditioning, identifying one principal component (56.6 % of variance) for the skills sessions and two principal components (combined 85.4% of variance) for the conditioning sessions. In the original analysis only one principal component which explained 51.8% of the variance in conditioning training was retained (Weaving et al., 2014). Collectively, this research suggests that multiple measures are likely required to appropriately characterise the load experienced by team sport athletes.

The use and successful implementation of ‘tactical periodisation’ has led to increased interest in its use in professional soccer (Delgado-Bordonau and Mendez-Villanueva, 2012). Planning sessions in this way also allows specific outcomes to be targeted, with specific physical, technical, and tactical aims alternated through a training week. It has also been suggested that planning using this method may minimise fatigue accumulation, as focussing on a given quality may allow other physical qualities to recover. (Buchheit et al., 2018). It is likely that the training methodology employed will be largely influenced by senior coaches, however, if training days were categorised targeting specific outcomes, then it would be beneficial for practitioners to select load measures to reflect objectives.

The aim of this chapter was to quantify and describe relationships between sRPE-TL and external measures of load in soccer players across sessions with different characteristics. The study incorporated analysis methods previously used to assess underlying structure of the relationships between variables and their ability to summarise the response (Weaving et al., 2017, Weaving et al., 2014). Increased knowledge in the context of soccer will support practitioners by evidencing a process to support the selection of variables to monitor when training has a planned outcome.

5.3 Methods

5.3.1 Experimental Approach to the Problem

The present study employed a prospective design with data collection across a 47-week season with Scottish professional youth soccer players. The data collection periods comprised a 6-week pre-season and two competitive phases lasting 20 weeks, and 19 weeks, respectively. The competitive phases were split by a 2-week winter break. Subjective measures of training load were collected via sRPE. Objective measures of training load were collected via commercially available GPS units. Data were collected for all training sessions and matches across the data collection period. Sessions in the lead up to a match, alongside match play recordings were assessed. Data collected and the retrospective nature of the data analysis conformed to the University of Glasgow research policies and were in accordance with the Declaration of Helsinki.

5.3.2 Participants

Twenty male professional youth soccer players (age 17.4 ± 1.3 yrs, height 178.0 ± 8.1 cm, mass 71.8 ± 7.2kg) were recruited during the 2018/19 season. Participants comprised multiple positions, with data collected from goalkeepers removed from the final analyses. Data recorded from a small selection of non-representative training sessions were removed to limit the influence of outliers (Malone et al., 2015). Only data recorded from team training (defined as sessions comprising both starting and non-starting players) were included in the analysis, with post-match training for non-starters (top-ups), rehabilitation training and non-pitch-based sessions such as gym-based recovery or resistance training sessions excluded. . Sessions in the lead up to a match, alongside match play recordings were included in the analysis. Sessions which took place in the days succeeding a match (i.e. MD+1/MD+2) or those that were not considered to be in preparation for a match, were discounted. This left a total of 2827 recordings consisting of 696 match play recordings and 2131 training recordings, including a mean of 134.6 ± 44 recordings per player with a range of 3 to 179 recordings per player.

5.3.3 Procedures

Session rating of perceived exertion scores was collected, in isolation, approximately 30 minutes after each training session using a scale previously used with soccer players (Foster et al., 1995, Impellizzeri et al., 2004). All players had previous experience using the scale. Each sRPE score was multiplied by session duration to obtain sRPE-TL (Foster et al., 2001). Players wore commercially available GPS Units (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27) previously used in research conducted in team sports (Weaving et al., 2018, Weaving et al., 2017, Jones et al., 2019). The units included a GPS receiver and a triaxial accelerometer collecting data at 10 Hz and 100 Hz, with velocity and acceleration dwell times set at 0.6 s and 0.4 s, respectively. Each player wore the same device for each session (Scott et al., 2016). Data were downloaded and analysed via the software package Openfield (Software version 1.19, Catapult Sports, Melbourne, Australia). Average satellite count was 10.7 ± 1.7 , the average horizontal dilution of precision (HDOP) was 0.8 ± 0.2. Variables selected to quantify external load were total distance (m); PlayerLoad (au); low intensity running (< 14.4 km•h^{-1}, m), running (19.8 - 24.98 km•h^{-1}, m); sprinting (> 24.98 km•h^{-1}, m); accelerations (> 2 m•s^{-2} frequency); and decelerations (< -2 m•s^{-2}, frequency).

5.3.4 Statistical Analysis

Where data were missing, these were treated as missing at random and imputed using the MICE package (Buuren and Groothuis-Oudshoorn, 2010). Relationships between sRPE-TL and external training load measures were quantified for each training day using Pearson's product moment correlation. Training and match load data were prepared for PCA by visually inspecting the correlation matrix to assess the factorability of the dataset (Tabachnick et al., 2007). PCA was performed on the correlation matrix of variables as metrics were on different scales. The suitability of data were then assessed using KMO measure of sampling adequacy, and the Bartlett test of sphericity (Bartlett, 1954). KMO (~chi-square) values were: 0.84 (10018), 0.75 (7443), 0.69 (2689), 0.77 (4236), and 0.72 (2205) for MD, MD-1, MD-2, MD-3 and MD-4, respectively. All tests of sphericity were significant ($p<0.001$). A KMO value of 0.5 or above has previously been identified as a suitable result to perform PCA (Hair et al., 1998, Kaiser, 1960), and has been used in similar research (Weaving et al., 2017, Weaving et al., 2014). Principal components with an eigenvalue >1 were retained for extraction (Kaiser, 1960). Briefly, an eigenvalue is a measure of how much variance there is in the data, therefore the component with the highest eigenvalue will be that which explains the majority of variance. When two or more principal components were retained based on their eigenvalue, varimax rotation was performed. For each retained principal component, only the original load variables with a principal component loading of >0.7 were retained (Hair et al., 1998). All analysis was carried out in the statistical environment R (R Foundation for Statistical Computing, Vienna, Austria, version 3.6.2).

5.3.5 Results

There were 2827 individual recordings included in the analysis, comprising of 696 MD recordings and 2131 training session recordings. Distribution of the mean training loads for match play and each training day are presented in Table 5.1. Results demonstrated that mean values for duration and all load variables were highest on MD and lowest on MD-1. MD-3 was characterised by higher mean values for external load variables in comparison to MD-2 and MD-4.

Table 5.1 – Distribution of mean training loads for match-day and each categorised training day across a season in professional youth soccer players

	Duration (mins)	sRPE-TL (au)	Total Distance (m)	PlayerLoad (au)	LIR (m)	HSR (m)	Sprinting (m)	Accel (f)	Decel (f)
MD	71.4 ± 28.3	548 ± 272	7973 ± 3291	821 ± 345	6275 ± 2578	377 ± 201	98.8 ± 90.4	27.1 ± 14.3	24.6 ± 12.6
MD-1	54.5 ± 12.2	246 ± 96.4	3802 ± 1055	434 ± 119	3356 ± 833	80.2 ± 92	14.0 ± 31.1	18.4 ± 8.44	11.3 ± 6.03
MD-2	65.1 ± 16.4	361 ± 143	4630 ± 1129	523 ± 131	3977 ± 938	134 ± 104	25.9 ± 38.7	23.9 ± 9.43	15.9 ± 8.03
MD-3	65.2 ± 16.1	381 ± 158	5343 ± 1742	591 ± 192	4479 ± 1358	197 ± 185	57.7 ± 63.7	23.3 ± 10.7	16.2 ± 8.68
MD-4	59.3 ± 11.9	325 ± 108	4599 ± 1078	528 ± 128	3912± 861	161 ± 173	30.1 ± 50.0	22.3 ± 10.4	14.7 ± 7.08

Key; MD – match day; MD-1 – training day prior to MD; MD-2 - training day two days prior to MD; MD-3 – training day three days prior to match day; MD-4 training day four days prior to match day; mins – minutes; sRPE-TL - sessional RPE training load; m – metres; au – arbitrary units; f - frequency; LIR – low-intensity running; HSR – high-speed running; Accel – accelerations; Decel - decelerations

Correlations including 95% confidence intervals for match-play and training are presented in Figure 5.1. Total Distance, PlayerLoad and LI.Running showed large to very-large correlations with sRPE-TL. High-Speed Running showed small to large correlations, whilst Sprint Distance showed trivial to moderate correlations. Finally, accelerations showed moderate correlations, whilst decelerations showed small to large correlations with sRPE-TL.

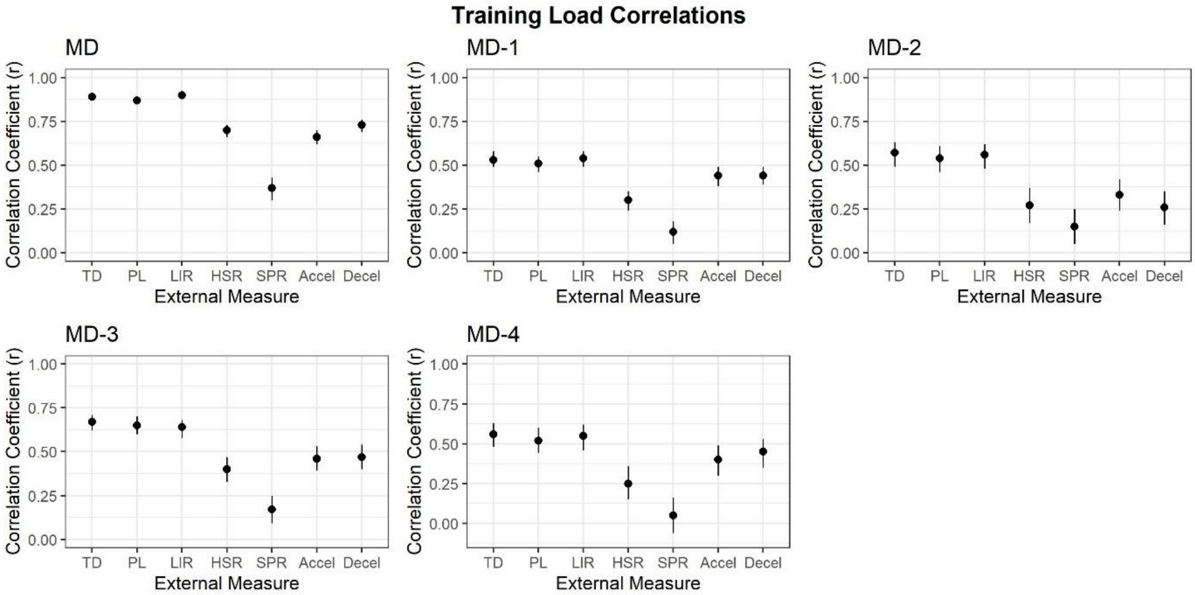

Figure 5.1 - Pearson’s product moment correlations between sRPE-TL and all external load measures (error bars represent 95% CI). TD - Total Distance, PL - PlayerLoad, LIR - Low intensity running, HSR – High- speed running, SPR - Sprinting, Accel - Accelerations, Decel - Decelerations.

Results of the PCA are presented in Table 5.2. Two principal components were identified for MD, MD-1, MD-3 and MD-4, whilst three principal components were identified for MD-2. Variance explained and loadings are presented for the components following varimax rotation. The components explained 89.72%, 71.31%, 80.02%, 74.15% and 72.86% of the variance for MD, MD-1, MD-2, MD-3 and MD-4 respectively.

Table 5.2 – Principal component analysis results for each category of training and match-day data.

	Principal Component				Principal Component		
	1	2	3		1	2	3
MD				MD-3			
Eigenvalue	6.1	1.1	-	Eigenvalue	4.9	1.1	-
% of Variance	76.0	13.7	-	% of Variance	60.6	13.5	-
Cumulative Variance %	76.0	89.7	-	Cumulative Variance %	60.6	74.25	-

	Rotated Component				Rotated Component		
	1	2	3		1	2	3
% of Variance	54.2	35.5	-	% of Variance	45.9	28.2	-
Rotated Component Loadings				Rotated Component Loadings			
	1	2	3		1	2	3
sRPE-TL	**0.89**	0.30	-	sRPE-TL	**0.79**	0.14	-
Total Distance	**0.94**	0.30	-	Total Distance	**0.89**	0.35	-
PlayerLoad	**0.91**	0.37	-	PlayerLoad	**0.89**	0.32	-
LIR	**0.96**	0.24	-	LIR	**0.92**	0.21	-
HSR	0.58	**0.72**	-	HSR	0.29	**0.72**	-
Sprinting		**0.94**	-	Sprinting		**0.89**	-
Accelerations	0.49	**0.77**	-	Accelerations	0.44	0.60	-
Decelerations	0.59	0.69	-	Decelerations	0.58	0.56	-
	Principal Component				Principal Component		
	1	2	3		1	2	3
MD-1				MD-4			
Eigenvalue	4.52	1.18	-	Eigenvalue	4.34	1.49	
% of Variance	56.55	14.75	-	% of Variance	54.22	18.65	
Cumulative Variance %	56.55	71.31	-	Cumulative Variance %	54.22	72.86	
	Rotated Component				Rotated Component		
	1	2	3		1	2	3
% of Variance	50.74	20.57	-	% of Variance	51.35	21.52	
Rotated Component Loadings				Rotated Component Loadings			
	1	2	3		1	2	3
sRPE-TL	0.69		-	sRPE-TL	0.68		-
Total Distance	**0.89**	0.28	-	Total Distance	**0.91**	0.21	-
PlayerLoad	**0.91**	0.16	-	PlayerLoad	**0.91**	0.13	-
LIR	**0.91**	0.13	-	LIR	**0.93**		-
HSR	0.39	**0.76**	-	HSR	0.24	**0.86**	-
Sprinting		**0.92**	-	Sprinting		**0.90**	-
Accelerations	0.68	0.15	-	Accelerations	**0.7**	0.29	-
Decelerations	**0.71**	0.3	-	Decelerations	**0.76**	0.13	-
	Principal Component						
	1	2	3				
MD-2							
Eigenvalue	4.15	1.23	1.02				
% of Variance	51.90	12.72	12.72				
Cumulative Variance %	51.90	67.30	80.02				
	Rotated Component						
	1	2	3				
% of Variance	39.60	20.74	19.68				
Rotated Component Loadings							
	1	2	3				
sRPE-TL	0.69	0.15					
Total Distance	**0.92**	0.21	0.25				
PlayerLoad	**0.88**	0.27	0.17				
LIR	**0.95**	0.16					
HSR	0.25	0.15	**0.81**				
Sprinting			**0.88**				
Accelerations	0.23	**0.86**	0.14				
Decelerations	0.22	**0.85**	0.12				

Key; MD – match day; MD-1 – training day prior to MD; MD-2 - training day two days prior to MD; MD-3 – training day three days prior to match day; MD-4 training day four days prior to match day; mins – minutes; sRPE-TL - sessional RPE training load; LIR – low-intensity running; HSR – high-speed running

5.4 Discussion

The main findings of the current study are the identification of multiple components in training days in the lead up to, and including, match play which differ across training day. This suggests that univariate assessments of load are insufficient when characterising the load experienced by players in training and match play. These findings are similar to those reported in professional rugby league players (Weaving et al., 2017, Weaving et al., 2014). Whilst match-play and three of the four training days produced two components; MD-2 identified three principal components. Analysis of the components revealed clear structures. Where two components were extracted, these showed that the first component was generally characterised by measures of training volume (Total Distance, PlayerLoad and LI.Running). The second component was characterised by measures of intensity (Running, Sprinting, Accelerations and Decelerations). Where three components were extracted, these followed a similar pattern, but the intensity measures were split with accelerations and decelerations present in the second component and running and sprinting within the third component. Where sRPE-TL was present within the components, it loaded in component one as a volume-based measure.

The findings of the present study coincide with those generated in professional rugby league players (Weaving et al., 2017, Weaving et al., 2014) demonstrating that a single training load measure is unable to capture the variance of multiple measures across different training themes. This has further implications for practitioners when investigating load response relationship with performance or injury, as a multivariate analysis may provide more clarity than univariate assessments (Weaving et al., 2017, Williams et al., 2017) All training days analysed in the present study produced 2 or 3 principal components explaining 71.3% to 89.7% of the cumulative variance. As with previous findings the component loadings appeared to reflect either training volume or intensity (Weaving et al., 2014). In the present study during match play the highest loadings for component one were; sRPE-TL (0.89), total distance (0.94), PlayerLoad (0.91) and low-intensity running (0.96). Conversely, for component two the highest loadings were for HSR (0.72), sprinting (0.94) and accelerations (0.77). Weaving et al. (Weaving et al., 2017) in their second study of professional rugby league players showed that variables that loaded in the first component alternated between measures of internal or external training load. In the present study only a single measure of internal load was collected and therefore we were unable to assess the reproducibility of this pattern.

The finding of two or three components is key as it suggests, as proposed by Weaving et al. (Weaving et al., 2014, Weaving et al., 2017), that the use of a single load measure will be unable to capture the complexity of the training response. Their finding that the PCA results were linked to the type of training session provides further support for the use of multiple training measurements to characterise training response in team sport players (Weaving et al., 2017). Selection of training load variables, and the methods used will affect the outcome of any dimension reduction technique such as PCA and potentially limit comparisons that can be made between studies (Weaving et al., 2017). Initially Weaving et al. (Weaving et al., 2014) used an arbitrary threshold of >15km•h^{-1} to assess high speed distance, which was then unable to account for additional variance during conditioning training. In their follow up study, they assigned high-speed distance thresholds individually based on results from a 30 - 15 Intermittent Fitness Test. They suggested this is a potential reason for the extraction of a second principal component for training categorised as conditioning, which was heavily loaded by high-speed distance and explained a further 29.4% of the variance. This individualisation, alongside systematic selection of load variables that have been shown to identify a dose-response relationship with training outcomes such as changes in fitness or performance (Akubat et al., 2012, Lovell et al., 2013, Manzi et al., 2009) is likely to lead to a more effective multivariate training load assessment model. These findings highlight opportunities for collaborations between researchers and practitioners to best determine procedures for selection of metrics, as well as methods of feedback specific to training modes. To achieve this the variables selected should be related to outcomes of injury, or changes in performance (Weaving et al., 2017). Whilst assessing the relationship between load and performance or injury was out with the scope of this article, it does appear that to assess training volume sRPE-TL could be used in combination with either total distance, PlayerLoad or low-intensity running. Whilst assessing intensity alongside this may be achieved by assessing running or sprinting distance.

A limitation of the current study includes categorisation of training based on proximity to MD rather than classifying sessions. This was done because soccer training sessions are generally categorised based on proximity to MD. However, categorisation of individual training sessions may lead to different results and linking these to more specific training themes could provide practitioners with information to aid training prescription and monitoring. If a day was categorised by larger pitch areas it is likely that alongside more total distance covered, practitioners may also identify higher values of running and sprinting activity. Conversely on days involving smaller-pitch sizes it may be that acceleration and deceleration efforts are more prevalent. Additionally, we did not account for the effect of starters vs non-starters in the analysis. Finally, practitioners should consider the reproducibility of this analysis within their own environments given we used data from a single team. Future research may also wish to include further analysis using internal load markers such as training impulse (TRIMP) to provide a broader understanding of the relationship between internal and external measures of load. Additionally, future research may also wish to include some reference to the prescribed load for players to give reference to relationships between actual load performed and programmed load.

5.5 Conclusion

To conclude, the current study provides further evidence that a single measure of training load is not sufficient to assess the load experienced by players in training and match play. Clearer categorisation of training themes, relative to match play, may provide greater insight to practitioners and improve monitoring practices and feedback of information. Future research using soccer players and potentially investigating labelling using different methods of categorising training sessions is required.

Chapter 6 – The Impact of Stage of Season on Training Load Measures in Youth Soccer Players

6.1 Prelude

Whilst it has been identified that there is a high level of multi-collinearity between training load measures, the variability when considering context of training theme suggests that a univariate approach to load monitoring is insufficient. The analyses in chapter 5 have identified relatively consistent relationships across training themes, with common measures of training volume being related, and while there was a strong relationship between measures of intensity it appears to be more variable. Subjective measures of load appear to relate strongly with objective measures of training volume, but not with measures related to intensity. Consideration of the effect of stage of season would be advantageous to practitioners, to identify whether these relationships remain consistent across pre-season and competitive phases and so will be considered in chapter 6.

The purpose of this chapter was to assess the relationships between subjective and external measures of training load in professional youth soccer players, whilst accounting for the effect of the stage of the season. Theoretically, the aims and objectives of training at different stages of the season will be varied, with greater emphasis placed on physical development within the pre-season phase. This modified focus of training may lead to variability of the multivariate relationships between load measures. Greater understanding of this will give practitioners greater confidence regarding the stability of these relationships.

6.2 Introduction

Soccer match play is characterised by frequent high intensity accelerations, decelerations, and running (Whitehead et al., 2018). As such, soccer training aims to prepare players for the physical demands of match play, alongside developing technical, tactical, and psychological understanding. Due to the high physical demands involved, match play and training to prepare soccer players can also present substantive risk of injury (Peterson et al., 2000). With the aim of improving performance, and reducing the risk of injury, practitioners supporting professional soccer players routinely monitor the physical load experienced by players (Drew and Finch, 2016). Whilst this route of investigation is common, it has been suggested that current practices relating load monitoring with injury are lacking in substantial evidence, possibly due to the shortcomings of available univariate load metrics (Kalkhoven et al., 2021) Load and the subsequent adaptations generated, can be characterised as being either physiological or biomechanical (Vanrenterghem et al., 2017). Features of training load describing the magnitude and amount of the physical work are considered the external load (Impellizzeri et al., 2019, Vanrenterghem et al., 2017), whereas, features describing the resultant physiological and biomechanical response are characterised as the internal load (Impellizzeri et al., 2019, Vanrenterghem et al., 2017). Generally, practitioners monitor prescribed physical work, which is represented by external load, alongside the players response which is characterised as the internal load (Vanrenterghem et al., 2017, Impellizzeri et al., 2019). A central aim of research is to accurately model relationships between external and internal load to create more effective and responsive training stimuli to enhance physical performance and its expression during match play (Halson, 2014).

A range of technologies, variables, data processing and analysis techniques are used when monitoring internal and external load. Common approaches to monitor internal load include subjective measurements such as sRPE-TL and objective measurements including HR based assessments in the form of TRIMP and time spent in specific HR zones (Impellizzeri et al., 2004). Development of technologies such as GPS and accelerometers has increased the availability of external load variables which are now common in professional soccer (Akenhead and Nassis, 2016). Whilst advances in technology and greater dissemination of research-based practices has made continuous load monitoring an essential component of elite athlete support, the lack of criterion measures of load has led practitioners to collect a range of variables posing a challenge to clear interpretation of the data (Weaving et al., 2014). Initial attempts to assess validity of outcomes or identify underlying structures to reduce the dimensionality of data have been achieved by comparing all measures against each other using correlation or principal component approaches, respectively (Weaving et al., 2014). Research investigating underlying structure has generally found that measures representing either the internal or external load are strongly related to each other (Weaving et al., 2014). However, as shown in Chapters 5, and via previous research, relationships between load monitoring variables may be influenced by different training modes (Weaving et al., 2017, Weaving et al., 2014). When comparing the results reported in Chapter 5, and research in rugby league (Weaving et al., 2017), different sports may display varying underlying relationships. Previous research in rugby league showed significant effects of training mode on relationships between internal and external load measures (Weaving et al., 2014). Similar findings were found in a follow up study in rugby league comparing relationships between load measures during skills and conditioning focused training sessions (Weaving et al., 2017). In contrast, the previous analyses in Chapter 5 in professional youth soccer found no changes in underlying structure when categorising training sessions based on their proximity to match day (e.g., MD-1, MD-2). In accordance with the analyses carried out within Chapter 4, the structure of load measures aligned themselves along measures of volume and intensity. It is plausible that the contrasting results may be influenced by the specificity of the training sessions, where mode of training is more clearly defined in rugby league and sessions can be categorised for example as ‘skills’ or ‘conditioning’ (Weaving et al., 2017). Conversely in soccer training, there is often less specificity and sessions are generally categorised based on their proximity to match day creating greater within-session variability and potentially masking more subtle changes in relationships.

Whilst preliminary evidence suggest that load relationships remain consistent across different training contexts in professional soccer, less is known about the effect of stage of season. Previous research investigating training load in professional soccer has compared internal and external load in the English Premier League (Malone et al., 2015). Malone et al. (Malone et al., 2015) reported no significant differences across the pre-season and in-season phases of training; however, it is worth noting that match play data was not included which may have the potential to influence overall load experienced, particularly during the in-season phase (Malone et al., 2015). The aims of the different phases of the season are generally different, with development of fitness a primary goal of pre-season (Malone et al., 2015) and often maintenance of previously developed physical qualities the aim during in-season to enable focus on technical and tactical development (Malone et al., 2015). Given the contrasting aims of different stages of the season, there is potential that the underlying structure described by the multivariate relationships between load measures may also change. As it is routine for practitioners to collect many load variables without criterion, greater understanding of underlying structure and the factors that can alter this will provide practitioners with better context to monitor players throughout the season. Therefore, the aim of the current chapter was to quantify and describe the relationship between internal and external load variables across phases of the season. Specifically, we aimed to assess the relationship between sRPE-TL and various external load measures collected via GPS technology.

