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DOTTORATO DI RICERCA IN FISIOPATOLOGIA MEDICA

XXXV CICLO

TITOLO: **An artificial intelligence approach to pinpoint performance and training load in team sports.**

TESI PRESENTATA DA: **Alexandru Nicolae Ungureanu**

TUTORS: **Prof. Alberto Rainoldi e Prof. Corrado Lupo**

COORDINATORE DEL DOTTORATO: **Prof. Franco Veglio**

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To my family

ABSTRACT

In order to elicit peak performance and to avoid overtraining in team sports, external (i.e., sprints, distance, impacts, jumps, etc.) and internal (i.e., rate of perceived exertion [RPE], heart rate [HR], hormonal and metabolic responses, etc.) training load (TL) are considered when developing training programs. In this regard, performance analysis (PA) is implemented to explore and monitor parameters that affect TL within both competitions and training sessions. Performance is usually investigated by means of the time-motion analysis (TMA) (e.g., using Global Positioning System-GPS, Local Positioning System-LPS, Video Tracking-VT) as well as by notational analysis (NA) (e.g., using video-based systems), that code athletes' relevant running activities and technical and tactical behaviors during on-field situations (i.e., game match or training sessions), respectively. The information resulting from the PA process is eventually elaborated to understand the technical and tactical, and physiological behavior of athletes. Nowadays the evolution in technology has impacted sports and led the way to massive data collection and storage, that has been termed "big data". Nevertheless, these data need to be reduced and simplified through proper statistical analyses such as principal component analysis (PCA) or cluster analysis in order to be informative and to simplify reporting and communication within the technical staff and among players. Moreover, complex scenarios such as performance in team sports might require a non-linear approach to better organize and explain high-dimensional datasets. In this perspective, the use of machine learning (i.e., statistical models that enable computers to automatically learn from data and to make better decisions from experience) such as linear and logistic regression, decision and classification tree, and artificial neural networks has proven to be an effective multivariate method for delivering appropriate prediction models for match results as well as for better understanding and planning the workload (both external and internal)-wellbeing relationship in players' team sports. In summary, the aim of this thesis was to investigate the PA methods and technologies, as well as the Machine Learning algorithms for data analysis to enhance the objectivity of decision making in team sports. Finally, the implementation of

these methods and algorithms was disseminated through the research papers published in the last 3 years, and reported in this Ph.D. Thesis.

Summary

List of published papers

Ungureanu, A. N., Condello, G., Pistore, S., Conte, D., & Lupo, C. (2019). Technical and tactical aspects in Italian youth rugby union in relation to different academies, regional tournaments, and outcomes. *The Journal of Strength & Conditioning Research, 33*(6), 1557-1569.

Ungureanu, A. N., Brustio, P. R., Mattina, L., & Lupo, C. (2019). "How" is more important than "how much" for game possession in elite northern hemisphere rugby union. *Biology of sport*, *36*(3), 265-272.

Ungureanu, A. N., Brustio, P. R., & Lupo, C. (2021). Technical and tactical effectiveness is related to time-motion performance in elite rugby. *The Journal of Sports Medicine and Physical Fitness*, *61*(2). https://doi.org/10.23736/s0022-4707.20.10998-8

Ungureanu, A. N., Lupo, C., & Brustio, P. R. (2022). Padel Match Analysis: Notational and Time-Motion Analysis during Official Italian Sub-Elite Competitions. *International Journal of Environmental Research and Public Health*, *19*(14), 8386.

Ungureanu, A. N., Brustio, P. R., Boccia, G., Rainoldi, A., & Lupo, C. (2021). Effects of presession well-being perception on internal training load in female volleyball players. *International Journal of Sports Physiology and Performance*, *16*(5), 622-627.

Ungureanu, A. N., Lupo, C., Boccia, G., & Brustio, P. R. (2021). Internal training load affects day-after-pretraining perceived fatigue in female volleyball players. *International Journal of Sports Physiology and Performance*, *16*(12), 1844-1850.

Ungureanu, A. N., Lupo, C., & Brustio, P. R. (2021). A machine learning approach to analyze home advantage during COVID-19 pandemic period with regards to margin of victory and to different tournaments in professional rugby union competitions. *International Journal of Environmental Research and Public Health, 18*(23), 12711.

1. Performance analysis in team sports

1.1. Introduction

Performance analysis in team sports requires objective recording and examination of the players' behavior during training and competition. The primary goal of PA is to sustain the coaching and physical training cycles by providing information to the technical staff and players in order to properly plan the subsequent practice and to improve performance. Performance analysis consists of two complementary approaches: Notational Analysis and Time-Motion Analysis. The first one is used to create a permanent record of tactical behaviors of players within a performance (either during a training session or a match) through hand-based or computerized video technology systems. These records allow the creation of high-dimensional data sets that offer opportunity to analyze network structures and spatio-temporal patterns within and between the teams.