6.3 Methods

6.3.1 Experimental Approach to the Problem

The present study employed a prospective design with data collection across a 47-week season with Scottish professional youth soccer players. The data collection periods comprised a 6-week pre-season and two competitive phases lasting 20 weeks (Comp1) and

19 weeks (Comp2), respectively. The competitive phases were split by a 2-week winter break. Subjective measures of training load were collected via sRPE. Objective measures of training load were collected via commercially available GPS units. Data were collected for all training sessions and matches. Data collected and the retrospective nature of the data analysis conformed to the University of Glasgow research policies and were in accordance with the Declaration of Helsinki.

6.3.2 Participants

Data were collected from 20 male professional youth soccer players (age 17.4 ± 1.3 yrs, height 178.0 ± 8.1 cm, mass 71.8 ± 7.2 kg). All data were collected during the 2018/19 season. Data comprised players from multiple positions, but data provided from goalkeepers were removed. In accordance with previous research (Malone et al., 2015), data recorded from a small selection of non-representative training sessions were removed to limit the influence of outliers. Post-Match top-ups, rehabilitation sessions, and non-pitch-based sessions such as resistance training were also excluded from the analysis. As the aim of this study was to compare different phases of the season, the winter break period was not included in the analyses.

6.3.3 Procedures

Session rating of perceived exertion scores were collected, in isolation, approximately 30 minutes after each training session using a commonly utilised modified BORG-CR10 scale (Impellizzeri et al., 2004, Foster et al., 1995) that had been used extensively with players before the study. Each sRPE score was multiplied by session duration to obtain subjective training load (Foster et al., 2001). Alongside this measurement of subjective training load, objective external training load was also collected. Players wore commercially available GPS units (Optimeye X4, Firmware version 7.27; Catapult Sports, Melbourne, Australia) previously used in research conducted in team sports (Weaving et al., 2017, Jones et al., 2019). The units include a GPS receiver and a triaxial accelerometer collecting data at 10 Hz and 100 Hz, respectively. Velocity and acceleration dwell times were set at 0.6 and 0.4 s, respectively. As per previous recommendations, each player wore the same device for each session (Scott et al., 2016). Following training or matches, data were downloaded and analysed via the Openfield software package (Software version 1.19, Catapult Sports). Average satellite count was 10.6 ± 1.7. The average horizontal dilution of precision (HDOP) was 0.8 ± 0.2. Variables selected to quantify external load were total distance (m), PlayerLoad (au), low intensity running (<14.4km•h^{-1}, m) high-speed running distance (19.8 – 24.98 km•h^{-1}, m) sprinting distance (>24.98km•h^{-1}, m), accelerations (> 2m•s^{-2}, frequency) and decelerations (> -2m•s^{-2}, frequency).

6.3.4 Statistical Analysis

Following procedures previously used in Chapters 4 and 5, a correlation analysis was carried out before performing PCA on each stage of season. Where data were missing, they were treated as missing at random and imputed using the MICE package in the R statistical environment (version 4.0.3; R Foundation for Statistical Computing, Vienna, Austria.) (Buuren and Groothuis-Oudshoorn, 2010). Relationships between all load variables were quantified during each stage of season using Pearson's product moment correlation. Following this, data were prepared for PCA by firstly visually inspecting the correlation matrix to assess the factorability of the dataset (Tabachnick et al., 2007). Prior to carrying out PCA, data within each variable were centred and scaled (Bro and Smilde, 2003). The suitability of data were then assessed using the KMO measure of sampling adequacy, and the Bartlett test of sphericity (Bartlett, 1954). KMO (~chi square) values were 0.76 (5187.241), 0.84 (16931.8), and 0.83 (16078.5) for Pre-Season, Comp1 and Comp2, respectively. All tests of sphericity were significant ($p<0.001$). A KMO value of 0.5 or above has previously been identified as a suitable result to perform PCA (Hair et al., 2006, Kaiser, 1960) and has been used in similar research (Weaving et al., 2017), and previous chapters. PCA was carried out using the 'prcomp' function of the R stats package (v3.6.2) (Team, 2013) and the 'principal' function of the psych package (v2.0.12) (Revelle and Revelle, 2015). Principal components with an eigenvalue ≥1.0 were retained for extraction (Kaiser, 1960). When two or more principal components were retained based on their eigenvalue, varimax rotation was performed. For each retained principal component, only the original load variables with a principal component loading of >0.7 were retained (Hair et al., 2006).

6.4 Results

There were 3207 individual recordings included in the analysis comprising 695 individual MD recording and 2512 individual training session recording. Distribution of the mean loads during each phase of the season are presented in Table 6.1. Correlations including 95% confidence intervals for each phase of season are presented in Figure 6.1. Total distance, PlayerLoad and low-intensity running showed very-large correlations ($r \geq 0.77$) across all phases of the season. High-speed running distance showed moderate to very-large correlations ($0.39 \leq r \leq 0.70$), whilst sprinting distance showed moderate correlations across the season ($0.32 \leq r \leq 0.45$). Finally, accelerations showed large correlations across all phases ($r \geq 0.52$), whilst decelerations showed large to very-large correlations ($0.54 \leq r \geq 0.75$).

Results of the PCA are presented in Tables 6.2 and 6.3. Two principal components were identified for pre-season whilst one component was identified for each competitive phase. Variance explained and loadings are presented for the pre-season phase following varimax rotation. The components explained 77.1% of the variance for the pre-season phase. The un-rotated principal components for Comp1 and Comp 2 explained 73.3% and 74.3% of the variance, respectively. The heaviest component loadings for Comp1 and Comp2 were total distance (Comp1 = 0.96, Comp2 = 0.95), PlayerLoad (Comp1 = 0.94, Comp2 = 0.95) and low intensity running (Comp1 = 0.93, Comp2 = 0.93).

Table 6.1 - Mean (± SD) duration and load measures across an entire season, with phases categorised as pre-season or competitive phases

	Duration (mins)	sRPE-TL (au)	Total Distance (m)	PlayerLoad (au)	LIR (m)	HSR (m)	Sprinting (m)	Accel (f)	Decel (f)
Pre-Season	57.8 ± 17.8	360 ± 191	4861 ± 2175	525 ± 220	3929 ± 1610	213 ± 246	37.1 ± 58.3	20.7 ± 12.2	14.5 ± 9.57
Comp1	64 ± 19.7	369 ± 200	5361 ± 2444	594 ± 251	4495 ± 1857	186 ± 181	46.9 ± 73.7	23.0 ± 11.5	16.5 ± 9.98
Comp2	60.3 ± 21.3	357 ± 215	5263 ± 2717	565 ± 275	4356 ± 2055	194 ± 185	48 ± 65	22.2 ± 11.4	16.3 ± 10.3

Key; sRPE-TL - sessional RPE training load; m – metres; au – arbitrary units; ; LI.Running – low-intensity running; Accel – accelerations; Decel - decelerations

Table 6.2 - Principal component analysis results across the pre-season phase.

	Pre-Season	
	Principal Component	
	1	2
Eigenvalue	5.11	1.06
% of Variance	63.9	13.21
Cumulative Variance %	63.9	77.11
Rotated Component		
	1	2
% of Variance	51.14	77.11
Rotated Component Loadings		
	1	2
sRPE-TL	**0.85**	0.18
Total Distance	**0.9**	0.32
PlayerLoad	**0.91**	0.31
LIR	**0.94**	0.18
HSR	0.26	**0.79**
Sprinting	0.16	**0.87**
Accelerations	0.53	0.57
Decelerations	0.69	0.33

Key; sRPE-TL - sessional RPE training load; LIR – low-intensity running; HSR – high-speed running

Table 6.3 – Principal component analysis results across both competitive phases of the season

	Comp1	Comp2
	Principal Component	
	1	1
Eigenvalue	5.86	5.95
% of Variance	73.25	74.32
	Component Loadings	
	1	1
sRPE-TL	**0.86**	**0.91**
Total Distance	**0.96**	**0.95**
PlayerLoad	**0.94**	**0.95**
LIR	**0.93**	**0.93**
HSR	**0.84**	**0.85**
Sprinting	0.67	0.64
Accelerations	**0.74**	**0.73**
Decelerations	**0.88**	**0.88**

Key; Key; sRPE-TL - sessional RPE training load; LIR – low-intensity running; HSR – high-speed running

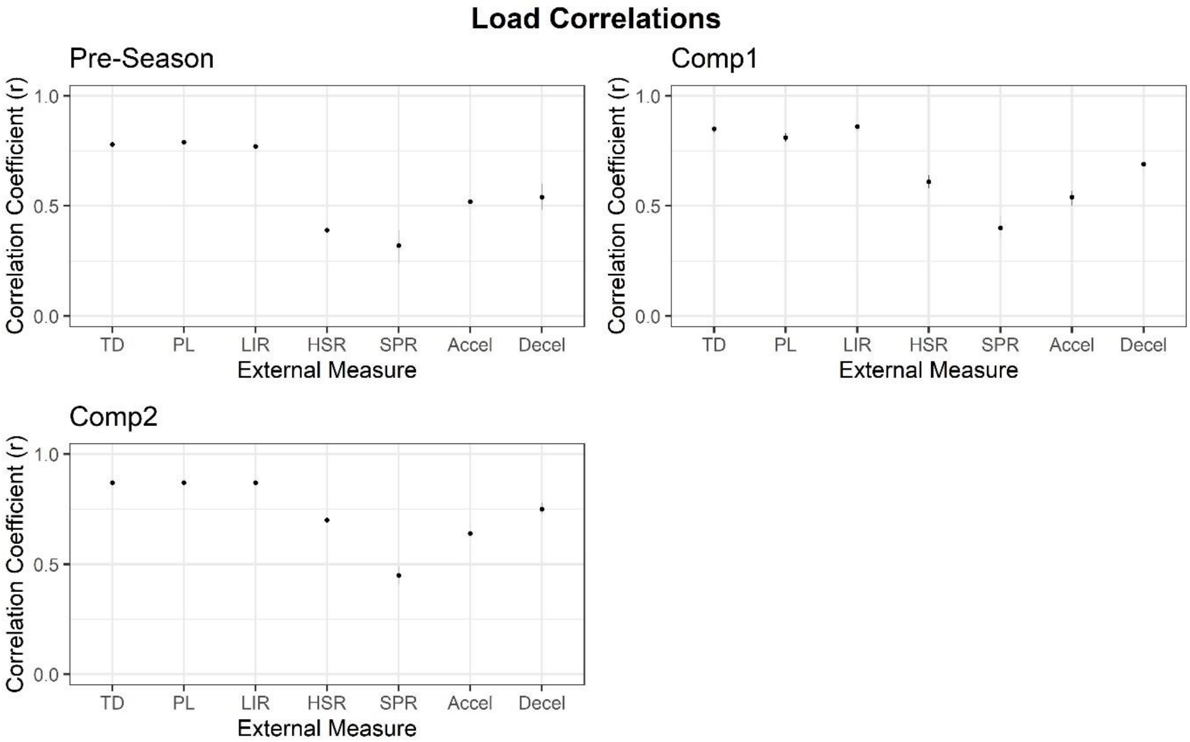

Figure 6.1 - Pearson's product moment correlations between sRPE-TL and all external load measures (error bars represent 95% CI). TD, Total Distance; PL, PlayerLoad; LIR, low intensity running; HSR, running; SPR, sprinting; Accel, accelerations; Decel, decelerations.

6.5 Discussion

The primary finding of this study was the identification of multiple components during the pre-season period, and conversely the identification of a single component within both competitive phases. This finding suggests in the pre-season phase univariate assessments of load may be insufficient when characterising the load experienced by players, which supports our findings in Chapters 4 and 5, and also those observed in previous research on rugby league (Weaving et al., 2017). Conversely, the identification of a single component with relatively similar loadings across all variables obtained during both competitive phases suggest that load measures may be used interchangeably.

Previous research in professional rugby league (Weaving et al., 2017, Weaving et al., 2014) has reported that multiple measures are required to capture the variance across different training themes when expressed as training mode. Whilst we showed in Chapter 5 similar results when training was categorised relative to match day. In each of these studies, two or more components were identified following PCA. To our knowledge this is the first assessment of this relationship when considering the phase of the season. In the present study the pre-season stage produced two components and following varimax rotation, the component loadings could be described as representative of either training volume or intensity, which is in accordance with our findings in Chapters 4 and 5. In the present study, PCA carried out on pre-season data produced two principal components which represented 77.11% of the cumulative variance. The highest rotated component loadings for component one were; sRPE-TL (0.85), total distance (0.9), PlayerLoad (0.91) and low-intensity running (0.94). For rotated component two, the highest loadings were high-speed running (0.79), sprinting (0.87) and acceleration (0.57). Studies in rugby league have shown that variables generally align based on categories of internal or external training load (Weaving et al., 2017, Weaving et al., 2014). In the present study we only included sRPE-TL as a measure of subjective internal load. This may have influenced our findings, however, there does still seem to be some relationship between measures which may provide similar information regarding either volume or intensity of training or match play.

Whilst the analysis produced multiple principal components when investigating the pre-season phase, we only identified one component when analysing both competitive phases. This would suggest that all load variables fit into one theoretical factor, and could, theoretically, be used interchangeably (Weaving et al., 2014). It is worth noting that this may be due to the method we selected for defining how many components would be retained for rotation. A recent review concerning the use of PCA in sport found that 62.2% of the studies analysed retained factors for rotation if they had an eigenvalue >1 (Rojas-Valverde et al., 2020). Other methods, such as visual analysis of an eigenvalue scree plot whereby the 'elbow' of the data would be identified (Tabachnick et al., 2007), may have led to retention of two principal components for competitive phase data. Had we included a second factor in both analyses then the results would have been comparable to our presented pre-season data (Table 6.2). Retention of two factors for Comp1 would have resulted in two principal components which would have explained 84.6% of the variance. Rotated component loadings would also have corresponded with our pre-season findings. Factor loadings for the first rotated component would have been 0.88, 0.9, 0.88 and 0.94 for sRPE, total distance, PlayerLoad and low-intensity running, respectively. The second rotated component would again have been best represented by high-speed running (0.77), sprinting (0.93), accelerations (0.63) and additionally decelerations (0.61). Similarly, for Comp2, retention of two factors would have results in a cumulative variance explained of 84.4%. Rotated component loadings would also have been similar to pre-season findings.

Component 1 would have been best represented by sRPE (0.88), total distance (0.91), PlayerLoad (0.92), and low-intensity running (0.94). Component 2 would again have been best represented by high-speed running (0.68) and sprinting (0.94). Interestingly loadings for accelerations and decelerations were slightly lower than may have been presented for Comp1 with values of 0.47 and 0.58 respectively. Clearly the method selected by practitioners for retaining factors will effect results, with the most popular method used currently in practice being the Kaiser criteria (eigenvalue >1) (Tabachnick et al., 2007).

The findings from the present chapter alongside previous results in Chapters 4 and 5 suggests that, as a measure, sRPE-TL is representative of volume. Previous research has shown that both sRPE and sRPE-TL are significantly related to several external load and intensity measures (Gaudino et al., 2015, Marynowicz et al., 2020). When analysing youth soccer players, the strongest within-individual correlations between sRPE-TL and various external load measures were found for duration ($r = 0.767$), distance ($r = 0.699$) and distance in acceleration ($r = 0.696$) (Marynowicz et al., 2020). Using generalized estimating equation (GEE) models, it was found that PlayerLoad, high-speed distance and distance in acceleration were the strongest contributory variables when estimating sRPE-TL (Marynowicz et al., 2020). However, in our present study it is worth noting the strong component loadings of acceleration and deceleration within the first rotated component of each analysis, which may suggest that subjective perception of effort, may also be strongly related to measures of acceleration and deceleration, but not high-speed running or sprinting.

The findings of the present study further evidence that measures of sRPE-TL appear to provide information regarding load volume, rather than intensity. Practitioners should consider this when analysing this measure to represent the load experienced by athletes. Whilst our analysis shows that this relationship is not consistent across stages of the season, this is likely due to retention criteria applied. Therefore, practitioners should consider the stage of the season, and the physical goals of that phase, when assessing load measurements.

The findings of the present study should be interpreted alongisde the following limitations of the research. The categorisation method used in the present study comprised three levels for analysis and a logical comparison between a pre-season phase, and two competitive phases. However, future analysis may wish to investigate shorter mesocycle periods within the competitive period, for example 6-week blocks, to provide a more in-depth comparison across the season. Additionally, the present study did not attempt to differentiate structure of load variables across different categories of players. Further differentiation in terms of partitioning within and between variance in structure, or potential differences across for example starters, non-starters, or fringe players, may also provide additional insight to the proposed relationships. Additionally, the present study only included one subjective measure of internal load due to player adherence with objective methods, such as heart-rate based measures. Further insight to objective measures of internal load may provide useful insight regarding previously observed relationships between internal and external measures of load (Weaving et al., 2014).

6.6 Conclusion

This study provides further evidence that univariate measures may not be sufficient when measuring the load experienced by players and that this limitation may be influenced by factors such as the stage of the season. These results, alongside previous results, would suggest that factoring load based on measures of volume and intensity would be appropriate. Whilst analyses of both competitive phases of the season identified only one principal component, which would suggest that variables may be used interchangeably during this period, it is worth noting that the criteria selected for retaining factors plays a key role in this process. As previously suggested, the dose-response relationship with changes in fitness, or injury occurrence, for these combined load measures should be a future aim of analyses.

Chapter 7 – Does Transforming Subjective measures of Load Better Represent Training and Match Play Intensity in Youth Soccer Players?

7.1 Prelude

There is some variability between pre-season and competitive phases when considering relationships between objective and subjective training load measures. The variability highlighted within the pre-season phase suggests that, as per previous findings, the use of univariate measures of training load may be insufficient. Whilst the similarity identified within the competitive phase possibly leads to an assumption that measures may be used interchangeably, this is heavily influenced by criteria used within statistical techniques. Using the findings of the previous chapters collectively it would appear that subjective measures of load are predominantly representative of training volume, giving limited insight to intensity. If subjective measures are to be used with aim of an insight to intensity, then techniques should be investigated which may augment relationships to give greater insight for practitioners and this is given consideration in the next chapter.

Collectively, the findings of the three previous chapters have highlighted that sRPE-TL is predominantly a measure representing training volume, therefore the purpose of this study was to investigate the structure of relationships between measures of training load and assess whether these can be modified through non-linear transformations. To do this, subjective measures were analysed in their raw form and through non-linear transformation by raising to a series of exponentials. The underlying structure of the data were investigated using principal component analysis.

7.2 Introduction

Training load has been described as an input variable that can be manipulated to illicit a desired athletic response (Impellizzeri et al., 2019). Monitoring of training load is an essential process in the development and management of high-level athletes (Drew and Finch, 2016, Coles, 2018) . In soccer, training load data are collected for individual players enabling practitioners to systematically plan and apply recovery and appropriate training prescription to impose physiological and biomechanical stress in pursuit of enhanced functional outcomes (Impellizzeri et al., 2019, McLaren et al., 2018a). The adaptations caused by successful application of recovery and training loads can increase physical performance, improve health, and reduce injury risk with training loads generally categorised as either internal or external (Impellizzeri et al., 2019). Quantifiable features of training load describing the magnitude and amount of the physical work are considered the external load, whereas quantifiable features describing the resultant physiological and biomechanical response are characterised as the internal load (Impellizzeri et al., 2019, Vanrenterghem et al., 2017). In team sports such as soccer, external loads are routinely quantified by measures of total distance covered or distance covered within specific velocity thresholds (Impellizzeri et al., 2019, Akenhead and Nassis, 2016), while internal loads are often quantified with HR derived variables or through subjective measures such as sRPE (Impellizzeri et al., 2019, Akenhead and Nassis, 2016). It is generally accepted that there is no criterion measure of either internal or external training load (Weaving et al., 2014), and as such a range of measures with varying degrees of validity are routinely collected by practitioners (Impellizzeri et al., 2019, Weaving et al., 2014). The validity of a given training load measure may also be influenced by the context in which it is collected, with previous research demonstrating that training mode (e.g. conditioning or skills-based training) can influence relationships between variables (Weaving et al., 2014, Impellizzeri et al., 2019).

Subjective measures of training load such as sRPE have been recommended as valid and reliable measures of training load (McLaren et al., 2018a). Sessional RPE-training load (sRPE-TL) has also been suggested as a method of accounting for the magnitude of internal load as it accounts for the sRPE and the duration of the session, giving some insight to the volume and intensity experienced by the athlete. However, the integration of session duration and intensity has been challenged as it is argued that it provides limited insights above considering duration alone (Weaving et al., 2020), the application of sRPE-TL has become popular due to cost-effectiveness and ease of use within large groups which are typical for team sports such as soccer (Impellizzeri et al., 2004, Akenhead and Nassis, 2016). Impellizzeri et al. (2004) reported correlations between 0.50 to 0.85 for sRPE-TL and measures of internal training load such as HR derived measures including Edwards' training load (TL) (Edwards, 1993), Lucia's TRIMP (Lucía et al., 2003) and Banister's training impulse (TRIMP) (Banister, 1991) (Impellizzeri et al., 2004). Edwards' TL (Edwards, 1993) calculates the summed product of the accumulated duration spent in five specific HR zones and their corresponding integer coefficient. Using a similar approach, Lucia's TRIMP (Lucía et al., 2003) includes the integer coefficients one to three and corresponding HR zones reflecting increased physiological demands below the ventilatory threshold (integer coefficient 1); between the ventilatory threshold and the respiratory compensation point (integer coefficient 2); and above the respiratory compensation point (integer coefficient 3). In contrast, Banister's TRIMP (Banister, 1991) accounts for the entire duration of the exercise bout, whilst also accounting for higher intensity exercise via a non-linear weighting factor. Banister's TRIMP (Banister, 1991), includes a ratio to quantify intensity measured via HR which includes measures relative to basal and maximal values (Eq. 9)

$$D\left(\frac{(HR_{ex} - HR_{rest})}{(HR_{max} - HR_{rest})}\right)Y$$

Equation 7 - Banister's TRIMP (Banister, 1991). D – Duration; HR_{ex} - mean exercising heart rate; HR_{rest} – resting heart rate; HR_{max} – maximal heart rate; Y – multiplication factor.

In the Banister model, Y is a non-linear multiplication factor that emphasises high-intensity training. This Y factor corrects bias introduced from long training sessions that involve periods of relatively low intensity (Morton et al., 1990). This weighting factor can be seen in Eq. 10.

$$Y = A^{bx}$$

Equation 8 – Weighting factor of Banister's TRIMP (Banister, 1991). A = 0.64 for men and 0.86 for women, B = 1.92 for men and 1.67 for women. x = Δ HR ratio.

Additionally, individualised TRIMP (iTRIMP) has been proposed as a method of introducing specific non-linearities into objective measures of internal load (Manzi et al., 2009). Here the weighting factor Y is calculated using an individual's relationship between fractional elevation in HR and blood lactate concentration (Manzi et al., 2009, Akubat et al., 2012). Banisters TRIMP (Banister, 1991) and iTRIMP ((Manzi et al., 2009) more effectively map to standard theories of training load measurement where non-linearities are introduced such that relatively small changes in intensity towards the upper regions result in substantively greater increases in the calculated training load. The inclusion of non-linearities has rarely been considered in more contemporary subjective measures of load. Considerations of these non-linearities is of relevance and importance to soccer practitioners given that subjective measures of load have been shown to be widely used in practice (Akenhead and Nassis, 2016).

In the absence of a criterion measure of load, different internal or external load variables are frequently compared with each other to infer validity (Lovell et al., 2013, Weaving et al., 2014). Previous results from Chapters 4, 5 and 6, investigating relationships between sRPE-TL and objective measures of training load, have shown that when using bivariate correlations sRPE-TL correlates with variables that quantify overall training volume, rather than training intensity. In addition, research employing PCA alongside our previous analysis in Chapter 4,5 and 6, within codes of football has more effectively described the underlying structure of relationships between variables, showing an intensity/volume divide and providing further support that sRPE-TL primarily reflects training volume (Weaving et al., 2017, Weaving et al., 2014). More specifically, similar analyses carried out in Chapter 5 have demonstrated that the intensity/volume divide and the loading of sRPE-TL with training volume remained stable whilst manipulating factors such as the training theme relative to match day. Collectively, the research base in soccer demonstrates that whilst sRPE-TL may provide a cost-effective method to quantify training load, it is likely to provide a bias towards training volume and therefore may not be sensitive to alterations in training intensity. This is of importance and relevance to practitioners as this measure may under-represent the frequent changes in movement and velocity which are critical components of the training load experienced by players (McLaren et al., 2018a). Additionally, aggregating training load across different durations of time is likely to disguise the true nature of the load imposed on athletes (Weaving et al., 2020, Renfree et al., 2021). For example, 10 minutes of training at a sRPE level of 10 and 100 minutes of training at an sRPE of 1 produces the same sRPE-TL value. However, the demands of the exercise bout, and the physiological response will be markedly different. Given the inclusion of non-linearities in previous training load variables, this raises the potential that sRPE and sRPE-TL can be modified using similar approaches providing the capability to better quantify training intensity or a more effective balance between training volume and intensity. Therefore, the aim of this research was to investigate the underlying structure of training load relationships with professional soccer players and determine whether sRPE and sRPE-TL can be modified to provide insight into training volume, training intensity or a combination of the two constructs.

7.3 Methods

7.3.1 - Experimental Approach to the Problem

This study employed a prospective semi-longitudinal design across a 47-week season with Scottish professional youth academy soccer players. Subjective measures of load were collected via sRPE, and objective measures of load were collected via microelectromechanical system (MEMS) devices worn during training and matches. The underlying structure of the relationships between variables were assessed by PCA before and after modifying sRPE and sRPE-TL through exponentials raised to a series of different values (1 to 3) creating different non-linear profiles. Data collected, and the prospective nature of the study conformed to the University of Glasgow research ethics policies and were in accordance with the declaration of Helsinki.

7.3.2 Participants

Twenty male professional youth soccer players (age = 17.4 ± 1.3 yrs, height = 178.0 ± 8.1 cm, mass = 71.8 ± 7.2 kg) were recruited as participants during the 2018/19 season. A total of 3324 individual recordings were collected across the season. In accordance with previous research (Malone et al., 2015), and previous chapters, data collected from goalkeepers and rehabilitation sessions were removed from the analysis. Non-pitch-based sessions such as gym-based recovery or resistance training sessions were also not included in the analysis as it was considered that these sessions were infrequent, not representative of general training, and more case specific. This left a total of 3220 individual recordings following the removal of 103 sessions.

7.3.3 - Procedures

Each player's sRPE was collected in isolation, approximately 30 minutes after each training session using a scale previously used with soccer players (modified Borg CR10) (Foster et al., 2001). All players were familiarised prior to data collection. Each sRPE score was multiplied by session duration to calculate sRPE-TL (Foster et al., 2001). Players wore commercially available MEMS devices (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27). These devices include a global positioning system (GPS) receiver alongside a triaxial accelerometer collecting data at 10 Hz and 100Hz, respectively. Per manufacturer reference values, velocity and acceleration dwell times were set at 0.6 s and 0.4 s, respectively. After training or match play, data were downloaded and analysed (Openfield v1.19, Catapult Sports, Melbourne, Australia). Raw training files were processed to remove inter-drill rest periods to ensure that data collected reflected the actual load experienced by players. Data collected from matches were processed to remove the half-time period. The average satellite count was 10.69 ± 1.73 and the average horizontal dilution of precision (HDOP) was 0.78 ± 0.21. The variables selected to quantify external training load were total distance (m); PlayerLoad^{TM} (au); low-speed running distance (< 14.4 km•h^{-1}, m), high-speed running distance (19.8 – 24.98km•h^{-1}, m); sprinting distance (> 24.98km•h^{-1}, m); accelerations (> 2m•s^{-2}, frequency) and decelerations (> 2m•s^{-2}, frequency). Variables were included for analysis due to their wide-spread usage in both practice and research (Akenhead and Nassis, 2016).

7.3.4 Statistical Analysis

Data were analysed in the statistical environment R (v4.0.3). Of the 3220 individual recording, 2.95% were missing sRPE-TL data, whereas 11.96% were missing external load data. Where data were missing, these were treated as missing at random (primarily due to technical errors such as battery failure) and imputed using the MICE package (Buuren and Groothuis-Oudshoorn, 2010).To modify low-frequency subjective measures of training load, methods previously used in high-frequency measures (Banister, 1991) were adapted. To create a modified version of Banister's TRIMP (RPE_{mod}), the maximum (RPE_{max}) and minimum (RPE_{min}) RPE reported across the season was used to create an RPE ratio (ΔRPE Ratio; Equation 11). A weighting component (Y) was included and in-line with previous measures included an exponential raised to a power equal to the ratio multiplied by a chosen coefficient. For the present study, a series of increasing coefficients from 1 to 3 were selected (e.g. Y = exp (coefficient × ΔRPE Ratio). To further investigate the effect of session duration, sessions were categorised based on their length, and assessed separately. Sessions were categorised based on mean session duration, with sessions ≤ 60 mins categorised as 'short' and sessions > 60 mins categorised as 'long'. This duration was selected as the mean session duration was 61.2mins, with 60mins providing a logical reference value for practitioners.

$$D\left(\frac{(RPE - RPE_{min})}{(RPE_{max} - RPE_{min})}\right)Y$$

Equation 9 - Modified Banister's TRIMP equation for low-frequency measures where D = session duration, RPE = reported rating of perceived exertion for session, RPE_{min} = minimum reported rating of perceived exertion value across analysis period, RPE_{max} =

maximum reported rating of perceived exertion value across analysis period, Y = weighting coefficient ranging from exp (1) to exp (3).

Relationships between sRPE, sRPE-TL, $sRPE_{mod}$, $sRPE\text{-}TL_{mod}$, and external training load measures were described using PCA. Prior to carrying out PCA, data within each variable were centred and scaled (Bro and Smilde, 2003). The suitability of data for PCA were assessed using KMO measure of sampling adequacy and the Bartlett test of sphericity (Bartlett, 1954). KMO values for all session durations were ≥ 0.5 and all tests of sphericity were significant ($p \leq 0.001$). A KMO value of 0.5 or above has previously been identified as a suitable result to perform PCA (Hair et al., 2006, Kaiser, 1960) and has been used in similar research (Weaving et al., 2014). Varimax rotation was performed to produce rotated components. To assist interpretation of results, all component loadings were then normalised relative to the maximum component loading obtained.

7.4 Results

There were 3220 individual recordings included in the analysis, comprising 696 match recordings and 2524 individual training recordings. Distribution of the mean loads are presented for all sessions in Table 7.1.

Table 7.1 - Descriptive Statistics (mean ± standard deviation [SD] of load variables across all sessions and categorised for 20 academy soccer players based on training duration

Variable	**All**	**Short (≤ 60 mins)**	**Long (> 60 mins)**
Observations (*f*)	3220	1601	1619
Duration (min)	61.2 ± 20.3	45.5 ± 13.0	76.7 ± 13.0
sRPE (au)	5.61 ± 1.88	4.91 ± 1.67	6.30 ± 1.82
sRPE-TL (au)	361 ± 205	227 ± 104	493 ± 194
Total Distance (m)	5208 ± 2515	3695 ± 1331	6705 ± 2515
PlayerLoad (au)	567 ± 257	405 ± 143	727 ± 244
LIR Distance (m)	4320 ± 1911	3115 ± 1060	5511 ± 1816
HSR Distance (m)	193 ± 194	125 ± 138	260 ± 216
Sprinting Distance (m)	46.0 ± 68.1	28.9 ± 47.7	62.9 ± 80.0
Accelerations (*f*)	22.2 ± 11.5	16.4 ± 8.86	28.0 ± 11.0
Decelerations (*f*)	16.0 ± 10.0	11.1 ± 6.79	20.9 ± 10.3

Key; Session rating of perceived exertion (sRPE); session rating of perceived exertion training load (sRPE-TL); LIR – low-intensity running; High-Speed Running (HSR); Arbitrary Units (au); Frequency (f)

PCA analyses for all sessions and those categorised as short or long duration are presented in Figure 7.1 and 7.2, respectively. Cumulative variance explained for the first and second rotated components ranged from 69.1% to 82.9%. Generally, the first rotated component was representative of training volume (RC_{volume}) with the highest loading variables including total distance, PlayerLoad and low-intensity running. In contrast, the second rotate component tended to represent training intensity ($RC_{intensity}$) with the highest loading variables including high-speed running and sprinting. Across the entire data set combining both short and long sessions, normalised loading coefficients for sRPE contributed more to RC_{volume} (0.72 to 0.77) compared to $RC_{intensity}$ (0.16 to 0.25). Similar results were obtained for sRPE-TL with normalised loading coefficients of 0.81 to 0.93 for RC_{volume}, and 0.19 to 0.29 for $RC_{intensity}$. Normalised loading coefficients for both sRPE and sRPE-TL remained similar when analysed across long duration sessions only. In contrast, for short duration sessions normalised loadings were more similar for sRPE-TL (RC_{volume}: 0.41 to 0.88; $RC_{intensity}$: 0.32 to 0.36) and aligned more to intensity ($RC_{intensity}$: 0.52 to 0.61; RC_{volume}: 0.23 to 0.44) for sRPE.

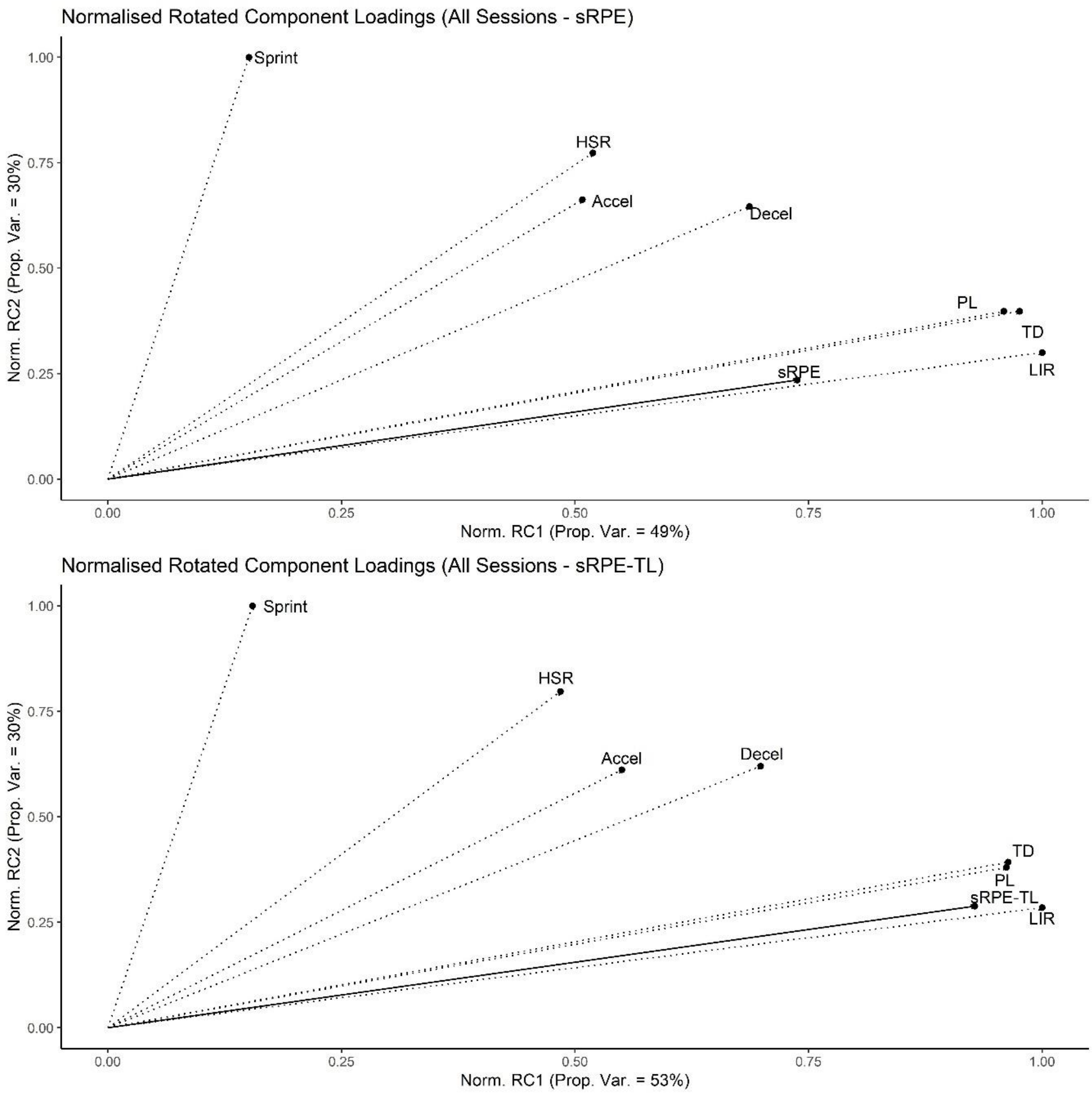

Figure 7.1 - Normalised Rotated Component Loadings for ratings of perceived exertion (RPE) and sessional ratings of perceived exertion-training load (sRPE-TL) for pooled sessions. TD (total distance); PL (PlayerLoad); LIR (low-intensity running); HSR (high-speed running); Accel (accelerations); Decel (decelerations).

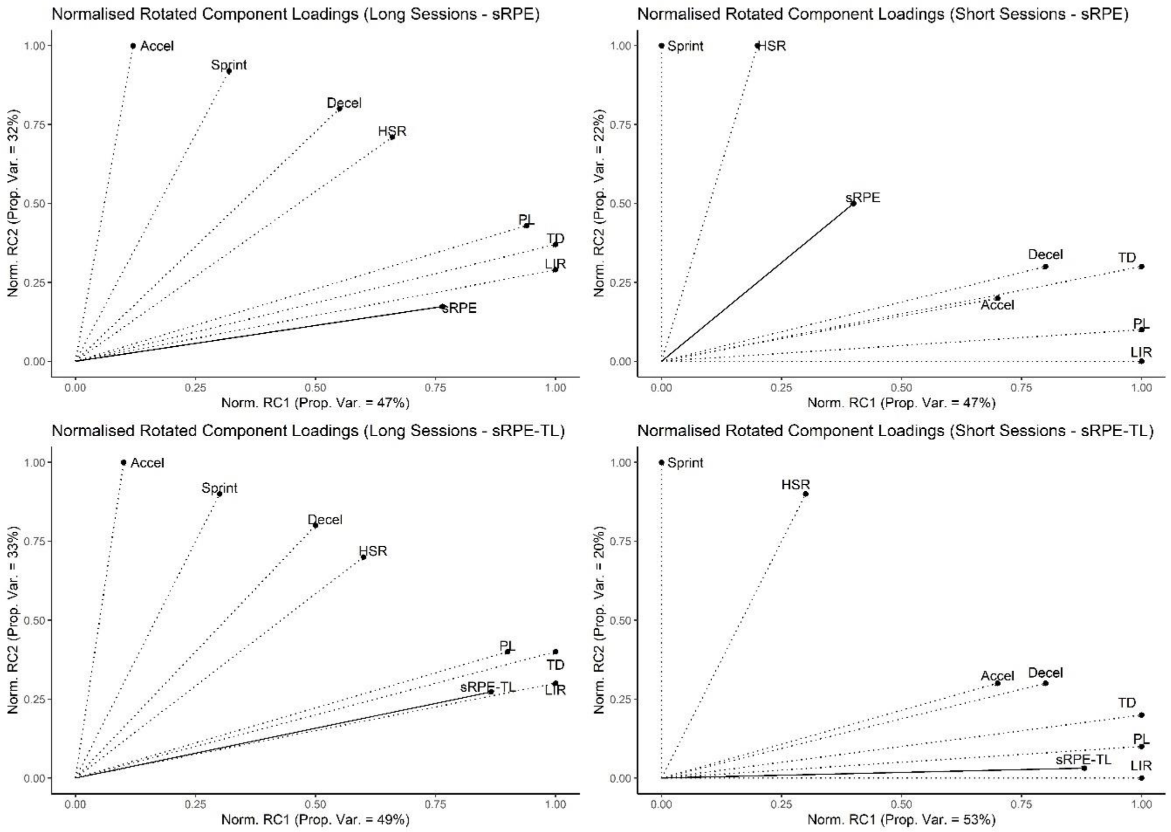

Figure 7.2 - Normalised Rotated Component Loadings for ratings of perceived exertion (RPE) and sessional ratings of perceived exertion-training load (sRPE-TL) for long (> 60mins) and short (≤ 60mins) sessions. TD (total distance); PL (PlayerLoad); LIR (low-intensity running distance); HSR (high-speed running distance); Sprint (sprinting distance); Accel (accelerations); Decel (decelerations).

Following modification of sRPE the ratio of RC_{volume} : $RC_{intensity}$ for pooled (1 : 0.32 to 1 : 0.21) and long (1 : 0.2 to 1 : 0.12) decreased as the weighting component increased from 1 to 3. These findings were also consistent for sRPE-TL with the ratio for pooled (1 : 0.32 to 1 : 0.24) and long (1 : 0.24 to 1 : 0.16) sessions decreasing as the weighting component increased. Conversely for short sessions the ratio increased as the weighting component increased for both sRPE (1 : 1.58 to 1 : 2.61) and sRPE-TL (1 : 0.49 to 1 : 0.87). Ratios of the normalised components between RC_{volume} and $RC_{intensity}$ are presented in Figure 7.3 for sRPE of short and long sessions, respectively.

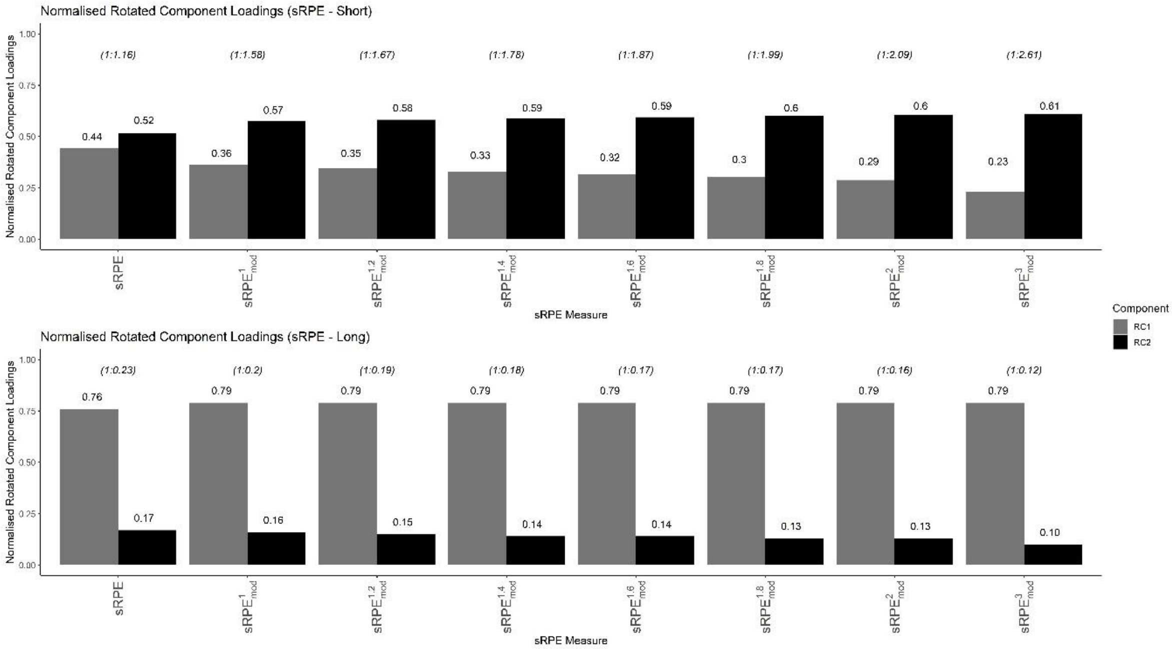

Figure 7.3 - Normalised Rotated Component Loadings for unmodified and modified ratings of perceived exertion (RPE) for short (≤ 60 mins) and long (>60 mins) sessions. Ratios of volume : intensity are presented for each measure in brackets.

7.5 Discussion

The aim of this chapter was to investigate the underlying structure of training load relationships within academy soccer players and determine whether sRPE-TL can be modified to provide insight into training volume, training intensity or a combination of the two constructs. The main finding from the data analysis shows that for short duration sessions, sRPE provides insight into both volume and intensity of training load. However, a greater bias towards intensity can be obtained when sRPE is raised to an exponential of increasing power. Additionally, relationships between volume and intensity are more equal following modification of sRPE-TL for short duration sessions. In accordance with our previous findings, before modifying subjective measures, multiple components describe the underlying structure of commonly collected training load variables in soccer players, with the volume-based component generally explaining most of the variance followed by an intensity-based component. The findings also demonstrate that across all sessions with no consideration of duration, sRPE and sRPE-TL predominantly reflect training volume. This volume-based interpretation of training load remains consistent even when undergoing non-linear transformation similar to Banisters TRIMP (Banister, 1991).

Previous research has shown that by aggregating session duration, time becomes the major contributory component to the variability in training load (Weaving et al., 2020). Thus, the contribution of training intensity is potentially under-represented. In the present study we have further evidenced the influence of duration on subjective measures of training load. When not accounting for session duration we showed that both sRPE and sRPE-TL were representative of volume. These findings were also consistent when assessing sessions that were categorised as long (i.e., > 60 min). However, when assessing short duration sessions (i.e., ≤ 60 min), we found that sRPE was a stronger contributor to the intensity-based component. Additionally, when applying a non-linear weighting coefficient, the loading constant changed from 0.52 to 0.61, as the exponential multiplier increased from 0 to 3 (Figure 7.3). This result suggests that non-linear modification of sRPE may allow a simple and cost-effective subjective measure to better reflect training intensity whilst also being influenced by training volume. Likely permitting practitioners within academy soccer programmes to better quantify and prescribe training loads which are appropriate for training microcycle (Malone et al., 2015) and age/maturation of players (Towlson et al., 2020).

To better account for periods of high-intensity within intermittent exercise, TRIMP methods have been applied to higher-frequency load monitoring techniques (Edwards, 1993, Banister, 1991, Lucía et al., 2003). These methods provide a more regular assessment of intensity, rather than aggregating intensity over a single length of time (Weaving et al., 2020). Additionally, commonly used HR-methods, Edward's TL (Edwards, 1993), Banister's TRIMP (Banister, 1991) Lucia's TRIMP (Lucía et al., 2003) and iTRIMP (Manzi et al., 2009), apply weighting factors to better account for intensity within sessions. To increase the frequency of subjective measures, intra-session sRPE could conceivably be used within team-sports environments. However, this method may come with challenges related to the increased demands on athlete recall and adherence. A common criticism of the Edward's (Edwards, 1993) method is the application of arbitrary values to arbitrary training zones, which does not reflect the individualised response to training (Akubat et al., 2012, Abt and Lovell, 2009). Whilst Lucia's TRIMP (Lucía et al., 2003) considers physiological systems within the training zones identified, the measure also features arbitrary weighting values (Akubat et al., 2012). Banister's TRIMP (Banister, 1991) and iTRIMP (Manzi et al., 2009) based weighting values on the relationship between elevation in HR and blood lactate concentration, observed during incremental exercise (Akubat et al., 2012). This method not only increased emphasis of the higher intensity periods of training, but also accounted for gender (Banister, 1991) or individual (Manzi et al., 2009) differences in the response to incremental work rates. In the present study, we adopted a method to modify sRPE applying high frequency methods, to lower frequency assessment. Additionally, we have assessed weighting components over an exponential range of 1 – 3 based on values used in previous high-frequency methods. In this analysis we have used an iterative and empirical method to assess the effect of a range of non-linearities based on previous recommendations. Whilst these results do not propose the use of specific weighting components, they highlight the potential use of modification to allow sRPE, when used alongside session duration, to better represent session intensity. This process can be used to generate modified values that best fit the needs of researchers or practitioners, who have targeted objectives.

There are limitations to the present study that should be considered. Restricting training load monitoring to measurements that combine intensity and duration in a linear manner is likely to misrepresent training load when performed at high intensities. However, the best approach to introduce non-linearities to the approach has received limited investigation (Renfree et al., 2021). For the present study we adapted a common training load metric (Banisters TRIMP) substituting sRPE values for HR. However, HR data can take a wide range of values, whereas sRPE values as collected in the present study were restricted to 10 integer values which may reduce the sensitivity of the scale. Previous research has also endorsed use of the Category Ratio (CR) 100 scale over the CR10 scale (Borg, 2007). Use of the CR100 scale to calculate modified measures of sRPE and sRPE-TL may enhance the sensitivity of readings by providing a greater range for athletes to quantify perceived exertion. Additionally, average HR potentially provides a more accurate reflection of an overall training intensity due to the increased frequency of measurement. Whereas a single sRPE value may not provide an accurate reflection of training load intensity, particularly as session duration increases. This situation could be improved potentially through intra-session RPE, which may give higher resolution and better ability to fit an area under the curve representing total training load. Additionally, the analysis was collected on a single team and findings may be susceptible to the idiosyncrasies of the team with regards to training practices and sRPE measurements.

7.6 Conclusions

Introducing non-linearities into a single measure of training load that combines volume and intensity is likely to be important. The present study considered a modification of one of the most common approaches used in sport and exercise science (Banisters TRIMP). To identify appropriate weightings further research is required, or practitioners may wish to combine previous data and various analytical models to select values. In the present study we used the underlying structure of a range of training load metrics to identify which weighting values may be appropriate in attempts to increase the intensity-based component. In contrast, where previous data exists, other models may include collection of coach-based assessments of training load and attempts to establish weighting coefficients which best align the objective measure and expert opinion. Alternatively, where practitioners use integrative training and performance models such as the Banisters fitness-fatigue model, weighting coefficients may be established to obtain best fit of model predictions and measured performance. Irrespective of the approach adopted, substantive increase in research in this area is required to enhance practice. Additionally, further analyses considering higher frequency subjective measures of load, such as intra-session RPE, should be considered, however their practical implementation should also be appraised.