In particular, notational analysis focuses on "what", "how", "where", "when" on-the-ball actions of players occur within a game, through hand-based or computerized systems using video technology. Then, these performance indicators are expressed as non-dimensional ratios by normalizing the occurrences of special events (e.g., the number of shots per game in soccer) with respect to broader categories of events (e.g., number of shots per game to number of shooting opportunities, number of shots per game on goal to number of shots per game, and number of goals per game to number of shots per game) to obtain more meaningful information (M. D. Hughes & Bartlett, 2010). Statistics of game play are used nowadays by sport journalists as well as by researchers for descriptive purposes and for correlational or comparative studies in order to investigate a relationship between some aspects of performance and victory or defeat ("Routledge Handbook of Sports Performance Analysis," 2013). Basic notational systems simply classify the type of actions performed by a player, while others gather information on position of the action on the field (i.e., "where"), on the time of actions (i.e., "when"), and finally allow spatiotemporal analysis. Specifically, these sophisticated notational data containing sequences of actions can be used to unhide patterns of play in relation to success (e.g., winning or losing games), to quality of opponents, the venue (i.e., home-advantage effect), or the game momentum (i.e., scoring-first effect) (M. Hughes & Franks, 2004).

On the other hand, Time-Motion Analysis is complementary to the notational analysis, and it is used to indirectly quantify the physical efforts of players in training and competition. More precisely, time-motion analysis quantifies the external load by coding and classifying locomotor activities according to the intensity of movements performed by players. These activity profiles allow data scientists to explore the specific demands of the sport (e.g., according to level of competition, age group categories, technical and tactical positions and roles) and to provide objective guidelines in terms of “work-to-rest” or “low-to-high intensity” ratios for optimizing the conditioning elements of training programmes. Time-Motion Analysis uses different techniques, such as *manual* (i.e., data capture via manual coding of movements [standing, jogging, running, sprinting] and specific playing activities [sprinting with or without the ball]), *automatic* (data recorder via automatic global or local position systems), and *semi-automatic* (automatic digital video systems that often require manual intervention by a human operator to correct tracking interruptions due to occlusions) tracking systems to collect data. In addition, technological advances in computer software and digital video techniques (e.g., high-definition video cameras, high-capacity storage, high-computational capacity), as well as miniaturized portable tracking devices (e.g., GPS receivers, accelerometers), provide opportunities for accumulating a substantial knowledge of the demands of play and for real-time monitoring of physical load. The technological aspects of the PA process (both notational and time-motion) are discussed below in the chapter 2.2 (i.e., Technology).

1.2 Practical applications

1.2.1 Paper #1

Technical and Tactical Aspects in Italian Youth Rugby Union in Relation to Different Academies, Regional Tournaments, and Outcomes

Alexandru N. Ungureanu,[1,2] Giancarlo Condello,[3] Simonluca Pistore,[2] Daniele Conte,[3,4] and Corrado Lupo[1]

[1]Department of Medical Sciences, NeuroMuscularFunction Research Group, School of Exercise and Sport Sciences (SUISM), University of Torino, Turin, Italy; [2]Italian Rugby Federation (FIR), Rome, Italy; [3]Department of Movement, Human and Health Sciences, University of Rome Foro Italico, Rome, Italy; and [4]Institute of Sport Science and Innovations, Lithuanian Sports University, Kaunas, Lithuania

Abstract

Ungureanu, AN, Condello, G, Pistore, S, Conte, D, and Lupo, C. Technical and tactical aspects in Italian youth rugby union in relation to different academies, regional tournaments, and outcomes. *J Strength Cond Res* 33(6): 1557–1569, 2019–This study aimed to analyze the technical and tactical aspects of the Italian under-18 Academy Rugby Union in relation to different academies, regional tournaments, and game outcomes. A notational analysis (44 indicators) was performed on 16 games (2014–15 season) to evaluate strong differences ($p \leq 0.05$; moderate-large effect sizes [ESs]) according to variables. Among academies, strong differences were showed for defensive breakdown, in which the defending support is much (range = 77–87%), equal (range = 11–32%), and less (range = 2–12%) numerous than the attacking support, total tackles (range = 64–122), and passes (range = 72–151), pass to possession ratio (range = 6–10), possession lost due to an error (range = 28–59%), and ball in play in own (range = 8–25%) and opponent (range = 7–31%) 22-m area indicators. For tournaments, effects emerged for offensive breakdown when the ball is used quickly using maximum 2 attacking supports (range = 20–30%) and is not used quickly (range = 28–41%), total penalty kicks (range = 11–16), and sequences period 0–10 (range = 26–35%) and 10–40 seconds (range = 47–55%). Conversely, winning and losing academies reported differences with small ESs. These results highlight that the technical and tactical aspects of the Italian under-18 Academy Rugby Union are quite homogeneous, suggesting that FIR coaching staffs are more oriented to players' skills than successful games. However, tactical and strength and conditioning coaches can benefit from the findings of this study, focusing training on cognitive, strength, and repeated sprint abilities with and without change of direction for improving the occurrence of "set pieces won/regained" and "ball in play in opponent 22 m area," which appear as the key of the game in this rugby competition level.

Key Words notational analysis, match analysis, technical and tactical indicators, youth performance, coaching

Address correspondence to Dr. Corrado Lupo, corrado.lupo@unito.it.

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Introduction

Although rugby has been recognized as a professional sport union only in 1995, this game is characterized by increasing performance requirements (26), and played all over the world, containing 118 national members (30).