Chapter 8 – Monitoring the Load Experienced by Players During the Transition from Academy to Youth Professional Soccer

8.1 Prelude

Subjective measures of training load may be attractive to practitioners due to their validity, reliability, and cost effectiveness. However, it appears that commonly used subjective measures predominantly represent training volume and give relatively limited information regarding the intensity of the training prescription by coaching staff or competition training. The previous chapter proposed a novel method of modifying low-frequency subjective measures of load to better represent intensity in soccer training and match-play. The results presented, alongside findings from previous chapters highlight the need to employ multivariate measures when analysing load. Additionally, these results also reinforce previous assertions that factoring load based on measures of volume and intensity would be appropriate. To account for this, a new measure, $sRPE_{mod}$ was proposed based on previous examples of modifications of measures, which introduce non-linearity, to greater account for high-intensity periods of training. It appears that the proposed method shows some promise, however this is largely for sessions lasting ≤ 60 mins. This method, therefore, will not allow greater representation of intensity from subjective measures, as a significant amount of training sessions, and crucially match-play last longer than 60 mins. Therefore, whilst this measure shows some promise, it cannot be considered as a solution. Despite this, the introduction of non-linearity within subjective measurements appears to be a worthwhile avenue for future research and would have important application for sports science practitioners. An example of such application will now be illustrated where the load experienced by soccer players transitioning from a youth academy to full-time professional environment is assessed by modified subjective measures. Therefore, the purpose of this chapter was to investigate the load experienced by players transitioning from academy to professional soccer, and to determine whether subjective measures of load can provide useful insight into training volume, training intensity, or a combination of the two constructs.

8.2 Introduction

Training load has previously been described as an input variable, which can be manipulated to elicit a desired training response (Impellizzeri et al., 2019). Monitoring load is common practice in senior (Weston, 2018), and academy (Salter et al., 2021) soccer. Additionally, load monitoring has been shown to be perceived by both coaches and practitioners as a worthwhile consideration when planning training (Weston, 2018). Load data are collected by practitioners with the aim of using the information to plan and adapt training programmes that impose appropriate physiological and biomechanical stresses to enhance functional outcomes (Impellizzeri et al., 2019, McLaren et al., 2018a). Commonly, training load markers are characterised as being either measures of external or internal load (Impellizzeri et al., 2019). External load has previously been defined as the physical work prescribed in the training plan (Impellizzeri et al., 2019, Impellizzeri et al., 2005, Coutts et al., 2017). Whilst internal load can be considered as the actual psychophysiological response of the body to external load (Impellizzeri et al., 2019). In soccer, devices such as microelectromechanical systems (MEMS) housing global positioning systems and accelerometer technology are commonly used to collect various measures of external load (Akenhead and Nassis, 2016). Measures of internal load are commonly taken through HR monitors or sRPE to provide objective and subjective markers (Akenhead and Nassis, 2016). It is generally accepted that there is no single, gold-standard measure of training load, and as such a range of measure with varying degrees of validity are collected by practitioners (Impellizzeri et al., 2019, Weaving et al., 2014). Previously, it has been suggested that since the internal load experienced determines the training outcome, then this should be the primary outcome measure when monitoring training load (Impellizzeri et al., 2019). Conversely, it has been accepted that it is not always practically feasible to use a valid indicator of internal load. Collectively, it appears that a situation specific monitoring strategy, collecting measures of both internal and external load can provide actionable information to both practitioners and coaches.

Session rating of perceived exertion has previously been shown to be a valid, reliable, and cost-effective measure of training load (McLaren et al., 2018a, Marynowicz et al., 2020). Sessional RPE-training load (sRPE-TL) has also been suggested as a valuable method, as it accounts for the magnitude of internal load, as it includes both the sRPE and the session duration, giving practitioners insight to both the volume and intensity experienced. Whilst previous research has shown strong correlations between sRPE-TL and various measures of objective internal load (Impellizzeri et al., 2004), results from previous chapters suggest that sRPE-TL is more reflective of training volume, rather than intensity when compared to external measures of load. Whilst bivariate analyses conducted within these chapters found similarly strong correlations between subjective and external load measures, multivariate methods of analysis found that subjective measures generally relate to measures of training volume. Using PCA to describe the underlying structure of relationships between variables showed an intensity/volume divide, suggesting that sRPE-TL primarily reflects training volume, this relationship was shown to be relatively when considering additional factors such as training theme or season phase discussed in Chapter 5 and Chapter 6 respectively. To combat this, a modified sRPE measure to greater account for the non-linear nature of training has been proposed within Chapter 7. This modified measure ($sRPE_{mod}$) was based on various measures of training impulse (Banister, 1991, Edwards, 1993, Lucía et al., 2003), and it was found that for short (≤60mins) sessions both sRPE and sRPE-TL could be modified to better represent training intensity. Additionally, it was found that for all training sessions, irrespective of time, sRPE and SRPE-TL were predominantly reflective of training volume, and this structure remained unaffected following the modification of both subjective measures. Therefore, practitioners should be wary of the use of subjective measures of load, as these are often representative of training volume, whilst efforts to modify this relationship has found some success, these findings are relatively limited.

Professional soccer academies aim to optimise the early detection and development of young players (Relvas et al., 2010, Buchheit et al., 2010). The predominant goals of youth academy programmes are to develop players for a club's 1st team, positively impact on the personal development of individuals, and to create opportunities for profit from future player sales (Relvas et al., 2010). Professional academies will consider the technical, tactical, psychological, and physical development of players to best prepare them for 1st team soccer (Williams and Reilly, 2000). Therefore, having some understanding of physical differences of the load demands placed on 1st team or academy players is crucial. It has been shown that there are significant differences between the weekly external load intensity of U19 and 1st team Dutch players (Houtmeyers et al., 2021). U19 players covered greater distance (35265 ± 3863m) than 1st team players during weeks which included one (31084 ± 2808m) or two competitive matches (30580 ± 2366m). However, this pattern was predominantly due to distances covered at low velocity ranges (<12km•h^{-1}). However, when considering distances covered above higher velocity thresholds (>25km•h^{-1}), U19 players covered less distance (214 ± 111m) than 1st team players during weeks including one (333 ± 128) or two (294 ± 154m) competitive matches. These findings, whilst limited to analysis of one club, suggest there are likely differences in the load profiles experienced by players at different stages of their professional careers. Considering a primary aim of academies is to prepare players for 1st team exposures, greater understanding of these differences is warranted. Therefore, the purpose of this study was to investigate the load experienced by players transitioning from academy to professional soccer and determine whether subjective measures of training load can provide useful insight into training volume, training intensity, or a combination of the two constructs.

8.3 Methods

8.3.1 Experimental Approach to the Problem

This study employed a prospective design across a 7-week block of training in amateur under-18 academy soccer players, and across a 15-week block of training with Scottish professional youth academy players. Subjective measures of load were collected via sRPE, and objective measures of locomotive load were collected via MEMS devices worn during training and matches. As per analyses in Chapter 4 to 7 the underlying structure of the relationships between variables were assessed using PCA . Data were then analysed using mixed linear modelling to assess influence of player transition on load measures. Data collected, and the prospective nature of the study conformed to the University of Glasgow research ethics policies and were in accordance with the declaration of Helsinki.

8.3.2 Participants

Twenty-three professional youth soccer players were recruited as participants. Players were categorised as Academy (n = 4, age = 15.9 ± 0.2yrs , height = 175.8 ± 3.5cm , mass = 68.8 ± 7.9kg), Transition ((n = 4, age = 16.2 ± 0.2yrs, height = 178.4 ± 5.2cm, mass = 71.0 ± 8.6kg), or Development Squad (n = 19, age = 17.9 ± 1.1yrs, height = 179.1 ± 6.7cm, mass = 75.7 ± 8.7kg). Academy players were those who had been offered professional contracts at the end of their academy season. The data from this group were collected across the final 7-weeks of their academy season. These same players were then categorised as Transition players and data were collected across the initial 15-weeks of their professional training. Development squad players were those who had already been full-time professional players in the previous season with data collected during the same 15-week period. In accordance with previous research (Malone et al., 2015), and previous chapters, data collected from goalkeepers and rehabilitation sessions were removed from the analysis. Non-pitch-based sessions, such as gym-based recovery or resistance training sessions were also not included in the analysis. This left a total of 1416 individual recordings within the development squad, following the removal of 71 sessions, and 82 academy individual recordings where no data were removed.

8.3.3 Procedures

Each players sRPE was collected in isolation, approximately 30 minutes after each training sessions using a scale previously used with soccer players (Foster et al., 2001). All players were familiarised prior to data collection. Each sRPE score was multiplied by session duration to calculate sRPE-TL (Foster et al., 2001). Transition and Development players wore commercially available MEMS devices (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27). These devices include a global positioning system (GPS) receiver, alongside a triaxial accelerometer collecting data at 10Hz and 100Hz, respectively. Per manufacturer reference values, velocity and acceleration dwell times were set at 0.6s and 0.4s, respectively. Following training or matches, data were downloaded and analysed (Openfield v1.19, Catapult Sports, Melbourne, Australia). Raw training files were processed to remove inter-drill rest periods to ensure that data collected reflected the load experienced by players. Data collected from matches were processed to remove the half-time period. The average satellite count was 10.54 ± 1.17 and the average horizontal dilution of precision (HDOP) was 0.82 ± 0.21 The variables selected to quantify objective measures of training load were total distance covered (m); PlayerLoad^{TM} (au); low-speed running distance (< 14.4 km•h^{-1}, m), high-speed running distance (19.8 – 24.98km•h^{-1}, m); sprinting distance (> 24.98km•h^{-1}, m); accelerations (> 2m•s^{-2}, frequency) and decelerations (> -2m•s^{-2}, frequency). Variables were included for analysis due to their wide-spread usage in both practice and research (Akenhead and Nassis, 2016). Additionally, modified subjective measures of load were included in the analysis. Briefly, these values, proposed in Chapter 7, involve non-linear modification of sRPE and sRPE-TL with the aim of greater accounting for training intensity.

8.3.4 Statistical Analysis

Data were analysed in the statistical environment R (v4.0.3). Where data were missing they were treated as missing at random, primarily due to technical errors such or battery failure, or player adherence to recording subjective load data and imputed using the MICE package

(Buuren and Groothuis-Oudshoorn, 2010). Relationships between all squad load data were initially assessed using Pearson's product moment correlation, following this the correlation matrix was then visually inspected to assess the factorability of the dataset (Tabachnick et al., 2007). PCA was then carried out using the "prcomp" function of the R stats package (v3.6.2) (Team, 2013) and the "principal" function of the psych package (v2.0.12) (Revelle and Revelle, 2015). Principal components with an eigenvalue of ≥1.0 were retained for extraction (Kaiser, 1960). When two or more principal components were retained based on their eigenvalue, varimax rotation was performed. PCA was carried out separately with inclusion of sRPE (PCA1), sRPE-TL (PCA2), $sRPE_{mod}$ (PCA3), sRPE-TL_{mod} (PCA4).

Data were then analysed per session and per total weekly value using mixed linear modelling as a flexible approach to account for the unbalanced repeated measures nature of the dataset. Fixed effects of the model were the professional status of the player. Random effects were associated with the individual player and single training sessions. Generalized likelihood ratio tests were conducted with models fit using the restricted maximum likelihood approach to test for statistical significance of the fixed effects. Due to the repeated measures design, effect sizes were obtained by calculating generalized eta squared values (η_G^2) with 95% confidence intervals using bootstrapping with 10,000 iterations and calculation of the 0.025 and 0.975 quantiles. Based on the recommendations of Bakeman (Bakeman, 2005) , η_G^2 threshold values of .02, .13 and .26 were used to categorise effects as small, medium and large, respectively. Effect sizes for which the 0.975 quantile was less than 0.01 are presented as 0.

8.4 Results

There were 82 individual academy observations comprising 47 training recordings and 36 match recording. There were 1416 individual recordings in the professional squad, comprising 1107 training recordings (Transition = 191, Development = 916) and 309 match recordings (Transition = 54, Development = 255). Distribution of the mean frequency and duration of training and match play, alongside subjective load data, are presented in Table 8.1. Distribution of objective load data for the professional squad are presented in Table 8.2.

Table 8.1 - Descriptive Statistics (mean ± standard deviation [SD]) of training and match play frequency and duration, and subjective load data across all sessions for academy and development squad soccer players

Variable	Academy	Transition	Development Squad
Observations (f)	82	245	1171
No. of Weeks (f)	7	15	15
No. of Training Sessions per player (f)	9 ± 1.63	47.8 ± 15.1	48.2 ± 8.99
No. of Match Sessions per player (f)	11.5 ± 1.73	13.5 ± 6.24	13.4 ± 4.27
No. of Training Sessions per week (f)	1.84 ± 0.9	3.82 ± 1.64	3.58 ± 1.58
No. of Matches per week (f)	1.38 ± 0.5	1.46 ± 0.80	1.45 ± 0.73
Training Duration (mins)	67.3 ± 16.6	57.9 ± 13.1	58.6 ± 13.0
Match Duration (mins)	75.1 ± 27.3	64.7 ± 30.2	62.1 ± 30.0
Weekly Training Duration (mins)	124 ± 57.8	221 ± 110	210 ± 101
Weekly Match Duration (mins)	104 ± 45.3	94.4 ± 35	90 ± 48.6
sRPE per session (au)	6.35 ± 1.18	6.27 ± 2.03	5.75 ± 1.97
sRPE-TL per session (au)	452 ± 180	388 ± 198	354 ± 190
Weekly sRPE-TL (au)	1324 ± 480	1862 ± 681	1600 ± 686
$sRPE_{mod}$ per session (au)	3.68 ± 5.81	5.28 ± 5.01	4.13 ± 5.03
$sRPE\text{-}TL_{mod}$ per session (au)	277 ± 492	342 ± 360	273 ± 379
Weekly $sRPE\text{-}TL_{mod}$ (au)	812 ± 819	1641 ± 943	1234 ± 911

Key; Frequency (f); Rating of Perceived exertion (RPE); session rating of perceived exertion training load (sRPE-TL); frequency (f); minutes (mins) Arbitrary Units (au); Modified session rating of perceived exertion ($sRPE_{mod}$); Modified session rating of perceived exertion training load ($sRPE\text{-}TL_{mod}$)

Table 8.2 - Descriptive statistics (mean ± standard deviation [SD]) of objective load data for professional academy players categorised as transition or development squad.

Variable	Transition	Development Squad

Total Distance – Match (m)	7236 ± 3297	7034 ± 3392
Total Distance – Training (m)	4061 ± 1588	4281 ± 1446
PlayerLoad – Match (au)	696 ± 315	692 ± 331
PlayerLoad – Training (au)	456 ± 161	471 ± 156
Low-intensity running distance- Match (m)	5742 ± 2666	5539 ± 2697
Low-intensity running distance- Training (m)	3322 ± 1015	3544 ± 968
High-speed running distance- Match (m)	376 ± 185	328 ± 187
High-speed running distance- Training (m)	195 ± 288	185 ± 271
Sprinting distance – Match (m)	116 ± 83.4	85.4 ± 80.4
Sprinting distance – Training (m)	32.1 ± 56.1	35.7 ± 56.2
High-intensity accelerations – Match (f)	28 ± 14	23.7 ± 13.7
High-intensity accelerations – Training (f)	22.7 ± 13.3	23.8 ± 12.7
High-intensity decelerations – Match (f)	21.3 ± 10.8	20.8 ± 11.7
High-intensity decelerations – Training (f)	11.3 ± 7.2	12.5 ± 7

Key; Meters (m); Frequency (f); Arbitrary Units (au)

Results of the PCA are presented in Figure 8.1. Four principal components were identified when including sRPE as the subjective load variable. When including sRPE-TL, $sRPE_{mod}$ and $sRPE\text{-}TL_{mod}$ three principal components were identified. Variance explained, and the coefficient loadings are presented for the components following varimax rotation. The heaviest loading in the first rotated component across the four analyses were for low-intensity running (PCA1 = 0.94, PCA2 = 0.94, PCA3 = 0.95 , PCA4 = 0.92), whilst the heaviest loadings in the second rotated components were accelerations (PCA1 = 0.89, PCA2 = 0.87, PCA3 = 0.76) and high-speed running distance (PCA4 = 0.82).

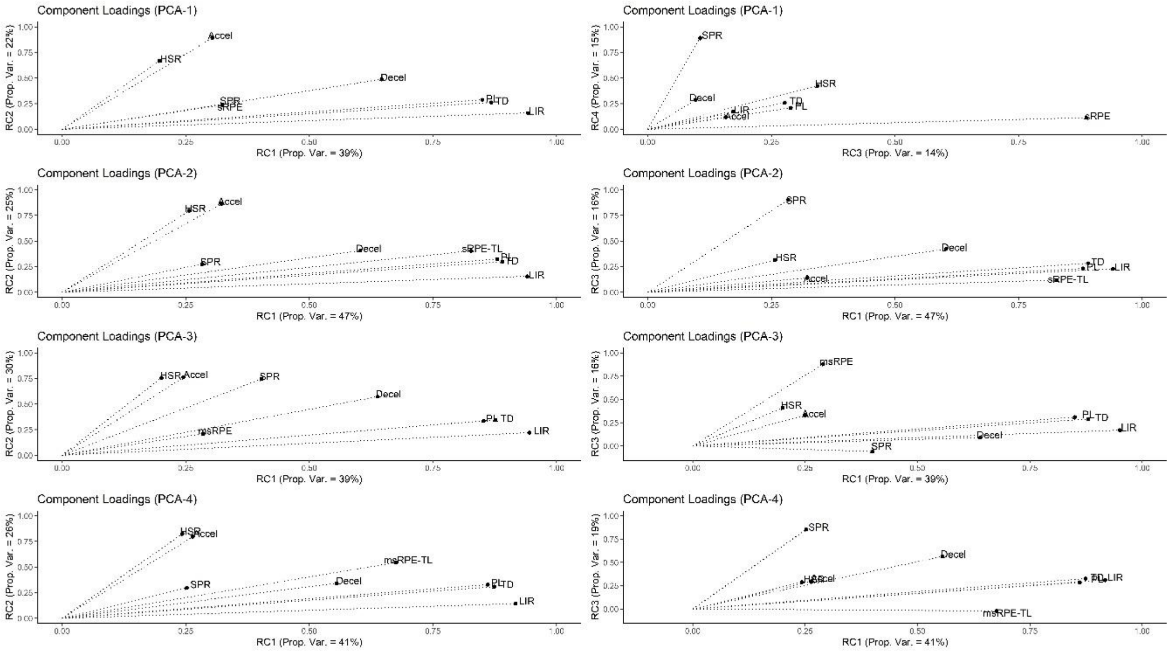

Figure 8.1 – Rotated component loadings following PCA analysed including RPE (PCA1), sRPE (PCA2), mRPE (PCA3), msRPE-TL (PCA4). Key; TD - total distance; PL - PlayerLoad; LIR -low-intensity running distance; HSR - high-speed running distance; SPR - sprinting distance; Accel - accelerations; Decel – decelerations; RPE – rating of perceived exertion; sRPE-TL – session rating of perceived exertion training load; mRPE – modified rating of perceived exertion; msRPE-TL – modified session rating of perceived exertion training load.

Results from the mixed linear models are presented in Tables 8.3 – 8.5. When analysing academy, transition and development players, likelihood ratio tests identified significance ($p<0.01$) for sessional values of duration, sRPE, RPE_{mod}, and $sRPE\text{-}TL_{mod}$. When analysing weekly values, likelihood ratio tests identified significance ($p<0.01$) for average $sRPE_{mod}$, weekly sRPE-TL, and weekly $sRPE\text{-}TL_{mod}$ and duration. For all variables $\eta_G^2 = 0$. No significant differences were identified for objective measures of load between development and transition players.

Table 8.3 – Regression coefficients for duration and each subjective training load variable for transition and development squad players relative to academy players

		Sessional										Weekly									
		Duration		RPE		sRPE-TL		mRPE		msRPE-TL		Duration		RPE (av.)		mRPE (av.)		sRPE-TL		msRPE-TL	
		Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Fixed Effects	Academy (Intercept)	69.8^{b,c}	2.95	6.37	0.32	449^{c}	28.1	3.75^{b}	0.88	288	63.9	207^{b}	28.72	6.35	0.32	3.98	0.98	1324^{b}	196	812^{b}	293
	Transition	-9.78^{a}	3.11	-0.03^{c}	0.32	-56.3	30.4	1.82^{a,c}	0.88	73	64.9	73.1^{a}	31.61	-0.06^{c}	0.34	1.58^{c}	1.02	501^{a}	215	843^{a}	283
	Development	-9.96^{a}	3.23	-0.57^{b}	0.35	-92^{a}	30.6	0.46^{b}	0.96	-10.7	70.2	57.9	33.05	-0.66^{b}	0.37	0.02^{b}	1.13	253	226	394	335
Random Effects	Player (SD)	2.33		0.31		19		0.85		59.9		25.2		0.34		1.04		176		361	
	Date/Week (SD)	10.3		1.09		94.8		3.08		219		56.2		0.59		1.89		386		512	
Explained Variance (%)		31.8		34.8		26.6		37.8		33.4		40.5		42		49.7		41.9		49.6	

Key; RPE – rating of perceived exertion; sRPE-TL – session rating of perceived exertion training load; mRPE – modified rating of perceived exertion; msRPE-TL – modified session rating of perceived exertion training load; Est – estimate; SE – standard error; SD – standard deviation; a – significantly different to academy players, b – significantly different to transition players, c – significantly different to development players

Table 8.4 – Regression coefficients for each external training load variable for transition players relative to development squad players within individual sessions during the pre-season phase

		Total Distance		PlayerLoad		LIR		HSR		Sprint		Accel		Decel	
		Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Fixed Effects	Development (Intercept)	4969	174	527	18.4	4032	130	230	22	47.6	5.64	24.8	1.08	14.83	0.69
	Transition	-42.23	232	-12.4	31.2	-62.3	196	19.7	22.2	5.32	9	0.98	1.66	-0.42	1.16
Random Effects	Player (SD)	336		51		298		31.7		14.8		2.67		1.85	
	Date/Week (SD)	1343		120		934		187		39.1		7.7		4.49	
Explained Variance (%)		34.1		32.8		31		50.1		38.6		37.8		29.2	

Key; LIR – low-intensity running distance; HSR – high-speed running distance; Sprint – sprinting distance; Accel – accelerations; Decel – decelerations; Est – estimate; SE – standard error; SD – standard deviation

Table 8.5 – Regression coefficients for each external training load variable for training players relative to development squad players for weekly measures of training load

		Total Distance		PlayerLoad		LIR		HSR		Sprint		Accel		Decel	
		Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Fixed Effects	Development (Intercept)	21736	1469	2316	173	17730	1149	957	137	206	25.9	106	8.71	63.7	4.81
	Transition	1109	1989	88.15	237	767	1586	160	135	41.9	44.9	9.39	10.5	2.08	6.83
Random Effects	Player (SD)	3069		379		2432		206		74		15.9		10.6	
	Week (SD)	4723		554		3663		484		70		29.3		15.1	
Explained Variance (%)		41.9		47.5		40.1		57.3		43.3		44.9		39.8	

Key; LIR – low-intensity running distance; HSR – high-speed running distance; Sprint – sprinting distance; Accel – accelerations; Decel – decelerations; Est – estimate; SE – standard error; SD – standard deviation

8.6 Discussion

The aims of the study were to investigate the load experienced by academy players transitioning into full-time soccer and determine whether subjective measures of training load can provide useful insight into training volume, training intensity, or a combination of the two constructs. The main findings of the study show that there were significant differences between academy and transition phase for sessional duration and $sRPE_{mod}$, and weekly sRPE and $sRPE\text{-}TL_{mod}$. There were no significant differences between academy and transition phase for daily sRPE or sRPE-TL. With regards to objective measures, there were no significant differences between transition and development phase players identified in either sessional or weekly measurements. These findings suggest that the main changes experienced by players transitioning from academy to full-time soccer are in relation to volume, rather than intensity. The analysis carried out in the previous chapters has shown that traditional subjective measures of load do not represent training intensity. Using a proposed modified subjective measure appears to identify differences in the load experienced by transition, academy, and development players, however the exact nature of this differences is unknown.

There is limited research available investigating differences between youth and first team players in regards to training load (Houtmeyers et al., 2021). Additionally, most investigations into transitions from youth to senior professional soccer have investigated psychological aspects (Morris et al., 2015). When investigating the training load experienced by players when transitioning from academy to senior soccer, we found that the main difference seems to be regarding training volume. When considering sessional values of estimate following analysis, there was a 14.04% difference in duration between players during the academy (69.8 ± 2.95) and transition (60 ± 3.11) phases (Table 8.3), however the frequency of training sessions per week increased from 1.84 ± 0.9 in the academy phase players to 3.82 ± 1.64 in transition phase (Table 8.1). This increase in training frequency was not replicated in an increase or decrease in match frequency with academy players involved in 1.38 ± 0.5 matches, and transition phase players involved in 1.46 ± 0.8 matches. Therefore, whilst match involvement appears consistent, and training duration decreased, the frequency of training in a full-time environment may have a significant influence on the load experienced by players when transitioning into full-time environments. Whilst previous analysis has focused on psychological considerations of players moving to full-time environments, there are acknowledgements of the physical adaptation experienced by players. Research investigating the youth-to-senior transition of players at English Premier League clubs found players and parents highlighted that greater consideration should be paid by clubs regarding the increase in physical demands (Morris et al., 2015). Additionally, a player who had experienced the transition highlighted the phenomenon of players becoming “swamped physically” when transitioning (Morris et al., 2015). Despite these anecdotal references to differences in physical demands, there is limited information regarding differences in load experienced by players across transitions, or at different tiers. Research in Dutch players which compared 1st team and U19 weekly load profiles found that U19 players generally covered more weekly distance, however this was done at lower intensities ($\leq$12km•h^{-1}). First team players generally covered more distance at higher intensities (>25km•h^{-1}), possibly due to increased physical capacity of older players. This would suggest that as players transition, they are likely to be exposed to higher intensity demands, however this isn’t reflected within our dataset, albeit this only includes subjective values for the academy players.