Senior and junior competitions share most rules, except for playing time (40 vs. 35 minutes for each half), scrum (max 1.5 m push), replacements, and substitutions (31). Coherently to guidelines for youth rugby training (28), deliberate practice and programming are the main focus in developing young players. Consequently, Italian Rugby Federation (FIR) established 32 not-residential training centers, 9 residential academies, and 1 national academy for under-16 players, under-18 players, and under-20 players, respectively, all aiming to develop players' abilities and skills for an excellence performance level (7). According to this selecting structure, the passage from the under-18 residential academies to the under-20 national academy could be considered as the most significant opportunity of playing as professional athlete in a close future. Therefore, to tend to the excellence performance level, at present, the FIR staffs of the nine residential academies try to share a common technical and tactical training strategy, aiming to concretely promote the development of technical and tactical skills, which could contribute the performance

TABLE 1. Definition of technical and tactical indicators used for the notational analysis performed on Italian under-18 academy games.

#	Performance indicator	Definition
1	Set pieces won/regained	All own and opponents' scrums, lineouts, starts, and restarts won or regained, respectively. Indicates the number of own possession useful to start attacking.
2	Set pieces lost	All own and opponents' scrums, lineouts, starts, and restarts won by the opponents. Indicates the opponents' number of possession useful to start attacking.
3	Offensive breakdown total	Sum of the following indicators 4–8.
4	Offensive breakdown "v++" (%)	An offensive breakdown when the ball is used quickly (≤3″) using maximum 2 attacking supports.
5	Offensive breakdown "v+" (%)	An offensive breakdown when the ball is used quickly (≤3″) with maximum 3 attacking supports.
6	Offensive breakdown "v−" (%)	An offensive breakdown when the ball is used quickly (≤3″) with more than 3 attacking supports.
7	Offensive breakdown "l" (%)	An offensive breakdown when the ball is not used quickly (>3″) regardless the number of attacking supports.
8	Offensive breakdown "− −" (%)	An offensive breakdown that results in a turnover or penalty/free kick against.
9	Defensive breakdown total	Sum of the following indicators 10–12.
10	Defensive breakdown ">>" (%)	A defensive breakdown where the defending support is much numerous than the attacking support.
11	Defensive breakdown " = " (%)	A defensive breakdown where the defending support is as numerous as the attacking support.
12	Defensive breakdown "<<" (%)	A defensive breakdown where the defending support is less numerous than the attacking support.
13	Tackles total	Sum of the following indicators 14–17.
14	Tackle "++" (%)	Dominant tackle that stops the opponent and the ball (stops the ball carrier from making a pass) and drives opposition player 1 or more steps backward.
15	Tackle "+" (%)	Tackle that stops the opponent and the ball (stops the ball carrier from making a pass) and the event happens on the collision point (opponent makes no more steps forward).
16	Tackle "−" (%)	Tackle that stops the opponent and the ball (stops the ball carrier from making a pass) and the tackler is driven backwards 1 or more steps by the ball carrier.
17	Tackle "− off" (%)	Tackle that stops the opponent but not the ball (allows the ball carrier to recycle the ball).
18	Missed tackle (%)	Tackle that does not stop the opponent.
19	Pass total	Sum of the following indicators 20–21.
20	Pass "+" (%)	Pass that centers the target (receiver's hands) and allows receiver to maintain speed and acceleration.
21	Pass "−" (%)	Pass forward or which does not center the target (receiver's hands) or which does not allow to maintain speed and acceleration.
22	Pass to possession ratio	Ratio between number of attempted passes ("+" + "-") and minutes of possession.
23	P.k. total	Sum of the following indicators 24–28.
24	P.k. on set piece (%)	A penalty kick conceded on a set piece situation (i.e., start, restart, scrum, lineout).
25	P.k. on breakdown (%)	A penalty kick conceded on a breakdown situation (i.e., ball non released, hands in ruck, entering a ruck or maul from the side, illegally collapsing a maul).
26	P.k. on tackle (%)	A penalty kick conceded on a tackle situation (i.e., dangerous tackle/shoulder charge/push, tackled not released. tackling or holding an opponent who is not in possession of the ball, obstructing an opponent from tackling the ball carrier-crossing).
27	P.k. on offside (%)	A penalty kick conceded on a offside situation.

28	P.k. unsportsmanlike (%)	A penalty kick conceded on a unsportsmanlike situation (i.e., violent or foul play: punching, elbowing, kicking, head-butting, tripping, ecc. throwing or knocking the ball forwards or out of play in any direction, any other action the referee considers to be "contrary to good sportsmanship").
29	P.k. quick played (%)	A penalty kick assigned for played quickly in order to immediate attack.
30	Possession lost total	Sum of the following indicators 31–34.
31	Possession lost due to an error (%)	Ball possession lost because the responsibility of the possessor (i.e., ball-handling error, forward pass).
32	Possession lost on kicks (%)	Ball possession lost on a kicking situation without gaining any territorial advantage (i.e., kicking the ball directly in touch out of the 22-m area or kicking the ball without contrasting the opponents attack).
33	Possession lost on turnover (%)	Ball possession lost on a turnover situation because a prompt and opportune action by the opponents.
34	Possession lost on set pieces (%)	Ball possession lost on a set piece situation (own set piece lost during play or because a penalty/free kick).
35	Ball in play	Ball in play period is considered since the scrum sets or since hooker throw in lineouts or since starts/restarts are kicked until referee stops the game. Kicking to touch, conversions are not considered as BIP period.
36	Time in possession (%)	Ball in play time spent in own possession.
37	Ball in play in own 22 m area (%)	Time spent playing (defending or attacking) in own 22 area.
38	Ball in play in own 22 m− halfway lines (%)	Time spent playing (defending or attacking) in the area between own 22 and halfway lines.
39	Ball in play in opponent halfway − 22 m lines (%)	Time spent playing (defending or attacking) in the area between halfway and opponents' 22 lines.
40	Ball in play in opponent 22 m area (%)	Time spent playing (defending or attacking) in the opponents' 22 area.
41	Sequences period 0–10 s (%)	Numbers of sequences last from 0 to 10 s.
42	Sequences period 11–40 s (%)	Numbers of sequences last from 11 to 40 s.
43	Sequences period 41–60 s (%)	Numbers of sequences last from 41 to 60 s.
44	Sequences period >60 s (%)	Numbers of sequences last more than 60 s.

development of 24 rugby players of the Italian national team (7). As consequence, a specific monitor and plan of training sessions and game performances result as necessary.

Although abilities and skills assessments (2,10,11) and anthropometric measurements (2) are generally applied for talent identification or team selection, the evaluation of the technical and tactical skills are equally essential. For this reason, notational analysis plays a crucial role on the investigation of rugby performance (18), and its aim is to describe an objective and simplified profile of sport performance based on indicators, which are defined as the selection and combination of variables that define some aspect of performance (16). However, rugby is characterized by complex and chaotic game dynamics, with heterogeneous conditions such as weather, strategies, and tactics, which make extremely difficult an observational and analysis system (29). Similar to other situational sports (4,12,20,21,27), notational and time-motion analyses suffer in terms of replication because of relevant situational nature complexity. Nevertheless, these methods have been shown to be effective tools for increasing the knowledge of team sports for better coaching (17). In addition, especially for rugby, performance and technical and tactical aspects could be effectively linked to provide valuable practical applications (9).

In senior rugby union, technical and tactical notational analyses have been mostly focused on defining winning tactical profiles (6). Useful information already emerged for the Eighties World Cup games, where successful teams were mainly characterized by contact and greater ball retention game situations (23). More recently (19), the notational analysis method was applied to discriminate tactical aspects between winning and losing European professional teams, highlighting only lineouts won on oppositions throw and tries scored as main predictors of game successful among 22 considered indicators. For the same rationale, 3 authors (24) analyzed 58 games from the 2003 to 2006 seasons of Six Nations tournament and highlighted that (a) in the phases of obtaining the ball and more specifically in scrummage and lineout, winning teams lose fewer balls than losing teams; (b) winning teams tend to play more with their feet when they obtain the ball, to use the maul as a way of attacking, and to break the defensive line more often compared with losing

Table 2. Mean values, standard deviations (differences; effects size), and mean differences (95% confidence interval) of all performance indicators in relation to each Italian under-18 rugby academy.*