Given previous findings regarding differences between 1st Team and U19 players (Houtmeyers et al., 2021), it would be reasonable to expect differences between transition and development players for load variables. Whilst differences were noted for sessional values of sRPE, sRPE$_{mod}$ and weekly average values of sRPE$_{mod}$ sRPE-TL$_{mod,}$ there was no significant differences identified for external load measures. This suggests that whilst both groups are performing similar training, academy players are perceiving the effort of this training harder (6.34 ± 0.22) than more experienced development squad players (5.8 ± 0.15). However, this difference isn’t reflected in differences between academy and transition players. A possible explanation for this is the substantial increase in training recordings in comparison to match recordings when comparing academy and transition training (Table 8.1). Previous research has shown significant differences between load experienced during match play, in comparison to training (Maughan et al., 2021). Finally, the lack of difference in external load experienced by transition and development players may be explained by the phase of the season. The pre-season phase is generally characterised by more controlled periodisation of load experienced by players and a greater focus on physical training (Malone et al., 2015). This physical focus, may reduce the variation imposed by more position specific technical and tactical training experienced during the competitive season (Malone et al., 2015). However, it has been shown when analysing load experienced across a season that there was limited differences between the pre-season and competitive phase, and that these differences were confined to total distance covered, low-intensity running and PlayerLoad (Maughan et al., 2021). Therefore, whilst it can be concluded that there doesn't appear to be a strategic approach to the introduction of transition players, there does appear to be a difference in perceived demands of transition and more experienced development players.

The findings of the present study should be interpreted with caution considering the following limitations. Whilst the access to data collected in professional soccer players and players from a professional academy provide useful insights, it is inappropriate to expect these findings to be generalisable across different clubs, national structures and indeed sports. The structure of progression and the training strategies employed by the development squad and academy in the current study may be dissimilar to others, therefore the load experienced by players in this transition will likely be different. The present study also only included on-pitch sessions and removed rehab sessions performed by players. It is possible that the inclusion of load experienced within gym-based strength and power sessions may have influenced outcomes. Additionally, due to monitoring practices within the club, only subjective values were available for academy players limiting the inferences which can be made from our findings. Future research should consider the collection of internal and external load variables across the academy and professional levels of squads to allow greater understanding of the initial transition to professional environments. Additionally, multi-club studies allowing some comparison between different training practices would significantly enhance this area of research.

8.7 Conclusion

Previous chapters have shown that commonly used measures of training load can be characterised as being representative of either volume or intensity. Measuring sRPE and sRPE-TL has been proposed as a feasible method for measuring training load, however this measure is predominantly representative of training volume. Introducing non-linearities into a single measure of training load that combines volume and intensity is likely to be important to allow greater representation of training intensity. This chapter aimed to investigate the load experienced by players undergoing a transition from youth to senior soccer where the literature has, anecdotally, highlighted that increased training intensity can be experienced by players during such transitions. The data from the current chapter, however, seems to suggest that the main differences experienced by players are related to the frequency and volume of training, which would be expected in a simple transition from part-time to full-time training. The use of modified subjective measures here appear to identify differences in the load experienced by transition, academy, and development players but cannot identify the nature of the difference. There is, therefore, a need for further research around the transition period in soccer players over the different contextual situations that can influence their training load and so provide practitioners with greater understanding of the potential load changes experienced by players. Additionally, further analyses considering higher frequency subjective measures of load, such as intra-session sRPE, need to be considered and developed.

8.8 Perspective

Subjective measures of load are commonly used by practitioners and have been shown to be a valid, reliable, and feasible method of monitoring load experienced by players. Little is known regarding the transition of players from youth academy environments to full-time senior squads, however there is qualitative literature that suggests that increases in intensity are experienced. This is problematic for practitioners, as subjective measures of load have been shown to predominantly relate to external load measures which are representative of training volume. In Chapter 7 a modified version of sRPE and sRPE-TL was shown to better relate to intensity measures, however this was predominantly related to shorter duration training sessions. The aim of Chapter 8 was to investigate the transition experience of players, and to implement the previously suggested measure. Results showed that differences in squads were related to training frequency and volume, however there were significant differences identified regarding the modified measures, however the exact nature of these differences is unknown. There is a need for greater understanding regarding both the proposed modified measure, and the transition experience of players with specific reference to load differences. The modified measure may benefit from use of increased frequency measurements such as intrasession sRPE. To greater understand the load experienced by players, larger cohort studies are needed to reduce the bias of single club studies.

Chapter 9 – Synthesis of Findings

The aim of this chapter is to consider the current findings and reflect on these in relation to the original aims and objectives of the thesis. Additionally, this chapter will also provide a more generalised discussion, specifically focussing on how the research findings can be used in the field by practitioners working with soccer players. This chapter will also discuss the limitations of the collective research studies, before making recommendations for future research.

9.1 Achievement of Aims and Objectives

The main aim of the project was to assess the suitability of subjective measures, specifically sRPE, for measuring progression of soccer players from academy to senior environments. More specifically, this was done through the completion of five separate investigations (Chapter 4,5,6,7,8) to meet the following individual objectives:

Objective One: Consider the suitability of subjective measures of load by assessing relationships between subjective and objective measures across a competitive season in professional youth soccer players.

To understand the suitability of metrics commonly used within the professional youth phase, an analysis was carried out within Chapter 4 to understand the relationships between external and subjective measures of load. Bivariate analysis showed that dRPE measures were all positively correlated to various external load measures. To understand the relationships between measures further, multivariate analysis was carried out via PCA and EFA, these additional assessments showed that there did not appear to be unique information provided by sRPE-TL, sRPETL-L, and sRPETL-B. Therefore, within this cohort, subjective monitoring of sRPE-TL would appear to be sufficient. Additionally, subjective measures appeared to be more closely related to external measures of volume, more specifically, total distance covered, PlayerLoad and low-intensity running distance. Relationships between sRPE-TL and measures indicative of intensity were weaker. It was identified at this stage that further understanding of contextual factors, such as stage of season and training theme, would further improve the understanding of the consistency of relationships between subjective and objective measures of load.

Objective Two: Investigate the influence of factors such as training theme and stage of season, on relationships between subjective and objective measures of load.

Based on the findings of Chapter 4, an analysis was carried out to understand the influence of training theme on multivariate relationships between load variables (Chapter 5). Categorising training sessions based on their proximity to MD (e.g., MD-1, MD-2, etc.), alongside match-play data, identified the presence of multiple components when utilising PCA, again highlighting the need for multivariate analyses when assessing load relationships. Additionally, the analyses identified clear structures within the components, highlighting the relationship between sRPE-TL and external measures of volume. Further consideration was then given to the influence of season phase, on these relationships (Chapter 6). Whilst previous assessments identified multiple components following PCA, the method used within this analysis returned mixed outcomes. For the pre-season phase, as with previous analyses, multiple components were identified, suggesting that bivariate analyses are insufficient when considering relationships between metrics. However, during the competitive phases, when using a selection criteria based upon the principal components eigenvalue, single components were identified. However, the single component was still weighted heavily with regards to sRPE-TL and measures of volume. This adds further evidence that factoring load based on volume and intensity would be appropriate within this cohort.

Objective Three: Propose alternative subjective load measures and test these within a practical context.

Initial analyses within the thesis (Chapter 4, 5 & 6) identified that there appears to be a consistent relationship between sRPE-TL and external load measures of volume. This suggests that practitioners working in the absence of technology such as MEMS devices should be wary of using subjective measures of load if there is a desire to understand the intensity of training and match-play. Therefore, the aim of Chapter 7, was to propose alternative subjective methods of assessing intensity. To do this, non-linearity was introduced to sRPE and sRPE-TL measures. This analysis showed that generally following modification of measures the relationship between components representing volume and intensity were unaffected. However, when shorter duration sessions were considered, the ratio between components representing volume and intensity were increased for both sRPE and sRPE-TL. This suggests that, even when undergoing non-linear modification, subjective measures of load appear to be interpretative of volume. However, for shorter duration sessions a greater indication of intensity can be obtained by employing non-linear modifications. Whilst the modification proposed may not be optimal, Chapter 8 aimed to show how it could be used to better understand transitions from academy to full-time soccer. This analysis suggested that the main differences between academy and full-time soccer were related to volume. Using the proposed modified measure identified differences between academy, transitioning and development players, however the exact nature of this seems uncertain.

9.2 General Discussion

This project investigated the relationships between objective and subjective markers of training load, before proposing alternative methods of subjective load which may be use of use to practitioners monitoring players undergoing the transition between youth to senior soccer. The main findings were that sRPE-TL is primarily representative of training volume and gives little insight to intensity. This relationship remains stable, even when sRPE and sRPE-TL undergo non-linear modification. However, for shorter duration sessions it was possible to gain a greater understanding of intensity following non-linear modification.

Training load monitoring is a topic of significant interest within research and practice (Impellizzeri et al., 2019) and has been referred to as an opportunity for coaches to have a greater understanding of the psychophysiological demands placed on athletes, and improve the coach to athlete interface (Foster et al., 2017). Recent commentary has questioned the use of the term “load”, due to its use within mechanics, leading to a misrepresentation of the term (Staunton et al., 2021). However, within the practice of training load monitoring, “load” can be considered as an input variable which is prescribed and engineered to elicit a desired response (Impellizzeri et al., 2019). Training load is generally defined as being either internal or external. External load has previously been defined as the physical work carried out by the athlete, with internal load being represented by the resultant psychophysiological response (Impellizzeri et al., 2019). Collectively, load has been described as the “dose” of a training session, and is generally a combination of both volume and intensity (Renfree et al., 2021). Recently the concept of non-linearity has highlighted with regards to training load monitoring, challenging current methods within practice (Renfree et al., 2021). This concept proposes that whilst overall training load may be the same across a training session, the psychophysiological response of the athlete will likely depend on the method of application across a training session. As discussed in Chapter 7, aggregating training load across different durations of time is likely to disguise the true nature of the load imposed on athletes (Weaving et al., 2020, Renfree et al., 2021). For example, 10 minutes of training at an sRPE level of 10 and 100 minutes of training at an sRPE of 1 produces the same sRPE-TL value. In the example below, using random data from Chapters 4-7, a player has performed seven separate bouts of exercise, results in sRPE-TL values ranging from 184 to 1031 au. The duration of exercise ranged from 46 to 155mins, with the sRPE values provided being 4, 6 and 8 (Figure 9.1). It would be logical to assume that sessions with the shorter duration and the higher intensity would lead to greater physiological stress, despite sessions leading to similar or identical sRPE-TL values. To further complicate this matter, the undertaken external load may be significantly different in sessions (Figure 9.2). This highlights an issue with using sRPE-TL when comparing higher intensity and lower intensity sessions. As suggested by Renfree et al. (2021) this may lead to underestimation of the load performed within high intensity sessions relative to low intensity sessions. Practitioners should be wary that sessions which ultimately possess vastly different structures of volume and intensity, leading to vastly different physiological adaptations, may ultimately produce similar training load scores.

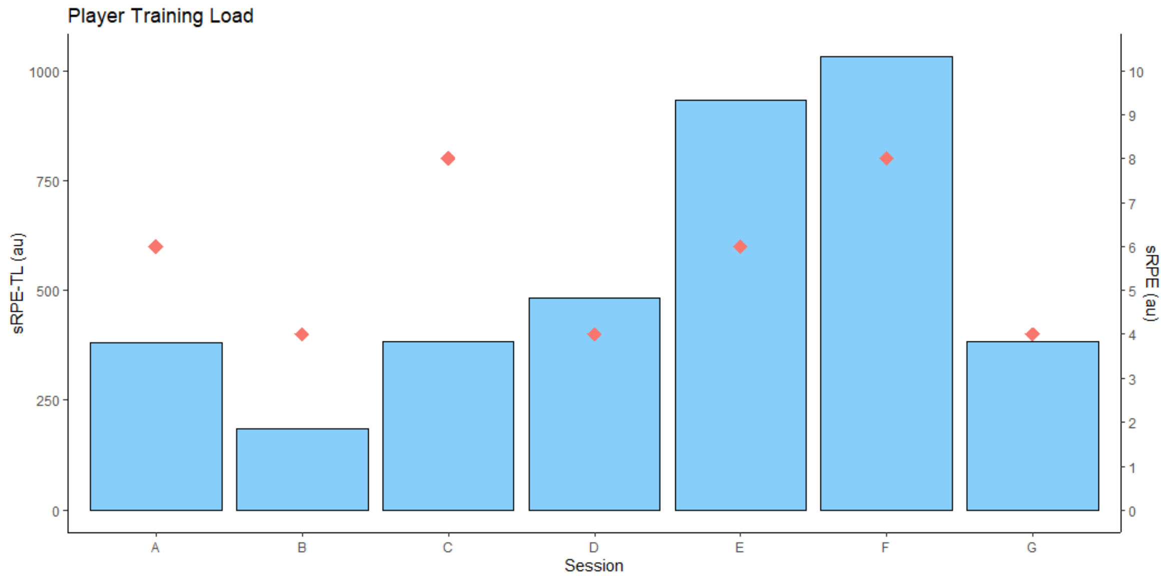

Figure 9.1 – Session rating of perceived exertion (RPE) and session rating of perceived exertion training load (sRPE-TL) data from seven sessions for one player to highlight impact of aggregating load over training duration. Key; sRPE-TL - session rating of perceived exertion training load; RPE – rating of perceived exertion; au – arbitrary units.

Additionally, Figure 9.2 highlights the potential risk of practitioners using sRPE-TL as a surrogate holistic load measure. When comparing sessions A and C, the sRPE value reported by the player in Session C is higher, however the high-speed running and sprint distance covered within Session A is significantly higher. Whilst there have been advancements in load monitoring practices, such as the use of the CR100® scale to account for the non-linear relationship between exercise and response, and the use of exponential weighting coefficients in internal load measures such as individualised TRIMP

(Manzi et al., 2009) it is still likely that sessions with notably different combinations of intensity and volume will lead to similar load outcomes (Renfree et al., 2021). Future research should further investigate the ability of statistical methods to represent the individualised and non-linear response to exercise. Additionally, reporting training load as a product of volume and intensity, alongside segregated measures of volume and intensity may be the best current method to communicate this complicated relationship to coaches.

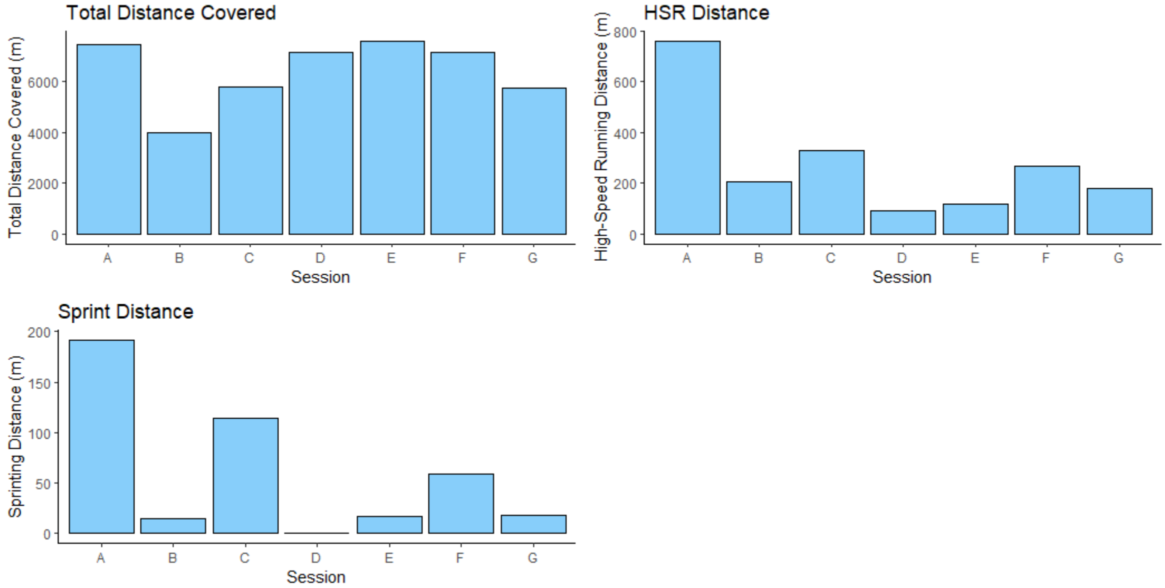

Figure 9.2 – External load data from seven sessions for one player to highlight impact of aggregating load over training duration. Key; HSR – high-speed running distance; m - metres

The results in Chapters 4 suggest that within the participant population dRPE provided limited additional insight above using sRPE in isolation. This is in contrast to previous research which suggests that dRPE measures provide unique information, and could give further insight for practitioners into exercise intensity and internal load in team sport training (McLaren et al., 2017). Recent research by Houtmeyers et al. (Houtmeyers et al., 2022b) highlighted that whilst there were notable levels of variability (0 to 64%) between-players when reporting sRPETL-B and sRPETL-L, differences between the two measures were only present in 22% of recorded sessions. Additionally, Houtmeyers et al. (2022b) showed that whilst sessions involving higher external load appeared to result in greater differentiation between sRPETL-B and sRPETL-L, the direction of this differentiation was not consistent. These results appear in line with findings in Chapter 4 of this thesis, which reports the significant relationship between sRPE-TL, sRPETL-B and sRPETL-L, assessed via bivariate correlation as well as multivariate methods of analyses. Further analysis by Houtmeyers et al. (2022a) in a lab-based setting, found that there were limited differences in sRPETL-B and sRPETL-L during sessions categorised as high-impact or low-impact based on running and jumping activities. Additionally, both measures were found to be greater within the low-impact session than high-impact session. Generally, there appears to be little consensus regarding the use of dRPE within team sports, with conflicting results presented within the literature.

Across Chapters 5 and 6 the aim of this thesis the aim was to investigate the influence of contextual factors such as training theme and phase of season on relationships between load measures presented in Chapter 4. Generally, relationships remained fairly consistent, with the first principal component generally being represented by sRPE-TL, total distance covered, PlayerLoad, and low-intensity running. The second retained component was generally represented by high-speed running, sprinting, accelerations, and decelerations. When investigating the effect of phase of season there were some notable differences, with two competitive phases having only one component meet the criteria for retention. This was, however, due to a different retention criteria being used in Chapter 6. Chapters 4 and 5 utilised the elbow method for selecting the number of components to retain following analysis, whilst Chapter 6 selected components for retention based on components having an eigenvalue of ≥1.0. PCA allows practitioners to select and extract variables that explain a significant amount of the total variance of a dataset, and is one of the most used statistical techniques in sport (Rojas-Valverde et al., 2020). Rojas-Valverde et al. (2020) highlight that due to the subjective nature of various elements of factor analysis, such as factor retention rules, there is a risk of methodological issues when data is analysed and interpreted. Analysing 45 studies from various team sports which utilised PCA as a method of factor analysis, Rojas-Valverde et al. (2020) found that in 62.2% of studies utilised an eigenvalue of >1 to determine factor retention, known as Kaiser's criteria. Visual analysis of the eigenvalues' scree plot, and identifying the 'elbow' of this plot, was also highlighted as a method used within analysis, although this does rely on practitioner judgement, increasing the subjectivity of factor retention (Rojas-Valverde et al., 2020). To reduce the influence of bias within factor retention, it appears appropriate for future research to utilise Kaiser's criteria to increase consistency of analysis.

The collective results from Chapters 4-6 suggest an intensity/volume divide in measures which characterise load, and evidence that sRPE-TL is reflective of training volume. This is potentially problematic for practitioners working in environments where technologies to allow external load monitoring are not feasible due to cost. A training load measure should provide insight which allows evaluation and adaptation of the training process

(Houtmeyers et al., 2022b, Windt et al., 2020). However, if sRPE-TL is not reflective of intensity, this may lead practitioners to underestimate the load experienced by athletes within training and match play. Therefore, the aim of Chapter 6 was to investigate and propose modifications of this measure to provide further insight into training volume, training intensity, or some combination of the two constructs. Producing metrics which involve the modification of load measures is not necessarily novel, with outcomes such as Banister's TRIMP (Banister, 1991), Lucia's TRIMP (Lucía et al., 2003), Edward's summation of HR zones (Edwards, 1993), and iTRIMP (Manzi et al., 2009) commonly used by practitioners. Banister's TRIMP and iTRIMP both involve non-linearities being introduced to allow relatively small changes towards the upper regions of intensity to be better reflected when calculating training load. With this in mind, the equation for calculating Banister's TRIMP was adapted (Equation 11), with weighting components ranging from 1-3 selected to investigate the potential for following this modification of objective internal load measures with modifications of subjective load measures.

Whilst our findings showed that outcomes could be modified, the magnitude of these results were not consistent. One key difference between our methods and those using Banister's equation is we used data collected across the season to quantify $sRPE_{min}$ and $sRPE_{max}$ rather than data collected within sessions. Future research may wish to investigate the impact of intra-session sRPE on these relationships. Intra-session sRPE involves the collection of subjective measures for various activities within a training session, for example a player may give a score of 3 (moderate) for an initial block of skills training, whilst reporting a 7 (very hard) for a block of games-based conditioning within a session. Having these multiple recordings within a session may allow improved use of our proposed methods, as a modified sRPE value would be provided based on the various levels of intensity experienced within an individual training session.

It is, however, worth remembering that one of the main attractions for practitioners to use the sRPE method is its ease of use and breadth of applicability across activities and populations (Foster et al., 2021). Additionally, it's worth noting that sRPE has been shown to be related to a range of internal load measures, such as average %HRR or blood lactate during a session (Foster et al., 1995), or Edwards' summated HR zones during interval based training (Foster et al., 2001). There is a large evidence base to support the use of sRPE, across a range of sports, with regards to its ability to provide a cost-effective, valid, and reliable surrogate measure of internal load across a session (Foster et al., 2021). What is less clear is the relationship between sRPE and external load, whilst sRPE may seem an attractive and more feasible option for practitioners who wish to monitor the load experienced by their athletes, this lack of clarity could lead to an underestimation of prescribed load. This is of particular interest during a transition from youth to senior environments in professional soccer, as this evolution is, anecdotally, characterised by increases in perceived intensity of training (Swainston et al., 2020). Chapter 8 of this thesis investigated the load experienced by players transitioning from academy to professional soccer in a Scottish Premiership club. Within the academy setting MEMS devices were not used, therefor subjective measures of load were compared between academy and development squad players. No significant difference was identified between weekly average sRPE values of transitioning players when either in the academy or professional system, however a significant difference was identified between session duration and sRPE-TL. This suggests that monitoring sRPE may not have any additional benefits over monitoring changes in session duration when monitoring transitions of players from academy to full-time soccer.

Whilst there was no significant difference between transitioning players and established development squad players of performed external load, there was a significant difference in average weekly sRPE, suggesting that whilst players are performing similar work, their experience of this is different. Modified sRPE appeared to highlight what would be expected across this transition. Transitional players reported significantly higher sessional modified sRPE values than when they were in the academy and reported significantly higher sessional modified sRPE values than established development squad players. However, when integrating duration within this measure these differences were less evident. Unfortunately, this research project was unable to utilise MEMS devices to allow comparison of external load performed across the compare newly promoted players to established development squad players. Whilst comparisons have been made between youth and senior groups of players (Houtmeyers et al., 2021), investigations of transitions within soccer seem to focus more on perceptual experiences of players, parents and coaches (Swainston et al., 2020). The lack of evidence supporting the proposed modified sRPE metric in longer duration sessions limits the validity of this measure. However, the impact this modification had on measures, and the ability to include intrasession sRPE in future analyses highlights its promise. Additionally, the lack of evidence regarding external load in academy players of the club participating in the study, reduces the ability to make clear conclusions or recommendations regarding the load experienced by players undergoing a transition. However, differences highlighted regarding the volume of training performed by players, and differences highlighted in the perception of effort between newly promoted and established development players suggest this is an area which warrants future investigation. Greater understanding of the experience of transition players would allow practitioners to plan and prescribe programmes to academy players which better prepare them for the demands of full-time soccer training. Additionally, understanding whether differences were related to either volume of training, or the intensity this training is performed at, would allow practitioners to design specific programmes in relation to this, thus reducing potential injury risk, and increasing potential of successful performance.