#	Performance indicators	Team 1 (4 games)	Team 2 (β) (4 games)	Team 3 (χ) (3 games)	Team 4 (δ) (4 games)	Team 5 (ε) (3 games)	Team 6 (ϕ) (3 games)	Team 7 (γ) (4 games)	Team 8 (η) (3 games)	Team 9 (†) (4 games)
1†	Set pieces won/ regained	24 ± 2.82	21.2 ± 3.86	26.6 ± 2.51	27.2 ± 0.95	23 ± 3.60	23 ± 1.73	25.2 ± 2.36	28 ± 1	24.5 ± 1.29
2†	Set pieces lost	23.2 ± 2.06	26 ± 2.70	23.6 ± 0.57	26 ± 2.70	27.6 ± 1.52	26.6 ± 2.08	21.2 ± 3.59	25 ± 4.35	24 ± 2.44
3†	Offensive breakdown total	34 ± 7.65	56.2 ± 25.0	54 ± 15.3	48.7 ± 7.41	48.3 ± 5.50	52 ± 8.66	59.2 ± 13.0	47 ± 16.0	44.5 ± 5.19
4†	Offensive breakdown "v++" (%)	28.5 ± 9.03	24.5 ± 7.50	23 ± 4.58	27.7 ± 9.63	21.3 ± 16.4	16.6 ± 4.04	37.7 ± 11.7	31 ± 9.16	19 ± 4.54
5†	Offensive breakdown "v+" (%)	10.7 ± 8.18	22.7 ± 3.77	25.3 ± 5.68	20.7 ± 8.01	17 ± 4	18 ± 5.56	22.2 ± 3.68	20.6 ± 4.04	18 ± 6.37
6‡	Offensive breakdown "v−" (%)	14.5 ± 11.3	12.2 ± 3.59	2.66 ± 0.57	9.25 ± 2.21	4.66 ± 2.30	14 ± 7.81	8.25 ± 3.30	7.33 ± 4.04	10.5 ± 4.93
7†	Offensive breakdown "I" (%)	31.2 ± 5.61	28 ± 5.41	42.6 ± 9.50	33.5 ± 15.5	36.3 ± 13.4	43.3 ± 10.4	25.7 ± 5.43	30.3 ± 9.07	38 ± 4.39
8‡	Offensive breakdown "− −" (%)	15.7 ± 7.97	12.7 ± 8.88	6.33 ± 1.52	8.75 ± 2.75	21.3 ± 4.50	8 ± 2.64	6.75 ± 2.98	10 ± 2	14.7 ± 7.5
9†	Defensive breakdown total	66 ± 18.0	44.2 ± 13.8	55 ± 15.5	41.7 ± 8.05	49.6 ± 12.0	41.3 ± 3.05	35.5 ± 14.4	53.3 ± 4.04	51 ± 7.39
10‡	Defensive breakdown ">>" (%)	77 ± 4.24	56 ± 11.6	79 ± 12	78.7 ± 7.58	82 ± 4.35	82.6 ± 8.14	79.7 ± 8.69	75 ± 3	87 ± 5.47
		β(0.014; 0.7), 0.14 (0.02, 0.27)	χ(0.017; 0.7), −0.15 (−0.29, −0.02) δδ(0.007; 0.7), −0.15 (−0.28, −0.03) εε(0.005; 0.8), −0.17 (−0.31, −0.04) ϕϕ(0.004; 0.8), −0.17 (−0.31, −0.04) γγ(0.005; 0.7), −0.16 (−0.29, −0.03) †††(<0.001; 0.8) −0.20 (−0.32, −0.07)							
11‡	Defensive breakdown "=" (%)	21.5 ± 2.64	32.2 ± 9.97	18 ± 8.54	15.7 ± 5.25	15.6 ± 4.50	15 ± 6.24	16.5 ± 6.55	16 ± 4.35	11 ± 6.73
			††(0.01; 0.8), 0.50 (0.08, 0.92)							
12§	Defensive breakdown "<<" (%)	1.5 ± 1.91	12 ± 4.96	3.33 ± 4.16	5.25 ± 1.89	2.33 ± 2.51	2.33 ± 2.08	3.75 ± 2.62	9 ± 2	2 ± 2.44
		β(0.02; 0.8), δ(0.037; 0.7), η(0.032; 0.8)	ϕ(0.034; 0.8), †(0.028; 0.8)					η(0.034; 0.8)	†(0.032; 0.8)	
13†	Tackles total	122 ± 19.6 δ(0.015; 0.8),	90.2 ± 29.2	85.6 ± 7.63	66.7 ± 14.0	88 ± 23.8	77.6 ± 16.9	63.7 ± 18.2	86.3 ± 16.5	88.7 ± 15.2

	55.5 (6.5, 104.5) γγ(0.009; 0.8), 58.5 (9.5, 107.5)								
14† Tackle "++" (%)	5.5 ± 3.51	6 ± 1.82	5.66 ± 0.57	8 ± 1.15	6.33 ± 5.03	7.33 ± 1.15	5.5 ± 4.79	5.66 ± 2.51	5.75 ± 3.09
15† Tackle "+" (%)	19 ± 3.74	23.2 ± 6.07	21 ± 5.56	25.2 ± 7.18	21.6 ± 7.57	29.3 ± 3.05	22.7 ± 3.30	29 ± 3.60	25 ± 4.24
16† Tackle "−" (%)	38.2 ± 5.18	39.2 ± 9.53	39 ± 1.73	39 ± 8.04	36.3 ± 8.08	33.3 ± 3.05	41.2 ± 10.3	41.3 ± 12.8	42.7 ± 4.11
17‡ Tackle "− off" (%)	12.5 ± 5.50	15.7 ± 9.94	11 ± 2	7.25 ± 2.62	15 ± 6.55	11.6 ± 7.23	10.5 ± 4.35	7.66 ± 4.04	8.75 ± 2.62
18† Missed tackle (%)	24.7 ± 5.56	16 ± 5.59	23 ± 4.58	20.2 ± 2.5	20.3 ± 6.02	17.6 ± 3.78	20.2 ± 6.18	16.3 ± 6.65	17.5 ± 3.69
19‡ Pass total	73.5 ± 12.3	101 ± 41.2	83 ± 14	104. ± 20.5	80 ± 8.54	81 ± 16.8	151 ± 15.3	87.3 ± 39.5	72.2 ± 7.80
	γ(0.019; 0.9), −0.32 (−0.6, −0.03)						†(0.017; 1.0), 0.32 (0.03, 0.61)		
20† Pass "+" (%)	87.5 ± 5.74	85.7 ± 4.85	81.6 ± 4.04	83.2 ± 4.64	80.6 ± 10.0	84 ± 1	85.5 ± 0.57	83.6 ± 5.03	82 ± 5.09
21† Pass "−" (%)	12.5 ± 5.74	14.2 ± 4.85	18.3 ± 4.04	16.7 ± 4.64	19.3 ± 10.0	16 ± 1	14.5 ± 0.57	16.3 ± 5.03	18 ± 5.09
22‡ Pass to possession ratio	6.65 ± 0.46	6.87 ± 1.12	6.36 ± 0.83	7.02 ± 1.25	6.26 ± 1.28	5.66 ± 0.90	9.97 ± 1.68	5.83 ± 1.67	5.4 ± 0.31
					γ(0.044; 0.8), −0.2 (−0.4, −0.01)	γγ(0.007; 0.9), −0.24 (−0.45, −0.04)	ηη(0.008; 0.7), 0.24 (0.04, 0.44)		
							†††(0.001; 0.9), 0.26 (0.08, 0.45)		
23† P.k. total	12.2 ± 6.44	11 ± 3.16	16.3 ± 5.50	12.7 ± 5.05	15 ± 6.55	16 ± 1.73	9 ± 1.41	12.3 ± 4.61	16.2 ± 4.78
24† P.k. on set piece (%)	8 ± 6.05	14.2 ± 10.9	27.3 ± 8.50	20.7 ± 17.9	19.3 ± 13.0	23.6 ± 11.3	21.7 ± 8.01	6.66 ± 6.50	27.5 ± 15.7
25† P.k. on breakdown (%)	35.5 ± 27.3	58.5 ± 11.2	46.6 ± 7.37	49.7 ± 19.0	50.3 ± 17.5	40.3 ± 18.1	49.7 ± 5.31	36.3 ± 6.35	33.2 ± 17.6
26§ P.k. on tackle (%)	15.2 ± 17.7	6 ± 6.97	4 ± 6.92	1.75 ± 3.5	2.33 ± 4.04	8.33 ± 2.30	12.5 ± 12.0	20.6 ± 8.02	9 ± 12.7
27‡ P.k. on offside (%)	39.2 ± 17.9	21 ± 9.79	16 ± 3.46	27.5 ± 4.20	27.6 ± 11.9	23.6 ± 11.3	16 ± 12.5	32 ± 7	23.5 ± 11.4
28‡ P.k. unsportsmanlike (%)	1.75 ± 3.5	0 ± 0	5.33 ± 6.11	0 ± 0	0 ± 0	4.33 ± 3.78	0 ± 0	4.66 ± 8.08	6.5 ± 2.08
29† P.k. quick played (%)	36.1 ± 16.0	26.6 ± 7.23	34.6 ± 6.11	34 ± 27.3	48.1 ± 8.52	34.1 ± 12.1	41.1 ± 17.2	16.7 ± 18.1	28.2 ± 11.4
30† Possession lost total	29.5 ± 8.06	35.5 ± 5.80	31 ± 5.56	30 ± 6.27	36.6 ± 0.57	26.6 ± 4.16	27.2 ± 6.07	30.6 ± 3.51	30.2 ± 5.73
31† Possession lost due to an error (%)	29.5 ± 9.94	30.5 ± 11.2	35.6 ± 11.0	44.2 ± 8.65	28.3 ± 3.78	42.6 ± 9.07	58.7 ± 14.4	30.3 ± 3.78	38.7 ± 11.6
	γ(0.018; 0.6), −29.3 (−55.5, −3)	γ(0.025; 0.5), −28.3 (−54.5, −2)			γ(0.026; 0.7), −30.4 (−58,7, −2.1)		η(0.049; 0.8), 28.4 (0.1, 56.7)		
32† Possession lost on kicks (%)	16.5 ± 6.95	12 ± 4.96	15.6 ± 6.65	15.5 ± 4.93	7.33 ± 7.02	18 ± 5	7.5 ± 5.74	13.3 ± 3.78	13.5 ± 4.93
33‡ Possession lost on turnover (%)	23.7 ± 7.45	19 ± 4.69	13.3 ± 4.72	13.5 ± 5.19	27.3 ± 4.61	11 ± 2	11.5 ± 4.04	20.3 ± 10.0	16.2 ± 5.67
34† Possession lost on set pieces (%)	30 ± 15.4	38.5 ± 9.29	34 ± 4	27 ± 2.44	37 ± 8.66	28 ± 6.92	22.5 ± 13.3	36 ± 12.1	31.2 ± 9.5
35§ Ball in play	26.2 ± 1.66	29.3 ± 3.43	27.3 ± 2.58	26.9 ± 0.29	26.8 ± 2.15	26.5 ± 1.52	29.2 ± 3.46	27.7 ± 2.38	27.3 ± 1.07
36† Time in possession (%)	40.9 ± 2.84	50.9 ± 11.7	49.4 ± 2.91	54.8 ± 3.71	45.7 ± 2.49	51.7 ± 3.87	58.1 ± 8.32	47.6 ± 7.31	49.1 ± 2.47
	γ (0.022; 0.5), −17.3 (−33.1, −1.5)								
37† Ball in play in own 22 m area (%)	21.8 ± 6.95	24.8 ± 12.7	19 ± 6.84	7.55 ± 2.60	22.2 ± 5.75	14.0 ± 5.09	7.52 ± 2.43	12.5 ± 4.74	15.9 ± 6.00
		δ(0.049; 0.7), 17.3 (0.1, 34.5) γ(0.048; 0.7), 17.3 (0.1, 34.5)							