9.3 Conclusions

When considering subjective and external load monitor variables collected across a season in male professional soccer players, all measures were related to each other when performing bivariate methods of analysis. When performing multifactorial analysis methods such as PCA and EFA, it was revealed that there was a consistent dichotomy between external load measures which could be perceived as representing training volume, such as total distance, and measures representing intensity, such as sprinting distance covered. Consistently, sRPE-TL was related to measures of training volume. This relationship was unchanging when considering the impact of training theme, or phase of season. Grounded in previous successful attempts at better representing intensity of internal load measures, attempts were made to propose a modified subjective measure. It was hoped that using similar non-linear modifications employed by Banister's TRIMP (Banister, 1991) and iTRIMP (Manzi et al., 2009) this could be achieved with subjective measures of load. Whilst a greater bias towards intensity was achieved when modifying sRPE and sRPE-TL this only achieved for sessions with a duration of $\leq$ 60mins. Whilst the primary aim of this thesis was to better understand the relationships between load measures commonly used in practice, a secondary aim was to propose alternative measures and understand how these may be implemented in practice. When analysing the transition experience of players from academy to professional soccer, the main differences highlighted were in relation to session volume. Additionally, significant differences in perception of effort within training were found between newly promoted development squad players, and established development squad players. Finally, when considering the modified sRPE variable, significant differences were found between all levels regarding perception of effort within training sessions. Whilst the proposed method for modifying sRPE may not be the solution for better representing training intensity with subjective measures, it is hoped that the data from this research project can provide practitioners with greater understanding of the advantages and limitations of using these measures. Additionally, it is hoped that proposals from this study can be used to guide further research with regards to use of intra-session sRPE, and with regards to further warranted investigation of the player transition from academy to professional soccer.

9.4 Project Limitations and Recommendations for Future Research

This project aimed to assess the suitability of subjective measures, specifically sRPE, for measuring training load with a specific interest in the progression of soccer players from academy to senior environments. Throughout this project, some limitations have been identified, from these recommendations for future research are suggested below.

Throughout Chapters 4-8 inclusion criteria were applied with regards to the sessions considered within each analysis. Generally, this meant that sessions including post-match top-up sessions for non-starters, rehabilitation training, and non-pitch-based sessions such as gym-based recovery or resistance training sessions were not included. Whilst this does provide an incomplete view of training load across a season, it won’t affect relationships between variables. However, use of different training modes, such as those used in rehabilitation, may influence the relationship between dRPE and other load metrics, supporting its use. Whilst there is evidence of dRPE providing useful information with regards to breathlessness and leg muscle exertion (McLaren et al., 2017), capturing sensitive and actionable information regarding local tissue loads remains as a limitation of subjective load monitoring with regards to rehabilitation (Vanrenterghem et al., 2017, Gabbett et al., 2021). The impact of inclusion criteria may have more influence when considering progressions of athletes from academy to senior environments, as the aim here was to quantify the load experienced by players progressing from a part-time to full-time environment (Chapter 8). The main findings within Chapter 8 was the large increase in volume of training when undergoing this transition. Any additional sessions would likely have increased the magnitude of this finding, particularly given the analysis compared an end of season competitive phase, to a pre-season phase in a professional environment. Generally, annual plans for soccer players are divided into three phases (pre-season, competition, and off-season) with each having clear and distinct aims and objectives (Walker and Hawkins, 2018). A key aim of the pre-season phase is to develop physical qualities in players, such as aerobic capacity, and strength and power. Therefore, this may lead to an increase in pitch-based session frequency and duration, and an increase in gym-based session frequency and duration when comparing competitive and pre-season phases. Whilst this was not assessed as part of this study, it would seem logical to assume that inclusion of these sessions within the analysis from part-time and full-time environments would further evidence the large increase in training volume.

Throughout this project objective measures of external load, collected via MEMS devices, and subjective measures of internal load, collected via sRPE were utilised. Objective measures of internal load, which would commonly be assessed via HR measures, was not assessed throughout this study. Firstly, this was due to the monitoring practices of the club who provided data for this study. A comprehensive monitoring system, will ideally include objective and subjective markers for all relevant physiological and psychological aspects of training (Schneider et al., 2018). This would provide a more holistic approach to athlete monitoring, and in theory allow practitioners to make more informed decisions. However, when designing monitoring systems practitioners must also consider factors such as player adherence to systems, and financial impact of additional monitoring. The analyses carried out throughout Chapters 4 to 7 provide insightful information regarding the relationship between various load measures, whilst Chapter 8 introduces some insight into the load experienced by players undergoing a transition. Undoubtedly, further insight into the objective internal load experienced by players undergoing transition, and the relationship between these measures and the measures assessed within the project would provide further insight for practitioners.

The transition from youth to senior soccer has previously been highlighted as a unique period, characterised by its chaotic nature (Swainston et al., 2020). Being prepared for this transition will place demands on a range of factors. It has previously been highlighted that simply being a talented youth academy player does not predict success in managing the transition from youth to senior soccer (Gledhill et al., 2017). When undergoing a transition a player is likely to face a multifactorial increase in demands, broadly characterised as increases in elements of psychological, physiological, technical and tactical requirements (Swainston et al., 2020, Haugaasen and Jordet, 2012). This project has isolated an element of physiological demands, considering the internal and external load completed by players, and the influence this has during a transition. This provides an incomplete assessment of the experience of a player undergoing a transition from youth to senior soccer. Previous research has focussed on psychosocial development as a priority for developing players towards senior soccer (Swainston et al., 2020, Stambulova et al., 2021). As has previously been acknowledged in studies concerning psychosocial development, there is no way of knowing if players who display certain characteristics over the course of a study will be successful in their future careers. Similarly, there is no way of definitively stating that players who perceive transitional workload as more manageable will be successful when entering first team environments. However, the quantifiable nature of this project provides further detail regarding the demands of the transition from youth to senior soccer and gives an insight into how individuals may perceive those demands. Future research may wish to investigate a combination of qualitative and quantitative research to provide a more holistic insight into the transition phase. This would provide further understanding regarding the specific workload demands prescribed for players, and the resultant experience of players.

9.5 – Practical Recommendations from the Present Thesis

One of the aims of this industry embedded project was to provide practitioners, both at the investigated club and more widely, with a greater understanding of subjective measures of load, and more specifically how these can be used around the transition period in youth soccer players. The practical recommendations from the thesis are as follows:

1. In the population investigated, there does not appear to be unique information provided by dRPE, with this cohort it appears sufficient for practitioners to monitor sRPE only, to attain a measure of training load. Additionally, many subjective and external load variables provide data that are highly related to each other, therefore the collection and monitoring of certain variables will be inefficient and create unwanted noise within a load monitoring system.

2. Relationships between load measures, and the distinction between groups of measures, appear to be consistent regardless of training theme, and season phase. This suggests that if factoring load based on volume and intensity practitioners can be confident that these relationships will remain consistent. This suggests that practitioners should use a combination of internal and external load measures during training (Weaving et al., 2014), however the theme of training doesn't necessarily need to influence this selection. Training sessions with clear differentiation may lead to a need for greater consideration of training mode when selecting load measures.

3. The consistency of these relationships has evidenced that sRPE-TL is predominantly related to external load measures of training volume, such as total distance covered, PlayerLoad, and low-intensity running. Therefore, if practitioners wish to gather information regarding training intensity, and certain load monitoring methods are not feasible, sRPE-TL is not a suitable measure. This may be of particular interest for practitioners investigating progression from youth to senior soccer, where increases in training and match play intensity may be expected.

4. Introducing non-linearities to subjective measures, to allow greater representation of high-intensity training and match play, may be a suitable method to address this situation, however the method proposed within this study is not sufficient and likely requires higher frequency measures. Use of higher frequency measures such as intra-session sRPE may provide a more robust measurement and allow greater representation of training intensity. Practitioners and academics working within the field may wish to further explore the method proposed within this thesis, as well as introducing higher frequency data to compare outcomes.

5. When comparing new and established senior soccer players, there was limited differences in external load profiles during the pre-season phase. If the transition from youth to senior soccer is characterised by an increase in intensity, then some form of training intervention, either within the pre-season phase or at the end of the preceding academy season may be required to better prepare players for this increase. This training phase could be treated as an “induction” to full-time football to allow players a phased entry to this increase in training load. Theoretically, this will provide players with the ability to better cope with load prescribed in a pre-season phase.

6. Currently, practitioners working in professional football should continue to include measures of both internal and external load within load monitoring practices. This process should allow them to represent and understand load experienced by players across a range of training modes at various stages of the season. Practitioners who are currently employing this strategy may wish to investigate more sophisticated statistical techniques employing multivariate analyses, such as PCA, to better communicate information to key stakeholders such as coaches. Furthermore, companies providing athlete monitoring systems to organisations should look to introduce these approaches within their software to reduce burden on practitioners.

9.6 - Personal Reflections

When beginning this PhD thesis, I had relatively limited knowledge regarding the importance of monitoring load in athletes, outside of a brief introduction to the process as part of my undergraduate degree. When joining Aberdeen Football Club as a sport scientist for the youth academy there was no monitoring of the load undertaken by players throughout the academy and within the early phase professionals, at that time U20 players. Across the 3-years of this PhD project my own practices evolved significantly alongside the resource that the club invested in providing a professional environment for their youth players.

The literature review, alongside an audit of the club at the time, worked as a catalyst for practitioners and key stakeholders to understand the club's current position and where they could go. From having 5 MEMS devices which were shared across an U20 squad of 20 players, we soon had all professional players equipped with the ability to monitor external load. My own interests soon led to me investigating and implementing the use of RPE, and eventually dRPE, to provide us with a more holistic view of load experienced by players. Implementation of these practices weren't without their problems, from development loan players forgetting to turn on devices before a lower league game, to trying to introduce valid and reliable methods of load monitoring within the chaotic environment of professional football. This took significant effort from all practitioners involved in the collection of load monitoring data, but over time we developed an athlete monitoring system which allowed us to make data-informed decisions which could influence coach decision making.

One of the key developments which was linked to this project, was highlighting the lack of variety in training of youth professional players at the club, largely due to our lack of training ground and facilities. The move to our training centre at Kingsford was a kickstart to a more variable training programme influenced by tactical periodisation and supported through coach education and collaborative working between various stakeholders. Having now left the club for a career in academia it's great to see that this has developed further and now influences the club more widely. Ultimately, load monitoring is a small but important part of the overall development of football players, and for a system to work efficiently and to influence decision making it needs the buy-in and clear vision of various stakeholders. Undoubtedly, I was lucky to have people around me pulling in the same direction who could see the value of what our department was trying to do.

There are still many areas which Aberdeen Football Club, and other clubs globally, can improve with regards to load monitoring. This is likely going to be reliant on future developments of technology, and development of software to create bespoke reports for clubs and players. This thesis introduces a measure which hoped to address the issue of modelling the non-linearity of training to subjective measures of load, an issue which has been highlighted in our field. Whilst the method proposed by the author is likely not "the way", hopefully it is a step in a positive direction to further improve this area of research and understanding.

Chapter 10 - References

ABT, G. & LOVELL, R., 2009. The use of individualized speed and intensity thresholds for determining the distance run at high-intensity in professional soccer. *Journal of Sports Sciences,* 27(9), pp. 893-898.

AKENHEAD, R., FRENCH, D., THOMPSON, K. G. & HAYES, P. R., 2014. The acceleration dependent validity and reliability of 10 Hz GPS. *Journal of Science and Medicine in Sport,* 17(5), pp. 562-566.

AKENHEAD, R., HAYES, P. R., THOMPSON, K. G. & FRENCH, D., 2013. Diminutions of acceleration and deceleration output during professional football match play. *Journal of Science and Medicine in Sport,* 16(6), pp. 556-561.

AKENHEAD, R. & NASSIS, G. P., 2016. Training load and player monitoring in high-level football: current practice and perceptions. *International journal of sports physiology and performance,* 11(5), pp. 587-593.

AKUBAT, I., PATEL, E., BARRETT, S. & ABT, G., 2012. Methods of monitoring the training and match load and their relationship to changes in fitness in professional youth soccer players. *Journal of Sports Sciences,* 30(14), pp. 1473-1480.

ALEXANDRE, D., DA SILVA, C. D., HILL-HAAS, S., WONG, D. P., NATALI, A. J., DE LIMA, J. R., BARA FILHO, M. G., MARINS, J. J., GARCIA, E. S. & KARIM, C., 2012. Heart rate monitoring in soccer: interest and limits during competitive match play and training, practical application. *The Journal of Strength & Conditioning Research,* 26(10), pp. 2890-2906.

ALEXIOU, H. & COUTTS, A. J., 2008. A comparison of methods used for quantifying internal training load in women soccer players. *International Journal of Sports Physiology and Performance,* 3(3), pp. 320-330.

AUGHEY, R. J., 2011. Applications of GPS technologies to field sports. *International Journal of Sports Physiology and Performance,* 6(3), pp. 295-310.

AVALOS, M., HELLARD, P. & CHATARD, J.-C., 2003. Modeling the training-performance relationship using a mixed model in elite swimmers. *Medicine and Science in Sports and Exercise,* 35(5), pp. 838.

BAKDASH, J. Z. & MARUSICH, L. R., 2017. Repeated measures correlation. *Frontiers in Psychology,* 8pp. 456.

BAKEMAN, R., 2005. Recommended effect size statistics for repeated measures designs. *Behavior research methods,* 37(3), pp. 379-384.

BANGSBO, J., NØRREGAARD, L. & THORSOE, F., 1991. Activity profile of competition soccer. *Canadian journal of sport sciences= Journal canadien des sciences du sport,* 16(2), pp. 110-116.

BANISTER, E., 1991. Modeling elite athletic performance. *Physiological testing of elite athletes,* pp. 403-424.

BANISTER, E., CALVERT, T., SAVAGE, M. & BACH, T., 1975. A systems model of training for athletic performance. *Aust J Sports Med,* 7(3), pp. 57-61.

BANISTER, E. & HAMILTON, C., 1985. Variations in iron status with fatigue modelled from training in female distance runners. *European Journal of Applied Physiology and Occupational Physiology,* 54(1), pp. 16-23.

BARBERO-ÁLVAREZ, J. C., COUTTS, A., GRANDA, J., BARBERO-ÁLVAREZ, V. & CASTAGNA, C., 2010. The validity and reliability of a global positioning satellite system device to assess speed and repeated sprint ability (RSA) in athletes. *Journal of Science and Medicine in Sport,* 13(2), pp. 232-235.

BARNES, C., ARCHER, D., BUSH, M., HOGG, R. & BRADLEY, P., 2014. The evolution of physical and technical performance parameters in the English Premier League. *International Journal of Sports Medicine,* 35pp. 1-6.

BARRETT, S., MIDGLEY, A. & LOVELL, R., 2014. PlayerLoad™: Reliability, Convergent Validity, and Influence of Unit Position During Treadmill Running. *International journal of sports physiology and performance,* 9(6), pp. 945-952.

BARROS, R. M., MISUTA, M. S., MENEZES, R. P., FIGUEROA, P. J., MOURA, F. A., CUNHA, S. A., ANIDO, R. & LEITE, N. J., 2007. Analysis of the distances covered by first division Brazilian soccer players obtained with an automatic tracking method. *Journal of sports science & medicine,* 6(2), pp. 233.

BARTLETT, M. S., 1954. A note on the multiplying factors for various χ2 approximations. *Journal of the Royal Statistical Society: Series B (Methodological),* 16(2), pp. 296-298.

BASTIDA-CASTILLO, A., GÓMEZ-CARMONA, C. D., DE LA CRUZ SANCHEZ, E. & PINO-ORTEGA, J., 2019. Comparing accuracy between global positioning systems and ultra-wideband-based position tracking systems used for tactical analyses in soccer. *European journal of sport science,* 19(9), pp. 1157-1165.

BATALLER-CERVERO, A. V., GUTIERREZ, H., DERENTERÍA, J., PIEDRAFITA, E., MARCÉN, N., VALERO-CAMPO, C., LAPUENTE, M. & BERZOSA, C., 2019. Validity and reliability of a 10 Hz GPs for assessing variable and mean running speed. *Journal of human kinetics,* 67(1), pp. 17-24.

BEATO, M., BARTOLINI, D., GHIA, G. & ZAMPARO, P., 2016. Accuracy of a 10 Hz GPS unit in measuring shuttle velocity performed at different speeds and distances (5–20 M). *Journal of human kinetics,* 54(1), pp. 15-22.

BEATO, M., DEVEREUX, G. & STIFF, A., 2018. Validity and reliability of global positioning system units (STATSports Viper) for measuring distance and peak speed in sports. *The Journal of Strength & Conditioning Research,* 32(10), pp. 2831-2837.

BISHOP, D., 2008. An applied research model for the sport sciences. *Sports Medicine,* 38(3), pp. 253-263.

BORG, D. N., NGUYEN, R. & TIERNEY, N. J., 2022. Missing data: current practice in football research and recommendations for improvement. *Science and Medicine in Football,* 6(2), pp. 262-267.

BORG, E. 2007. *On perceived exertion and its measurement.* Stockholm University.

BORG, E. & BORG, G., 2002. A comparison of AME and CR100 for scaling perceived exertion. *Acta Psychologica,* 109(2), pp. 157-175.

BORG, E., BORG, G., LARSSON, K., LETZTER, M. & SUNDBLAD, B. M., 2010. An index for breathlessness and leg fatigue. *Scandinavian Journal of Medicine and Science in Sports,* 20(4), pp. 644-650.

BORG, G., 1970. Perceived exertion as an indicator of somatic stress. *Scandinavian Journal of Rehabilitation Medicine,* 2pp. 92-98.

BORG, G., 1982a. A category scale with ratio properties for intermodal and interindividual comparisons. *Psychophysical judgment and the process of perception,* pp. 25-34.

BORG, G. & DAHLSTRÖM, H. 1960. *The perception of muscular work*, Publications of the Umea Research Library.

BORG, G., HASSMÉN, P. & LAGERSTRÖM, M., 1987. Perceived exertion related to heart rate and blood lactate during arm and leg exercise. *European Journal of Applied Physiology and Occupational Physiology,* 56(6), pp. 679-685.

BORG, G., LJUNGGREN, G. & CECI, R., 1985. The increase of perceived exertion, aches and pain in the legs, heart rate and blood lactate during exercise on a bicycle ergometer. *European Journal of Applied Physiology and Occupational Physiology,* 54(4), pp. 343-349.

BORG, G. A., 1962. Physical performance and perceived exertion.

BORG, G. A., 1982b. Psychophysical bases of perceived exertion. *Medicine and Science in Sports and Exercise,* 14(5), pp. 377-381.

BORRESEN, J. & LAMBERT, M. I., 2008. Quantifying training load: a comparison of subjective and objective methods. *International Journal of Sports Physiology and Performance,* 3(1), pp. 16-30.

BORRESEN, J. & LAMBERT, M. I., 2009. The Quantification of Training Load, the Training Response and the Effect on Performance. *Sports Medicine,* 39(9), pp. 779-795.

BOURDON, P. C., CARDINALE, M., MURRAY, A., GASTIN, P., KELLMANN, M., VARLEY, M. C., GABBETT, T. J., COUTTS, A. J., BURGESS, D. J. & GREGSON, W., 2017. Monitoring athlete training loads: consensus statement. *International Journal of Sports Physiology and Performance,* 12(s2), pp. S2-161-S2-170.

BOWEN, L., GROSS, A. S., GIMPEL, M., BRUCE-LOW, S. & LI, F.-X., 2019. Spikes in acute:chronic workload ratio (ACWR) associated with a 5–7 times greater injury rate in English Premier League football players: a comprehensive 3-year study. *British Journal of Sports Medicine,* pp. bjsports-2018-099422.

BOWEN, L., GROSS, A. S., GIMPEL, M. & LI, F.-X., 2017. Accumulated workloads and the acute: chronic workload ratio relate to injury risk in elite youth football players. *British journal of sports medicine,* 51(5), pp. 452-459.

BOYD, L. J., BALL, K. & AUGHEY, R. J., 2011. The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *Int J Sports Physiol Perform,* 6(3), pp. 311-321.

BRADLEY, P. S., DI MASCIO, M., PEART, D., OLSEN, P. & SHELDON, B., 2010. High-Intensity Activity Profiles of Elite Soccer Players at Different Performance Levels. *The Journal of Strength & Conditioning Research,* 24(9).

BRADLEY, P. S., SHELDON, W., WOOSTER, B., OLSEN, P., BOANAS, P. & KRUSTRUP, P., 2009. High-intensity running in English FA Premier League soccer matches. *Journal of Sports Sciences,* 27(2), pp. 159-168.

BREDT, S. D. G. T., CHAGAS, M. H., PEIXOTO, G. H., MENZEL, H. J. & DE ANDRADE, A. G. P., 2020. Understanding player load: Meanings and limitations. *Journal of human kinetics,* 71pp. 5.

BREDT, S. D. G. T., PRAÇA, G. M., FIGUEIREDO, L. S., PAULA, L. V. D., SILVA, P. C. R., ANDRADE, A. G. P. D., GRECO, P. J. & CHAGAS, M. H., 2016. Reliability of physical, physiological and tactical measures in small-sided soccer Games with numerical equality and numerical superiority. *Revista Brasileira de Cineantropometria & Desempenho Humano,* 18(5), pp. 602-610.

BRO, R. & SMILDE, A. K., 2003. Centering and scaling in component analysis. *Journal of chemometrics,* 17(1), pp. 16-33.

BUCHHEIT, M., AL HADDAD, H., SIMPSON, B. M., PALAZZI, D., BOURDON, P. C., DI SALVO, V. & MENDEZ-VILLANUEVA, A., 2014. Monitoring accelerations with GPS in football: time to slow down? *International Journal of Sports Physiology and Performance,* 9(3), pp. 442-445.

BUCHHEIT, M., GRAY, A. & MORIN, J.-B., 2015. Assessing stride variables and vertical stiffness with GPS-embedded accelerometers: preliminary insights for the monitoring of neuromuscular fatigue on the field. *Journal of Sports Science & Medicine,* 14(4), pp. 698.

BUCHHEIT, M., LACOME, M., CHOLLEY, Y. & SIMPSON, B. M., 2018. Neuromuscular responses to conditioned soccer sessions assessed via GPS-embedded accelerometers: insights into tactical periodization. *International Journal of Sports Physiology and Performance,* 13(5), pp. 577-583.

BUCHHEIT, M. & LAURSEN, P. B., 2013. High-intensity interval training, solutions to the programming puzzle. *Sports Medicine,* 43(10), pp. 927-954.

BUCHHEIT, M., MENDEZ-VILLANUEVA, A., SIMPSON, B. & BOURDON, P., 2010. Match running performance and fitness in youth soccer. *International journal of sports medicine,* 31(11), pp. 818-825.

BUCHHEIT, M. & SIMPSON, B. M., 2017. Player-tracking technology: half-full or half-empty glass? *International Journal of Sports Physiology and Performance,* 12(s2), pp. S2-35-S2-41.

BURGESS, D., NAUGHTON, G. & NORTON, K., 2006. Profile of movement demands of national football players in Australia. *Journal of Science and Medicine in Sport,* 9(4), pp. 334-341.

BUSH, M., BARNES, C., ARCHER, D. T., HOGG, B. & BRADLEY, P. S., 2015. Evolution of match performance parameters for various playing positions in the English Premier League. *Human movement science,* 39pp. 1-11.

BUSSO, T., 2003. Variable dose-response relationship between exercise training and performance. *Medicine and Science in Sports and Exercise,* 35(7), pp. 1188-1195.

BUSSO, T., CANDAU, R. & LACOUR, J.-R., 1994. Fatigue and fitness modelled from the effects of training on performance. *European Journal of Applied Physiology and Occupational Physiology,* 69(1), pp. 50-54.

BUSSO, T., HÄKKINEN, K., PAKARINEN, A., CARASSO, C., LACOUR, J., KOMI, P. & KAUHANEN, H., 1990. A systems model of training responses and its relationship to hormonal responses in elite weight-lifters. *European journal of applied physiology and occupational physiology,* 61(1-2), pp. 48-54.

BUSSO, T., HÄKKINEN, K., PAKARINEN, A., KAUHANEN, H., KOMI, P. & LACOUR, J., 1992. Hormonal adaptations and modelled responses in elite weightlifters during 6 weeks of training. *European Journal of Applied Physiology and Occupational Physiology,* 64(4), pp. 381-386.

BUUREN, S. V. & GROOTHUIS-OUDSHOORN, K., 2010. mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software,* pp. 1-68.

CALVERT, T. W., BANISTER, E. W., SAVAGE, M. V. & BACH, T., 1976. A systems model of the effects of training on physical performance. *IEEE Transactions on systems, man, and cybernetics,* (2), pp. 94-102.

CAMPOS-VAZQUEZ, M. A., MENDEZ-VILLANUEVA, A., GONZALEZ-JURADO, J. A., LEÓN-PRADOS, J. A., SANTALLA, A. & SUAREZ-ARRONES, L., 2015. Relationships between rating-of-perceived-exertion-and heart-rate-derived internal training load in professional soccer players: a comparison of on-field integrated training sessions. *International Journal of Sports Physiology and Performance,* 10(5), pp. 587-592.

CARDINALE, M. & VARLEY, M. C., 2017. Wearable training-monitoring technology: applications, challenges, and opportunities. *International Journal of Sports Physiology and Performance,* 12(s2), pp. S2-55-S2-62.

CASAMICHANA, D. & CASTELLANO, J., 2015. The relationship between intensity indicators in small-sided soccer games. *Journal of human kinetics,* 46(1), pp. 119-128.

CASAMICHANA, D., CASTELLANO, J., CALLEJA-GONZALEZ, J., SAN ROMÁN, J. & CASTAGNA, C., 2013. Relationship between indicators of training load in soccer players. *The Journal of Strength & Conditioning Research,* 27(2), pp. 369-374.

CASTAGNA, C., D'OTTAVIO, S. & ABT, G., 2003. Activity profile of young soccer players during actual match play. *The Journal of Strength & Conditioning Research,* 17(4), pp. 775-780.