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38‡ Ball in play in own 22 m– halfway lines (%)	38.4 ± 7.72	30.9 ± 5.34	38.0 ± 12.3	29.1 ± 3.35	46.1 ± 7.72	30.7 ± 9.79	26.1 ± 2.52	36.6 ± 14.7	32.7 ± 6.69
39† Ball in play in opponent halfway–22 m lines (%)	28.6 ± 4.78	31.8 ± 10.8	29.8 ± 4.47	45.7 ± 7.35	24.7 ± 4.15	32.5 ± 8.65	35.0 ± 5.41	35.9 ± 7.88	37.5 ± 11.8
40‡ Ball in play in opponent 22 m area (%)	10.7 ± 5.04	12.2 ± 5.19	13.0 ± 4.00	17.5 ± 4.08	6.8 ± 2.02	22.8 ± 3.43	31.2 ± 6.47	14.7 ± 11.0	13.8 ± 4.18
	γ(0.016; 0.8), −0.49 (−0.93, −0.06)				φ(0.029; 0.7), −0.54 (−1, −0.03) γγ(0.001; 0.9), −0.67 (−1.1, −0.19)				
41§ Sequences period 0–10 s (%)	27.5 ± 3.69	23.2 ± 3.86	35.6 ± 3.78	29.2 ± 7.80	27.3 ± 9.29	35 ± 5.56	25.7 ± 5.90	23 ± 9.53	33 ± 2.94
42† Sequences period 11–40 s (%)	52.5 ± 2.08	56.2 ± 5.05	44.6 ± 1.15	54 ± 5.94	53.3 ± 2.30	49.6 ± 3.21	56.2 ± 4.64	53.3 ± 7.09	47.7 ± 4.34
43† Sequences period 41–60 s (%)	11.5 ± 4.04	12.2 ± 4.11	12 ± 4.58	11 ± 2.44	12.6 ± 5.68	10 ± 2.64	10.7 ± 4.99	14.6 ± 4.04	13 ± 2.16
44† Sequences period >60 s (%)	8.25 ± 3.30	8.25 ± 2.62	8.33 ± 1.52	5.75 ± 2.98	7 ± 5.29	5.66 ± 2.30	7.5 ± 2.08	9.33 ± 4.04	7 ± 2.94

*β, χ, δ, ε, φ, γ, η, † ($p \leq 0.05$); ββ, χχ, δδ, εε, φφ, γγ, ηη, †† ($p \leq 0.01$); βββ, χχχ, δδδ, εεε, φφφ, γγγ, ηηη, ††† ($p \leq 0.001$) difference with respect to Team 2, 3, 4, 5, 6, 7, 8, 9, respectively.

†Parametric statistics.

‡Parametric statistics after logarithmic transformation.

§Nonparametric statistics.

TABLE 3. Mean values, standard deviations (differences; effects size), and mean differences (95% confidence interval) of all performance indicators in relation to each Italian under-18 regional tournament (North, Center, and South).