CASTAGNA, C., IMPELLIZZERI, F., CECCHINI, E., RAMPININI, E. & ALVAREZ, J. C. B., 2009. Effects of intermittent-endurance fitness on match performance in young male soccer players. *The Journal of Strength & Conditioning Research,* 23(7), pp. 1954-1959.

CASTAGNA, C., MANZI, V., IMPELLIZZERI, F., WESTON, M. & ALVAREZ, J. C. B., 2010. Relationship between endurance field tests and match performance in young soccer players. *The Journal of Strength & Conditioning Research,* 24(12), pp. 3227-3233.

CASTELLANO, J., CASAMICHANA, D., CALLEJA-GONZÁLEZ, J., SAN ROMÁN, J. & OSTOJIC, S. M., 2011. Reliability and accuracy of 10 Hz GPS devices for short-distance exercise. *Journal of Sports Science & Medicine,* 10(1), pp. 233.

CHAMBERS, R., GABBETT, T. J., COLE, M. H. & BEARD, A., 2015. The use of wearable microsensors to quantify sport-specific movements. *Sports Medicine,* 45(7), pp. 1065-1081.

CHIU, L. Z. & BARNES, J. L., 2003. The fitness-fatigue model revisited: Implications for planning short-and long-term training. *Strength & Conditioning Journal,* 25(6), pp. 42-51.

CLARKE, N., FARTHING, J. P., NORRIS, S. R., ARNOLD, B. E. & LANOVAZ, J. L., 2013. Quantification of training load in Canadian football: application of session-RPE in collision-based team sports. *The Journal of Strength & Conditioning Research,* 27(8), pp. 2198-2205.

CLAUDINO, J. G., CRONIN, J., MEZÊNCIO, B., MCMASTER, D. T., MCGUIGAN, M., TRICOLI, V., AMADIO, A. C. & SERRÃO, J. C., 2017. The countermovement jump to monitor neuromuscular status: A meta-analysis. *Journal of Science and Medicine in Sport,* 20(4), pp. 397-402.

COLES, P. A., 2018. An injury prevention pyramid for elite sports teams. *British Journal of Sports Medicine,* 52(15), pp. 1008-1010.

CORMIE, P., MCBRIDE, J. M. & MCCAULLEY, G. O., 2009. Power-time, force-time, and velocity-time curve analysis of the countermovement jump: impact of training. *The Journal of Strength & Conditioning Research,* 23(1), pp. 177-186.

COUTTS, A. J., CROWCROFT, S. & KEMPTON, T. 2017. Developing athlete monitoring systems: theoretical basis and practical applications. *Sport, Recovery, and Performance.* Routledge.

COUTTS, A. J. & DUFFIELD, R., 2010. Validity and reliability of GPS devices for measuring movement demands of team sports. *Journal of Science and Medicine in Sport,* 13(1), pp. 133-135.

CUMMINS, C., ORR, R., O'CONNOR, H. & WEST, C., 2013. Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Medicine,* 43(10), pp. 1025-1042.

CURRELL, K. & JEUKENDRUP, A. E., 2008. Validity, reliability and sensitivity of measures of sporting performance. *Sports Medicine,* 38(4), pp. 297-316.

DALEN, T., JØRGEN, I., GERTJAN, E., HAVARD, H. G. & ULRIK, W., 2016. Player load, acceleration, and deceleration during forty-five competitive matches of elite soccer. *The Journal of Strength & Conditioning Research,* 30(2), pp. 351-359.

DELANEY, J. A., THORNTON, H. R., ROWELL, A. E., DASCOMBE, B. J., AUGHEY, R. J. & DUTHIE, G. M., 2018. Modelling the decrement in running intensity within professional soccer players. *Science and Medicine in Football,* 2(2), pp. 86-92.

DELGADO-BORDONAU, J. L. & MENDEZ-VILLANUEVA, A., 2012. Tactical periodization: Mourinho's best-kept secret. *Soccer Journal,* 57(3), pp. 29-34.

DELLAL, A., OWEN, A., WONG, D., KRUSTRUP, P., VAN EXSEL, M. & MALLO, J., 2012. Technical and physical demands of small vs. large sided games in relation to playing position in elite soccer. *Human movement science,* 31(4), pp. 957-969.

DI PRAMPERO, P., FUSI, S., SEPULCRI, L., MORIN, J.-B., BELLI, A. & ANTONUTTO, G., 2005. Sprint running: a new energetic approach. *Journal of Experimental Biology,* 208(14), pp. 2809-2816.

DI SALVO, V., BARON, R., TSCHAN, H., CALDERON MONTERO, F. J., BACHL, N. & PIGOZZI, F., 2007. Performance Characteristics According to Playing Position in Elite Soccer. *International journal of sports medicine,* 28(3), pp. 222-227.

DI SALVO, V., GREGSON, W., ATKINSON, G., TORDOFF, P. & DRUST, B., 2009. Analysis of high intensity activity in Premier League soccer. *International Journal of Sports Medicine,* 30(03), pp. 205-212.

DODD, A. L., MANSELL, W., SADHNANI, V., MORRISON, A. P. & TAI, S., 2010. Principal components analysis of the Hypomanic Attitudes and Positive Predictions Inventory and associations with measures of personality, cognitive style and analogue symptoms in a student sample. *Behavioural and Cognitive Psychotherapy,* 38(1), pp. 15-33.

DREW, M. K. & FINCH, C. F., 2016. The relationship between training load and injury, illness and soreness: a systematic and literature review. *Sports Medicine,* 46(6), pp. 861-883.

DRUST, B., REILLY, T. & CABLE, N., 2000. Physiological responses to laboratory-based soccer-specific intermittent and continuous exercise. *Journal of sports sciences,* 18(11), pp. 885-892.

EDGECOMB, S. & NORTON, K., 2006. Comparison of global positioning and computer-based tracking systems for measuring player movement distance during Australian football. *Journal of Science and Medicine in Sport,* 9(1-2), pp. 25-32.

EDWARDS, S., 1993. High performance training and racing. *The heart rate monitor book,* 12(2), pp. 113-123.

EGAN, A. D., WINCHESTER, J. B., FOSTER, C. & MCGUIGAN, M. R., 2006. Using session RPE to monitor different methods of resistance exercise. *Journal of Sports Science and Medicine,* 5(2), pp. 289-295.

FANCHINI, M., FERRARESI, I., MODENA, R., SCHENA, F., COUTTS, A. J. & IMPELLIZZERI, F. M., 2016. Use of the CR100 scale for session rating of perceived exertion in soccer and its interchangeability with the CR10. *International journal of sports physiology and performance,* 11(3), pp. 388-392.

FAUDE, O., KINDERMANN, W. & MEYER, T., 2009. Lactate Threshold Concepts: how valid are they? *Sports Medicine,* 39(6), pp. 469-490.

FEDEROLF, P., REID, R., GILGIEN, M., HAUGEN, P. & SMITH, G., 2014. The application of principal component analysis to quantify technique in sports. *Scandinavian Journal of Medicine and Science in Sports,* 24(3), pp. 491-499.

FINN, J. & MCKENNA, J., 2010. Coping with academy-to-first-team transitions in elite English male team sports: The coaches' perspective. *International Journal of Sports Science & Coaching,* 5(2), pp. 257-279.

FORD, P. R., BORDONAU, J. L. D., BONANNO, D., TAVARES, J., GROENENDIJK, C., FINK, C., GUALTIERI, D., GREGSON, W., VARLEY, M. C. & WESTON, M., 2020. A survey of talent identification and development processes in the youth academies of professional soccer clubs from around the world. *Journal of Sports Sciences,* 38(11-12), pp. 1269-1278.

FOSTER, C., 1988. Translation of exercise test response to exercise prescription. *Clinical exercise programs Mouvement Publications, Ithaca, NY,* pp. 169-178.

FOSTER, C., 1998. Monitoring training in athletes with reference to overtraining syndrome. *Medicine and Science in Sports and Exercise,* 30pp. 1164-1168.

FOSTER, C., BOULLOSA, D., MCGUIGAN, M., FUSCO, A., CORTIS, C., ARNEY, B. E., ORTON, B., DODGE, C., JAIME, S. & RADTKE, K., 2021. 25 years of session rating of perceived exertion: historical perspective and development. *International journal of sports physiology and performance,* 16(5), pp. 612-621.

FOSTER, C., FLORHAUG, J. A., FRANKLIN, J., GOTTSCHALL, L., HROVATIN, L. A., PARKER, S., DOLESHAL, P. & DODGE, C., 2001. A new approach to monitoring exercise training. *The Journal of Strength & Conditioning Research,* 15(1), pp. 109-115.

FOSTER, C., HECTOR, L. L., WELSH, R., SCHRAGER, M., GREEN, M. A. & SNYDER, A. C., 1995. Effects of specific versus cross-training on running performance. *European Journal of Applied Physiology and Occupational Physiology,* 70(4), pp. 367-372.

FOSTER, C., RODRIGUEZ-MARROYO, J. A. & DE KONING, J. J., 2017. Monitoring training loads: the past, the present, and the future. *International journal of sports physiology and performance,* 12(s2), pp. S2-2-S2-8.

FUDGE, B. W., WILSON, J., EASTON, C., IRWIN, L., CLARK, J., HADDOW, O., KAYSER, B. & PITSILADIS, Y. P., 2007. Estimation of oxygen uptake during fast running using accelerometry and heart rate. *Medicine & Science in Sports & Exercise,* 39(1), pp. 192-198.

GABBETT, T., JENKINS, D. & ABERNETHY, B., 2010. Physical collisions and injury during professional rugby league skills training. *Journal of Science and Medicine in Sport,* 13(6), pp. 578-583.

GABBETT, T., SANCHO, I., DINGENEN, B. & WILLY, R. W. 2021. When progressing training loads, what are the considerations for healthy and injured athletes? : BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine.

GABBETT, T. J., 2013. Quantifying the physical demands of collision sports: does microsensor technology measure what it claims to measure? *The Journal of Strength & Conditioning Research,* 27(8), pp. 2319-2322.

GABBETT, T. J., 2016. The training—injury prevention paradox: should athletes be training smarter and harder? *British journal of sports medicine,* 50(5), pp. 273-280.

GABBETT, T. J. & DOMROW, N., 2007. Relationships between training load, injury, and fitness in sub-elite collision sport athletes. *Journal of Sports Sciences,* 25(13), pp. 1507-1519.

GABBETT, T. J., JENKINS, D. G. & ABERNETHY, B., 2012. Physical demands of professional rugby league training and competition using microtechnology. *Journal of Science and Medicine in Sport,* 15(1), pp. 80-86.

GALLO, T., CORMACK, S., GABBETT, T., WILLIAMS, M. & LORENZEN, C., 2015. Characteristics impacting on session rating of perceived exertion training load in Australian footballers. *Journal of Sports Sciences,* 33(5), pp. 467-475.

GAUDINO, P., IAIA, F. M., STRUDWICK, A. J., HAWKINS, R. D., ALBERTI, G., ATKINSON, G. & GREGSON, W., 2015. Factors influencing perception of effort (session rating of perceived exertion) during elite soccer training. *International journal of sports physiology and performance,* 10(7), pp. 860-864.

GIL-REY, E., LEZAUN, A. & LOS ARCOS, A., 2015. Quantification of the perceived training load and its relationship with changes in physical fitness performance in junior soccer players. *Journal of Sports Sciences,* 33(20), pp. 2125-2132.

GIMENEZ, J. V., GARCIA-UNANUE, J., NAVANDAR, A., VIEJO-ROMERO, D., SANCHEZ-SANCHEZ, J., GALLARDO, L., HERNANDEZ-MARTIN, A. & FELIPE, J. L., 2020. Comparison between Two Different Device Models 18 Hz GPS Used for Time–Motion Analyses in Ecological Testing of Football. *International Journal of Environmental Research and Public Health,* 17(6), pp. 1912.

GLEDHILL, A., HARWOOD, C. & FORSDYKE, D., 2017. Psychosocial factors associated with talent development in football: A systematic review. *Psychology of Sport and Exercise,* 31pp. 93-112.

GOMEZ-PIRIZ, P. T., JIMÉNEZ-REYES, P. & RUIZ-RUIZ, C., 2011. Relation between total body load and session rating of perceived exertion in professional soccer players. *The Journal of Strength & Conditioning Research,* 25(8), pp. 2100-2103.

GRAY, A. J., JENKINS, D., ANDREWS, M. H., TAAFFE, D. R. & GLOVER, M. L., 2010. Validity and reliability of GPS for measuring distance travelled in field-based team sports. *Journal of Sports Sciences,* 28(12), pp. 1319-1325.

GREEN, J. M., MCINTOSH, J. R., HORNSBY, J., TIMME, L., GOVER, L. & MAYES, J. L., 2009. Effect of exercise duration on session RPE at an individualized constant workload. *European Journal of Applied Physiology,* 107(5), pp. 501.

GREGSON, W., DRUST, B., ATKINSON, G. & SALVO, V., 2010. Match-to-match variability of high-speed activities in premier league soccer. *Int J Sports Med,* 31(4), pp. 237-242.

HAGSTROM, A. D. & SHORTER, K. A., 2018. Creatine kinase, neuromuscular fatigue, and the contact codes of football: A systematic review and meta-analysis of pre-and post-match differences. *European journal of sport science,* 18(9), pp. 1234-1244.

HAIR, J. F., BLACK, W. C., BABIN, B. J., ANDERSON, R. E. & TATHAM, R. 2006. Multivariate data analysis . Uppersaddle River. NJ: Pearson Prentice Hall.

HAIR, J. F., BLACK, W. C., BABIN, B. J., ANDERSON, R. E. & TATHAM, R. L. 1998. *Multivariate data analysis*, Prentice hall Upper Saddle River, NJ.

HALSON, S. L., 2014. Monitoring training load to understand fatigue in athletes. *Sports Medicine,* 44(2), pp. 139-147.

HARLEY, J. A., BARNES, C. A., PORTAS, M., LOVELL, R., BARRETT, S., PAUL, D. & WESTON, M., 2010. Motion analysis of match-play in elite U12 to U16 age-group soccer players. *Journal of Sports Sciences,* 28(13), pp. 1391-1397.

HAUGAASEN, M. & JORDET, G., 2012. Developing football expertise: a football-specific research review. *International review of sport and exercise psychology,* 5(2), pp. 177-201.

HELGERUD, J., ENGEN, L. C., WISLOFF, U. & HOFF, J., 2001. Aerobic endurance training improves soccer performance. *Medicine and Science in Sports and Exercise,* 33(11), pp. 1925-1931.

HELLARD, P., AVALOS, M., MILLET, G., LACOSTE, L., BARALE, F. & CHATARD, J.-C., 2005. MODELING THE RESIDUAL EFFECTS AND THRESHOLD SATURATION OF TRAINING: ACASE STUDY OF OLYMPIC SWIMMERS. *The Journal of Strength & Conditioning Research,* 19(1), pp. 67-75.

HENDELMAN, D., MILLER, K., BAGGETT, C., DEBOLD, E. & FREEDSON, P., 2000. Validity of accelerometry for the assessment of moderate intensity physical activity in the field. *Medicine and Science in Sports and Exercise,* 32(9 Suppl), pp. S442-9.

HOPKINS, W., MARSHALL, S., BATTERHAM, A. & HANIN, J., 2009. Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise,* 41(1), pp. 3.

HOPKINS, W. G., 2000. Measures of reliability in sports medicine and science. *Sports Medicine,* 30(1), pp. 1-15.

HOPPE, M. W., BAUMGART, C., POLGLAZE, T. & FREIWALD, J., 2018. Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PloS One,* 13(2).

HOUTMEYERS, K. C., BRINK, M. S., HELSEN, W. F., HAELEWIJN, N., HAGEN, M., JASPERS, A. & VANRENTERGHEM, J., 2022a. A lab-based comparison of differential ratings of perceived exertion between a run and jump protocol involving low or high impacts on the lower extremities. *European Journal of Sport Science,* pp. 1-9.

HOUTMEYERS, K. C., JASPERS, A., BRINK, M. S., VANRENTERGHEM, J., VARLEY, M. C. & HELSEN, W. F., 2021. External load differences between elite youth and professional football players: ready for take-off? *Science and Medicine in Football,* 5(1), pp. 1-5.

HOUTMEYERS, K. C., ROBBERECHTS, P., JASPERS, A., MCLAREN, S. J., BRINK, M. S., VANRENTERGHEM, J., DAVIS, J. J. & HELSEN, W. F., 2022b. Differential Ratings of Perceived Exertion: Relationships With External Intensity and Load in Elite Men's Football. *International journal of sports physiology and performance,* 1(aop), pp. 1-10.

HULIN, B. T., GABBETT, T. J., JOHNSTON, R. D. & JENKINS, D. G., 2017. Wearable microtechnology can accurately identify collision events during professional rugby league match-play. *Journal of Science and Medicine in Sport,* 20(7), pp. 638-642.

HULIN, B. T., GABBETT, T. J., LAWSON, D. W., CAPUTI, P. & SAMPSON, J. A., 2016. The acute: chronic workload ratio predicts injury: high chronic workload may decrease injury risk in elite rugby league players. *British Journal of Sports Medicine,* 50(4), pp. 231-236.

HUNTER, F., BRAY, J., TOWLSON, C., SMITH, M., BARRETT, S., MADDEN, J., ABT, G. & LOVELL, R., 2015. Individualisation of time-motion analysis: a method comparison and case report series. *International journal of sports medicine,* 36(01), pp. 41-48.

IAIA, F. M., ERMANNO, R. & BANGSBO, J., 2009. High-intensity training in football. *International Journal of Sports Physiology and Performance,* 4(3), pp. 291-306.

IMPELLIZZERI, F. M., MARCORA, S., CASTAGNA, C., REILLY, T., SASSI, A., IAIA, F. & RAMPININI, E., 2006. Physiological and performance effects of generic versus specific aerobic training in soccer players. *International Journal of Sports Medicine,* 27(06), pp. 483-492.

IMPELLIZZERI, F. M., MARCORA, S. M. & COUTTS, A. J., 2019. Internal and external training load: 15 years on. *International journal of sports physiology and performance,* 14(2), pp. 270-273.

IMPELLIZZERI, F. M., MENASPÀ, P., COUTTS, A. J., KALKHOVEN, J. & MENASPA, M. J., 2020. Training Load and Its Role in Injury Prevention, Part I: Back to the Future. *Journal of athletic training,* 55(9), pp. 885-892.

IMPELLIZZERI, F. M., RAMPININI, E., COUTTS, A. J., SASSI, A. & MARCORA, S. M., 2004. Use of RPE-based training load in soccer. *Medicine and Science in Sports and Exercise,* 36(6), pp. 1042-1047.

IMPELLIZZERI, F. M., RAMPININI, E. & MARCORA, S. M., 2005. Physiological assessment of aerobic training in soccer. *Journal of Sports Sciences,* 23(6), pp. 583-592.

INGEBRIGTSEN, J., DALEN, T., HJELDE, G. H., DRUST, B. & WISLØFF, U., 2015. Acceleration and sprint profiles of a professional elite football team in match play. *European journal of sport science,* 15(2), pp. 101-110.

JASPERS, A., BRINK, M. S., PROBST, S. G., FRENCKEN, W. G. & HELSEN, W. F., 2017. Relationships between training load indicators and training outcomes in professional soccer. *Sports Medicine,* 47(3), pp. 533-544.

JEFFRIES, A. C., MARCORA, S. M., COUTTS, A. J., WALLACE, L., MCCALL, A. & IMPELLIZZERI, F. M., 2021. Development of a revised conceptual framework of physical training for use in research and practice. *Sports Medicine,* pp. 1-16.

JENNINGS, D., CORMACK, S., COUTTS, A. J., BOYD, L. & AUGHEY, R. J., 2010a. The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *International Journal of Sports Physiology and Performance,* 5(3), pp. 328-341.

JENNINGS, D., CORMACK, S., COUTTS, A. J., BOYD, L. J. & AUGHEY, R. J., 2010b. Variability of GPS units for measuring distance in team sport movements. *International Journal of Sports Physiology and Performance,* 5(4), pp. 565-569.

JOHNSTON, R. J., WATSFORD, M. L., KELLY, S. J., PINE, M. J. & SPURRS, R. W., 2014. Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *The Journal of Strength & Conditioning Research,* 28(6), pp. 1649-1655.

JOHNSTON, R. J., WATSFORD, M. L., PINE, M. J., SPURRS, R. W., MURPHY, A. J. & PRUYN, E. C., 2012. The validity and reliability of 5-Hz global positioning system units to measure team sport movement demands. *The Journal of Strength & Conditioning Research,* 26(3), pp. 758-765.

JOHNSTON, R. J., WATSFORD, M. L., PINE, M. J., SPURRS, R. W. & SPORRI, D., 2013. Assessment of 5 Hz and 10 Hz GPS units for measuring athlete movement demands. *International Journal of performance analysis in sport,* 13(1), pp. 262-274.

JONES, C. M., GRIFFITHS, P. C. & MELLALIEU, S. D., 2017. Training load and fatigue marker associations with injury and illness: a systematic review of longitudinal studies. *Sports Medicine,* 47pp. 943-974.

JONES, R. N., GREIG, M., MAWÉNÉ, Y., BARROW, J. & PAGE, R. M., 2019. The influence of short-term fixture congestion on position specific match running performance and external loading patterns in English professional soccer. *Journal of Sports Sciences,* 37(12), pp. 1338-1346.

JOSSE, J. & HUSSON, F., 2016. missMDA: a package for handling missing values in multivariate data analysis. *Journal of Statistical Software,* 70(1), pp. 1-31.

KAISER, H. F., 1960. The application of electronic computers to factor analysis. *Educational and Psychological Measurement,* 20(1), pp. 141-151.

KALKHOVEN, J. T., WATSFORD, M. L., COUTTS, A. J., EDWARDS, W. B. & IMPELLIZZERI, F. M., 2021. Training load and injury: causal pathways and future directions. *Sports Medicine,* pp. 1-14.

KALKHOVEN, J. T., WATSFORD, M. L. & IMPELLIZZERI, F. M., 2020. A conceptual model and detailed framework for stress-related, strain-related, and overuse athletic injury. *Journal of Science and Medicine in Sport,* 23(8), pp. 726-734.

KELLY, D. M., STRUDWICK, A. J., ATKINSON, G., DRUST, B. & GREGSON, W., 2020. Quantification of training and match-load distribution across a season in elite English Premier League soccer players. *Science and Medicine in Football,* 4(1), pp. 59-67.

KRASNOFF, J. B., KOHN, M. A., CHOY, F. K., DOYLE, J., JOHANSEN, K. & PAINTER, P. L., 2008. Interunit and intraunit reliability of the RT3 triaxial accelerometer. *Journal of Physical Activity and Health,* 5(4), pp. 527-538.

KUBAYI, A., 2019. Evaluation of match-running distances covered by soccer players during the UEFA EURO 2016. *South African Journal of Sports Medicine,* 31(1).

LACOME, M., PEETERS, A., MATHIEU, B., BRUNO, M., CHRISTOPHER, C. & PISCIONE, J., 2019. Can we use GPS for assessing sprinting performance in rugby sevens? A concurrent validity and between-device reliability study. *Biology of Sport,* 36(1), pp. 25.

LARRUSKAIN, J., LEKUE, J. A., MARTIN-GARETXANA, I., BARRIO, I., MCCALL, A. & GIL, S. M., 2021. INJURIES ARE NEGATIVELY ASSOCIATED WITH PLAYER PROGRESSION IN AN ELITE FOOTBALL ACADEMY. *Science and Medicine in Football,* (just-accepted).

LARSSON, P., 2003. Global positioning system and sport-specific testing. *Sports Medicine,* 33(15), pp. 1093-1101.

LARSSON, P. & HENRIKSSON-LARSÉN, K., 2001. The use of dGPS and simultaneous metabolic measurements during orienteering. *Medicine and Science in Sports and Exercise,* 33(11), pp. 1919-1924.

LEVINE, J., BAUKOL, P. & WESTERTERP, K., 2001. Validation of the Tracmor triaxial accelerometer system for walking. *Medicine and Science in Sports and Exercise,* 33(9), pp. 1593-1597.

LITTLE, R. J. & RUBIN, D. B. 2019. *Statistical analysis with missing data*, John Wiley & Sons.

LOLLI, L., BATTERHAM, A. M., HAWKINS, R., KELLY, D. M., STRUDWICK, A. J., THORPE, R. T., GREGSON, W. & ATKINSON, G. 2019. The acute-to-chronic workload ratio: an inaccurate scaling index for an unnecessary normalisation process? : BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine.

LOS ARCOS, A., MÉNDEZ-VILLANUEVA, A., YANCI, J. & MARTÍNEZ-SANTOS, R., 2016. Respiratory and muscular perceived exertion during official games in professional soccer players. *International Journal of Sports Physiology and Performance,* 11(3), pp. 301-304.

LOVELL, R. & ABT, G., 2013. Individualization of time–motion analysis: a case-cohort example. *International journal of sports physiology and performance,* 8(4), pp. 456-458.

LOVELL, T. W., SIROTIC, A. C., IMPELLIZZERI, F. M. & COUTTS, A. J., 2013. Factors affecting perception of effort (session rating of perceived exertion) during rugby league training. *International journal of sports physiology and performance,* 8(1), pp. 62-69.

LUCÍA, A., HOYOS, J., SANTALLA, A., EARNEST, C. & CHICHARRO, J. L., 2003. Tour de France versus Vuelta a Espana: which is harder? *Medicine and Science in Sports and Exercise,* 35(5), pp. 872-878.

LUTEBERGET, L. S., HOLME, B. R. & SPENCER, M., 2018. Reliability of wearable inertial measurement units to measure physical activity in team handball. *International journal of sports physiology and performance,* 13(4), pp. 467-473.

MACLEOD, H., MORRIS, J., NEVILL, A. & SUNDERLAND, C., 2009. The validity of a non-differential global positioning system for assessing player movement patterns in field hockey. *Journal of Sports Sciences,* 27(2), pp. 121-128.

MACLEOD, S. J., HAGAN, C., EGAÑA, M., DAVIS, J. & DRAKE, D., 2018. The use of microtechnology to monitor collision performance in professional rugby union. *International journal of sports physiology and performance,* 13(8), pp. 1075-1082.

MALLO, J., MENA, E., NEVADO, F. & PAREDES, V., 2015. Physical demands of top-class soccer friendly matches in relation to a playing position using global positioning system technology. *Journal of human kinetics,* 47(1), pp. 179-188.

MALONE, J. J., DI MICHELE, R., MORGANS, R., BURGESS, D., MORTON, J. P. & DRUST, B., 2015. Seasonal training-load quantification in elite English premier league soccer players. *International journal of sports physiology and performance,* 10(4), pp. 489-497.

MALONE, J. J., LOVELL, R., VARLEY, M. C. & COUTTS, A. J., 2017. Unpacking the black box: applications and considerations for using GPS devices in sport. *International journal of sports physiology and performance,* 12(s2), pp. S2-18-S2-26.

MALONE, S., OWEN, A., NEWTON, M., MENDES, B., COLLINS, K. D. & GABBETT, T. J., 2016. The acute: chonic workload ratio in relation to injury risk in professional soccer.

MANZI, V., BOVENZI, A., IMPELLIZZERI, M. F., CARMINATI, I. & CASTAGNA, C., 2013. INDIVIDUAL TRAINING-LOAD AND AEROBIC-FITNESS VARIABLES IN PREMIERSHIP SOCCER PLAYERS DURING THE PRECOMPETITIVE SEASON. *Journal of Strength and Conditioning Research,* 27(3), pp. 631-636.

MANZI, V., IELLAMO, F., IMPELLIZZERI, F., D'OTTAVIO, S. & CASTAGNA, C., 2009. Relation between individualized training impulses and performance in distance runners. *Medicine and Science in Sports and Exercise,* 41(11), pp. 2090-2096.

MARRIS, J., BARRETT, S., ABT, G. & TOWLSON, C., 2022. Quantifying technical actions in professional soccer using foot-mounted inertial measurement units. *Science and Medicine in Football,* 6(2), pp. 203-214.

MARYNOWICZ, J., KIKUT, K., LANGO, M., HORNA, D. & ANDRZEJEWSKI, M., 2020. Relationship Between the Session-RPE and External Measures of Training Load in Youth Soccer Training. *The Journal of Strength & Conditioning Research,* 34(10), pp. 2800-2804.

MAUGHAN, P. C., MACFARLANE, N. G. & SWINTON, P. A., 2021. Quantification of training and match-play load across a season in professional youth football players. *International Journal of Sports Science & Coaching,* pp. 17479541211000328.

MCCALL, A., DAVISON, M., ANDERSEN, T. E., BEASLEY, I., BIZZINI, M., DUPONT, G., DUFFIELD, R., CARLING, C. & DVORAK, J., 2015. Injury prevention strategies at the FIFA 2014 World Cup: perceptions and practices of the physicians from the 32 participating national teams. *British Journal of Sports Medicine,* 49(9), pp. 603-608.

MCGUIGAN, M. R., EGAN, A. D. & FOSTER, C., 2004. Salivary cortisol responses and perceived exertion during high intensity and low intensity bouts of resistance exercise. *Journal of Sports Science & Medicine,* 3(1), pp. 8-15.

MCGUIGAN, M. R. & FOSTER, C., 2004. A New Approach to Monitoring Resistance Training. *Strength & Conditioning Journal,* 26(6), pp. 42-47.

MCLAREN, S. J., GRAHAM, M., SPEARS, I. R. & WESTON, M., 2016a. The sensitivity of differential ratings of perceived exertion as measures of internal load. *International journal of sports physiology and performance,* 11(3), pp. 404-406.

MCLAREN, S. J., MACPHERSON, T. W., COUTTS, A. J., HURST, C., SPEARS, I. R. & WESTON, M., 2018a. The relationships between internal and external measures of training load and intensity in team sports: a meta-analysis. *Sports Medicine,* 48(3), pp. 641-658.

MCLAREN, S. J., SMITH, A., BARTLETT, J. D., SPEARS, I. R. & WESTON, M., 2018b. Differential training loads and individual fitness responses to pre-season in professional rugby union players. *Journal of Sports Sciences,* 36(21), pp. 2438-2446.

MCLAREN, S. J., SMITH, A., SPEARS, I. R. & WESTON, M., 2017. A detailed quantification of differential ratings of perceived exertion during team-sport training. *Journal of Science and Medicine in Sport,* 20(3), pp. 290-295.

MCLAREN, S. J., WESTON, M., SMITH, A., CRAMB, R. & PORTAS, M. D., 2016b. Variability of physical performance and player match loads in professional rugby union. *Journal of Science and Medicine in Sport,* 19(6), pp. 493-497.

MENDEZ-VILLANUEVA, A., BUCHHEIT, M., SIMPSON, B. & BOURDON, P., 2013. Match play intensity distribution in youth soccer. *International Journal of Sports Medicine,* 34(02), pp. 101-110.

METELSKI, A., 2021. Factors affecting the value of football players in the transfer market. *Journal of Physical Education and Sport,* 21(2), pp. 1150-1155.

MILLS, A., BUTT, J., MAYNARD, I. & HARWOOD, C., 2012. Identifying factors perceived to influence the development of elite youth football academy players. *Journal of Sports Sciences,* 30(15), pp. 1593-1604.

MOHR, M., KRUSTRUP, P. & BANGSBO, J., 2003. Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of Sports Sciences,* 21(7), pp. 519-528.

MORGAN, W. P., 1994. Psychological components of effort sense. *Medicine and Science in Sports and Exercise*.

MORGANS, R., ORME, P., ANDERSON, L. & DRUST, B., 2014. Principles and practices of training for soccer. *Journal of Sport and Health Science,* 3(4), pp. 251-257.

MORRIS, R., TOD, D. & OLIVER, E., 2015. An analysis of organizational structure and transition outcomes in the youth-to-senior professional soccer transition. *Journal of Applied Sport Psychology,* 27(2), pp. 216-234.

MORTON, R., FITZ-CLARKE, J. & BANISTER, E., 1990. Modeling human performance in running. *Journal of Applied Physiology,* 69(3), pp. 1171-1177.

MUÑOZ-LÓPEZ, A., GRANERO-GIL, P., PINO-ORTEGA, J. & DE HOYO, M., 2017. The validity and reliability of a 5-hz GPS device for quantifying athletes' sprints and movement demands specific to team sports. *Journal of Human Sport and Exercise,* 12(1), pp. 156-166.

NASSIS, G. P., MASSEY, A., JACOBSEN, P., BRITO, J., RANDERS, M. B., CASTAGNA, C., MOHR, M. & KRUSTRUP, P. 2020. Elite football of 2030 will not be the same as that of 2020: Preparing players, coaches, and support staff for the evolution. Wiley Online Library.

NIKOLAIDIS, P. T., CLEMENTE, F. M., VAN DER LINDEN, C. M., ROSEMANN, T. & KNECHTLE, B., 2018. Validity and reliability of 10-Hz global positioning system to assess in-line movement and change of direction. *Frontiers in Physiology,* 9pp. 228.

NUMERATO, D. 2018. *Football fans, activism and social change*, Routledge.

OSGNACH, C., POSER, S., BERNARDINI, R., RINALDO, R. & DI PRAMPERO, P. E., 2010. Energy cost and metabolic power in elite soccer: a new match analysis approach. *Medicine and Science in Sports and Exercise,* 42(1), pp. 170-178.

PATEL, R., NEVILL, A., SMITH, T., CLOAK, R. & WYON, M., 2020. The influence of birth quartile, maturation, anthropometry and physical performances on player retention: observations from an elite football academy. *International Journal of Sports Science & Coaching,* 15(2), pp. 121-134.

PETERSEN, C., PYNE, D., PORTUS, M. & DAWSON, B., 2009. Validity and reliability of GPS units to monitor cricket-specific movement patterns. *International Journal of Sports Physiology and Performance,* 4(3), pp. 381-393.

PETERSON, L., JUNGE, A., CHOMIAK, J., GRAF-BAUMANN, T. & DVORAK, J., 2000. Incidence of football injuries and complaints in different age groups and skill-level groups. *The American journal of sports medicine,* 28(5_suppl), pp. 51-57.

PORTAS, M. D., HARLEY, J. A., BARNES, C. A. & RUSH, C. J., 2010. The validity and reliability of 1-Hz and 5-Hz global positioning systems for linear, multidirectional, and soccer-specific activities. *International Journal of Sports Physiology and Performance,* 5(4), pp. 448-458.

PUSTINA, A. A., SATO, K., LIU, C., KAVANAUGH, A. A., SAMS, M. L., LIU, J., UPTMORE, K. D. & STONE, M. H., 2017. Establishing a duration standard for the calculation of session rating of perceived exertion in NCAA division I men’s soccer. *Journal of Trainology,* 6(1), pp. 26-30.

RAMPININI, E., ALBERTI, G., FIORENZA, M., RIGGIO, M., SASSI, R., BORGES, T. & COUTTS, A., 2015. Accuracy of GPS devices for measuring high-intensity running in field-based team sports. *International Journal of Sports Medicine,* 36(01), pp. 49-53.

RAMPININI, E., COUTTS, A. J., CASTAGNA, C., SASSI, R. & IMPELLIZZERI, F., 2007. Variation in top level soccer match performance. *International Journal of Sports Medicine,* 28(12), pp. 1018-1024.

RAWSTORN, J. C., MADDISON, R., ALI, A., FOSKETT, A. & GANT, N., 2014. Rapid directional change degrades GPS distance measurement validity during intermittent intensity running. *PloS One,* 9(4).

REARDON, C., TOBIN, D. P. & DELAHUNT, E., 2015. Application of individualized speed thresholds to interpret position specific running demands in elite professional rugby union: a GPS study. *PloS One,* 10(7).

REBELO, A., BRITO, J., SEABRA, A., OLIVEIRA, J. & KRUSTRUP, P., 2014. Physical match performance of youth football players in relation to physical capacity. *European journal of sport science,* 14(sup1), pp. S148-S156.

REILLY, T., 2003. Motion analysis and physiological demands. *Science and soccer,* 2pp. 59-72.

REILLY, T., BANGSBO, J. & FRANKS, A., 2000. Anthropometric and physiological predispositions for elite soccer. *Journal of Sports Sciences,* 18(9), pp. 669-683.

REILLY, T. & WILLIAMS, A. M. 2003. *Science and soccer*, Routledge.

RELVAS, H., LITTLEWOOD, M., NESTI, M., GILBOURNE, D. & RICHARDSON, D., 2010. Organizational structures and working practices in elite European professional football clubs: Understanding the relationship between youth and professional domains. *European Sport Management Quarterly,* 10(2), pp. 165-187.

RENFREE, A., CASADO, A. & MCLAREN, S., 2021. Re-thinking athlete training loads: would you rather have one big rock or lots of little rocks dropped on your foot? *Research in Sports Medicine,* pp. 1-4.

REVELLE, W. & REVELLE, M. W., 2015. Package 'psych'. *The comprehensive R archive network,* 337pp. 338.

RODRÍGUEZ-MARROYO, J. A. & ANTOÑAN, C., 2015. Validity of the session rating of perceived exertion for monitoring exercise demands in youth soccer players. *International journal of sports physiology and performance,* 10(3), pp. 404-407.

ROJAS-VALVERDE, D., PINO-ORTEGA, J., GÓMEZ-CARMONA, C. D. & RICO-GONZÁLEZ, M., 2020. A Systematic Review of Methods and Criteria Standard Proposal for the Use of Principal Component Analysis in Team's Sports Science. *International Journal of Environmental Research and Public Health,* 17(23), pp. 8712.

ROSENBLAT, M. A., GRANATA, C. & THOMAS, S. G., 2022. Effect of interval training on the factors influencing maximal oxygen consumption: a systematic review and meta-analysis. *Sports Medicine,* 52(6), pp. 1329-1352.

ROSSEEL, Y., OBERSKI, D., BYRNES, J., VANBRABANT, L., SAVALEI, V., MERKLE, E. & JORGENSEN, T. 2017. lavaan: Latent variable analysis (Version 0.5-23.1097).

ROWLANDS, A. V., THOMAS, P. W., ESTON, R. G. & TOPPING, R., 2004. Validation of the RT3 triaxial accelerometer for the assessment of physical activity. *Medicine and Science in Sports and Exercise,* 36(3), pp. 518-524.

SALTER, J., CROIX, M. B. D. S., HUGHES, J. D., WESTON, M. & TOWLSON, C., 2021. Monitoring practices of training load and biological maturity in UK soccer academies. *International journal of sports physiology and performance,* 16(3), pp. 395-406.

SARMENTO, H., MARCELINO, R., ANGUERA, M. T., CAMPANIÇO, J., MATOS, N. & LEITÃO, J. C., 2014. Match analysis in football: a systematic review. *Journal of Sports Sciences,* 32(20), pp. 1831-1843.

SCELLES, N., 2017. Star quality and competitive balance? Television audience demand for English Premier League football reconsidered. *Applied Economics Letters,* 24(19), pp. 1399-1402.

SCHAFER, J. L. & GRAHAM, J. W., 2002. Missing data: our view of the state of the art. *Psychological Methods,* 7(2), pp. 147.

SCHNEIDER, C., HANAKAM, F., WIEWELHOVE, T., DÖWELING, A., KELLMANN, M., MEYER, T., PFEIFFER, M. & FERRAUTI, A., 2018. Heart rate monitoring in team sports—a conceptual framework for contextualizing heart rate measures for training and recovery prescription. *Frontiers in Physiology,* 9pp. 639.

SCOTT, B. R., LOCKIE, R. G., KNIGHT, T. J., CLARK, A. C. & DE JONGE, X. A. J., 2013a. A comparison of methods to quantify the in-season training load of professional soccer players. *International Journal of Sports Physiology and Performance,* 8(2), pp. 195-202.

SCOTT, D. & LOVELL, R., 2018. Individualisation of speed thresholds does not enhance the dose-response determination in football training. *Journal of sports sciences,* 36(13), pp. 1523-1532.

SCOTT, M. T., SCOTT, T. J. & KELLY, V. G., 2016. The validity and reliability of global positioning systems in team sport: a brief review. *The Journal of Strength & Conditioning Research,* 30(5), pp. 1470-1490.

SCOTT, T. J., BLACK, C. R., QUINN, J. & COUTTS, A. J., 2013b. Validity and reliability of the session-RPE method for quantifying training in Australian football: a comparison of the CR10 and CR100 scales. *The Journal of Strength & Conditioning Research,* 27(1), pp. 270-276.

SELIGER, V. C., 1968. Heart rate as an index of physical load in exercise. *Scripta Medica,* 41(23), pp. 1-240.

SELYE, H. 1956. *The stress of life*.

SKINNER, J. S., WILMORE, K. M., KRASNOFF, J. B., JASKÓLSKI, A., JASKÓLSKA, A., GAGNON, J., PROVINCE, M. A., LEON, A. S., RAO, D. & WILMORE, J. H., 2000. Adaptation to a standardized training program and changes in fitness in a large, heterogeneous population: the HERITAGE Family Study. *Medicine and Science in Sports and Exercise,* 32(1), pp. 157-161.

SPENCER, M., LAWRENCE, S., RECHICHI, C., BISHOP, D., DAWSON, B. & GOODMAN, C., 2004. Time–motion analysis of elite field hockey, with special reference to repeated-sprint activity. *Journal of Sports Sciences,* 22(9), pp. 843-850.

STAMBULOVA, N., ALFERMANN, D., STATLER, T. & CÔTÉ, J., 2009. ISSP position stand: Career development and transitions of athletes. *International journal of sport and exercise psychology,* 7(4), pp. 395-412.

STAMBULOVA, N. B., RYBA, T. V. & HENRIKSEN, K., 2021. Career development and transitions of athletes: The international society of sport psychology position stand revisited. *International Journal of Sport and Exercise Psychology,* 19(4), pp. 524-550.

STAUNTON, C. A., ABT, G., WEAVING, D. & WUNDERSITZ, D. W., 2021. Misuse of the term 'load'in sport and exercise science. *Journal of Science and Medicine in Sport*.

STØLEN, T., CHAMARI, K., CASTAGNA, C. & WISLØFF, U., 2005. Physiology of soccer. *Sports Medicine,* 35(6), pp. 501-536.

STRATTON, G., REILLY, T., RICHARDSON, D. & WILLIAMS, A. M. 2004. *Youth soccer: From science to performance*, Psychology Press.

STROYER, J., HANSEN, L. & KLAUSEN, K., 2004. Physiological profile and activity pattern of young soccer players during match play. *Medicine and Science in Sports and Exercise,* 36(1), pp. 168-174.

SWAINSTON, S. C., WILSON, M. R. & JONES, M. I., 2020. Player experience during the junior to senior transition in professional football: a longitudinal case study. *Frontiers in Psychology,* 11pp. 1672.

SWEET, T. W., FOSTER, C., MCGUIGAN, M. R. & BRICE, G., 2004. Quantitation of resistance training using the session rating of perceived exertion method. *The Journal of Strength & Conditioning Research,* 18(4), pp. 796-802.

TABACHNICK, B. G., FIDELL, L. S. & ULLMAN, J. B. 2007. *Using multivariate statistics*, Pearson Boston, MA.

TAYLOR, J. B., WRIGHT, A. A., DISCHIAVI, S. L., TOWNSEND, M. A. & MARMON, A. R., 2017. Activity demands during multi-directional team sports: a systematic review. *Sports Medicine,* 47(12), pp. 2533-2551.

TEAM, R. C., 2013. R: A language and environment for statistical computing.

THOMAS, J. R., NELSON, J. K. & SILVERMAN, S. J. 2015. *Research methods in physical activity*, Human kinetics.

TIERNEY, P. J., YOUNG, A., CLARKE, N. D. & DUNCAN, M. J., 2016. Match play demands of 11 versus 11 professional football using Global Positioning System tracking: Variations across common playing formations. *Human movement science,* 49pp. 1-8.

TOWLSON, C., SALTER, J., ADE, J. D., ENRIGHT, K., HARPER, L. D., PAGE, R. M. & MALONE, J. J., 2020. Maturity-associated considerations for training load, injury risk, and physical performance within youth soccer: One size does not fit all. *J Sport Health Sci*.

TOWNSHEND, A. D., WORRINGHAM, C. J. & STEWART, I. B., 2008. Assessment of speed and position during human locomotion using nondifferential GPS. *Medicine and Science in Sports and Exercise,* 40(1), pp. 124-132.

VAHIA, D., KELLY, A., KNAPMAN, H. & WILLIAMS, C. A., 2019. Variation in the correlation between heart rate and session rating of perceived exertion-based estimations of internal training load in youth soccer players. *Pediatric Exercise Science,* 31(1), pp. 91-98.

VAN GOOL, D., VAN GERVEN, D. & BOUTMANS, J., 1983. Heart rate telemetry during a soccer game: a new methodology. *Journal of Sports Sciences,* 1pp. 154.

VANRENTERGHEM, J., NEDERGAARD, N. J., ROBINSON, M. A. & DRUST, B., 2017. Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Medicine,* 47(11), pp. 2135-2142.

VARLEY, M. C. & AUGHEY, R. J., 2013. Acceleration profiles in elite Australian soccer. *International Journal of Sports Medicine,* 34(01), pp. 34-39.

VARLEY, M. C., FAIRWEATHER, I. H. & AUGHEY1, ROBERT J, 2012. Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *Journal of Sports Sciences,* 30(2), pp. 121-127.

VARLEY, M. C., JASPERS, A., HELSEN, W. F. & MALONE, J. J., 2017. Methodological considerations when quantifying high-intensity efforts in team sport using global positioning system technology. *International Journal of Sports Physiology and Performance,* 12(8), pp. 1059-1068.

VICKERY, W. M., DASCOMBE, B. J., BAKER, J. D., HIGHAM, D. G., SPRATFORD, W. A. & DUFFIELD, R., 2014. Accuracy and reliability of GPS devices for measurement of sports-specific movement patterns related to cricket, tennis, and field-based team sports. *The Journal of Strength & Conditioning Research,* 28(6), pp. 1697-1705.

VIEIRA, L. H. P., CARLING, C., BARBIERI, F. A., AQUINO, R. & SANTIAGO, P. R. P., 2019. Match running performance in young soccer players: A systematic review. *Sports Medicine,* 49(2), pp. 289-318.

VIGNE, G., GAUDINO, C., ROGOWSKI, I., ALLOATTI, G. & HAUTIER, C., 2010. Activity profile in elite Italian soccer team. *International journal of sports medicine,* 31(5), pp. 304-310.

WALDRON, M., WORSFOLD, P., TWIST, C. & LAMB, K., 2011. Concurrent validity and test–retest reliability of a global positioning system (GPS) and timing gates to assess sprint performance variables. *Journal of Sports Sciences,* 29(15), pp. 1613-1619.

WALKER, G. J. & HAWKINS, R., 2018. Structuring a program in elite professional soccer. *Strength & Conditioning Journal,* 40(3), pp. 72-82.

WEAVING, D., DALTON-BARRON, N., MCLAREN, S., SCANTLEBURY, S., CUMMINS, C., ROE, G., JONES, B., BEGGS, C. & ABT, G., 2020. The relative contribution of training intensity and duration to daily measures of training load in professional rugby league and union. *Journal of Sports Sciences,* 38(14), pp. 1674-1681.

WEAVING, D., DALTON, N. E., BLACK, C., DARRALL-JONES, J., PHIBBS, P. J., GRAY, M., JONES, B. & ROE, G. A., 2018. The Same Story or a Unique Novel? Within-Participant Principal-Component Analysis of Measures of Training Load in Professional Rugby Union Skills Training. *International Journal of Sports Physiology and Performance,* 13(9), pp. 1175-1181.

WEAVING, D., JONES, B., MARSHALL, P., TILL, K. & ABT, G., 2017. Multiple measures are needed to quantify training loads in professional rugby league. *International journal of sports medicine,* 38(10), pp. 735-740.

WEAVING, D., MARSHALL, P., EARLE, K., NEVILL, A. & ABT, G., 2014. Combining internal-and external-training-load measures in professional rugby league. *International journal of sports physiology and performance,* 9(6), pp. 905-912.

WESTON, M., 2013. Difficulties in determining the dose-response nature of competitive soccer matches. *Journal of Athletic Enhancement,* 2(1).

WESTON, M., 2018. Training load monitoring in elite English soccer: A comparison of practices and perceptions between coaches and practitioners. *Science and Medicine in Football,* 2(3), pp. 216-224.

WESTON, M., DRUST, B. & GREGSON, W., 2011. Intensities of exercise during match-play in FA Premier League referees and players. *Journal of Sports Sciences,* 29(5), pp. 527-532.

WESTON, M., SIEGLER, J., BAHNERT, A., MCBRIEN, J. & LOVELL, R., 2015. The application of differential ratings of perceived exertion to Australian Football League matches. *Journal of Science and Medicine in Sport,* 18(6), pp. 704-708.

WHITEHEAD, S., TILL, K., WEAVING, D. & JONES, B., 2018. The use of microtechnology to quantify the peak match demands of the football codes: a systematic review. *Sports Medicine,* 48(11), pp. 2549-2575.

WILLIAMS, A. M. 2020. Talent identification and development in soccer: An update and contemporary perspectives. Taylor & Francis.

WILLIAMS, A. M. & REILLY, T., 2000. Talent identification and development in soccer. *Journal of Sports Sciences,* 18(9), pp. 657-667.

WILLIAMS, S., TREWARTHA, G., CROSS, M. J., KEMP, S. P. & STOKES, K. A., 2017. Monitoring what matters: a systematic process for selecting training-load measures. *International Journal of Sports Physiology and Performance,* 12(Suppl 2), pp. S2-101-S2-106.

WILMORE, J. H. & HASKELL, W. L., 1972. Body composition and endurance capacity of professional football players. *Journal of Applied Physiology,* 33(5), pp. 564-567.

WINDT, J., MACDONALD, K., TAYLOR, D., ZUMBO, B. D., SPORER, B. C. & MARTIN, D. T., 2020. "To tech or not to tech?" A critical decision-making framework for implementing technology in sport. *Journal of Athletic Training,* 55(9), pp. 902-910.

WITTE, T. & WILSON, A., 2004. Accuracy of non-differential GPS for the determination of speed over ground. *Journal of Biomechanics,* 37(12), pp. 1891-1898.

WRIGLEY, R., DRUST, B., STRATTON, G., SCOTT, M. & GREGSON, W., 2012. Quantification of the typical weekly in-season training load in elite junior soccer players. *Journal of Sports Sciences,* 30(15), pp. 1573-1580.