#	Performance indicators	Italian regional tournaments		
		North	Center (η)	South (†)
1*	Set pieces won/regained	24.7 ± 1.8	26.1 ± 2.7	23.5 ± 2.0
2*	Set pieces lost	24.8 ± 1.6	26.2 ± 1.3	23.5 ± 2.4
3*	Offensive breakdown total	50.2 ± 5.0	48.0 ± 0.9	49.8 ± 13.8
4*	Offensive breakdown "v++" (%)	19.6 ± 3.2 †(0.035; 0.7), −10.8 (−20.9, −0.6)	26.7 ± 4.9	30.3 ± 6.8
5*	Offensive breakdown "v+" (%)	20.4 ± 4.2	19.5 ± 2.1	18.6 ± 6.8
6‡	Offensive breakdown "v−" (%)	9.1 ± 5.8	7.1 ± 2.3	11.7 ± 3.2
7*	Offensive breakdown "l" (%)	41.3 ± 2.9 §(0.005; 0.9), 12.7 (3.3, 22)	33.4 ± 3.0	28.3 ± 2.8
8‡	Offensive breakdown "− −" (%)	9.7 ± 4.5	13.4 ± 6.9	11.8 ± 4.6
9*	Defensive breakdown total	49.1 ± 7.0	48.3 ± 5.9	48.6 ± 15.7
10‡	Defensive breakdown ">>" (%)	82.9 ± 4.0 †(0.032; 0.5), −0.08 (−0.15, −0.01)	78.6 ± 3.5	70.9 ± 13.0
11‡	Defensive breakdown "=" (%)	14.7 ± 3.5 †(0.13; 0.5), 0.23 (0.04, 0.43)	15.8 ± 0.2	23.4 ± 8.0
12‖	Defensive breakdown "<<" (%)	2.6 ± 0.7	5.5 ± 3.3	5.8 ± 5.5
13*	Tackles total	84.0 ± 5.7	80.4 ± 11.8	92.1 ± 29.3
14*	Tackle "++" (%)	6.3 ± 0.9	6.7 ± 1.2	5.7 ± 0.3
15*	Tackle "+" (%)	25.1 ± 4.2	25.3 ± 3.7	21.7 ± 2.3
16*	Tackle "−" (%)	38.4 ± 4.7	38.9 ± 2.5	39.6 ± 1.5
17‡	Tackle "− off" (%)	10.5 ± 1.5	10.0 ± 4.4	12.9 ± 2.6
18*	Missed tackle (%)	19.4 ± 3.1	19.0 ± 2.3	20.3 ± 4.4
19‡	Pass total	78.8 ± 5.7	90.7 ± 12.7	108.8 ± 39.2
20*	Pass "+" (%)	82.6 ± 1.3	82.5 ± 1.6	86.3 ± 1.1
21*	Pass "−" (%)	17.4 ± 1.3	17.5 ± 1.6	13.8 ± 1.1
22‡	Pass to possession ratio	5.8 ± 0.5 §(0.006; 0.6), 0.13 (0.03, 0.22)	6.4 ± 0.6	7.8 ± 1.9
23*	P.k. total	16.2 ± 0.2 †(0.018; 0.9), 5.5 (0.8, 10.1)	13.4 ± 1.4	10.8 ± 1.6
24*	P.k. on set piece (%)	26.2 ± 2.2	15.6 ± 7.8	14.7 ± 6.9
25*	P.k. on breakdown (%)	40.1 ± 6.7	45.5 ± 7.9	47.9 ± 11.6
26‖	P.k. on tackle (%)	7.1 ± 2.7	8.3 ± 10.8	11.3 ± 4.8
27‡	P.k. on offside (%)	21.1 ± 4.4	29.1 ± 2.6	25.4 ± 12.2
28‡	P.k. unsportsmanlike (%)	5.4 ± 1.1	1.6 ± 2.7	0.6 ± 1.0
29*	P.k. quick played (%)	32.4 ± 3.6	33.0 ± 15.7	34.6 ± 7.3
30*	Possession lost total	29.3 ± 2.3	32.4 ± 3.7	30.8 ± 4.3
31*	Possession lost due to an error (%)	39.0 ± 3.5	34.3 ± 8.7	39.6 ± 16.6
32*	Possession lost on kicks (%)	15.7 ± 2.3	12.1 ± 4.2	12.0 ± 4.5
33‡	Possession lost on turnover (%)	13.5 ± 2.6	20.4 ± 6.9	18.1 ± 6.2
34*	Possession lost on set pieces (%)	31.1 ± 3.0	33.3 ± 5.5	30.3 ± 8.0
35‖	Ball in play	27.1 ± 0.5	27.2 ± 0.5	28.3 ± 1.7
36*	Time in possession (%)	50.1 ± 1.4	49.4 ± 4.8	50.0 ± 8.7
37*	Ball in play in own 22 m area (%)	16.3 ± 2.5	14.1 ± 7.5	18.1 ± 9.3
38‡	Ball in play in own 22 m–halfway lines (%)	33.8 ± 3.8	37.3 ± 8.5	31.8 ± 6.2
39*	Ball in play in opponent halfway–22 m lines (%)	33.3 ± 3.9	35.5 ± 10.5	31.8 ± 3.2
40‡	Ball in play in opponent 22 m area (%)	16.6 ± 5.4	13.0 ± 5.6	18.1 ± 11.5

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41‖	Sequences period 0–10 s (%)	34.6 ± 1.4 ¶(<0.001; 0.8)	26.5 ± 3.2	25.5 ± 2.1
42*	Sequences period 11–40 s (%)	47.4 ± 2.5 ¶(0.001; 0.9), −6.2 (−11.1, −1.3)	53.6 ± 0.4 ‖(0.009; 0.4), −7.6 (−12.2, 3)	55.0 ± 2.2
43*	Sequences period 41–60 s (%)	11.7 ± 1.5	12.8 ± 1.8	11.5 ± 0.8
44*	Sequences period >60 s (%)	7.0 ± 1.3	7.4 ± 1.8	8.0 ± 0.4

*Nonparametric statistics.
†($p \leq 0.05$) differences with respect to South.
‡Parametric statistics.
§Parametric statistics after logarithmic transformation.
‖($p \leq 0.01$) differences with respect to South.
¶($p \leq 0.001$) differences with respect to South.

teams; and (c) on defense, winning teams recovered more balls and completed more tackles than losing teams. Coherently to this experimental approach, another study focused on the analysis of International Rugby Board and Southern Hemisphere Regional teams (29) reported that, only for the latter competition level, technical and tactical aspects such as kicking the ball away and making more tackles than the opposition were able to significantly discriminate winning and losing teams' performances, whereas the key of success in the higher championship resulted rather obscured by differences playing styles.

Although elite senior rugby union performance was abundantly investigated in terms of physical demands and technical and tactical aspects (6,18,19,23,24,29), only a few studies are available on the elite youth rugby players. In particular, for the latter rugby player category, studies were mainly focused on injuries (13,22) and talent identification (5,25), whereas no study was provided about notational analyses of technical and tactical aspects, specifically related to this category.

Therefore, the aim of this study was to analyze the technical and tactical aspects of the Italian under-18 elite rugby academies, during the 2014–15 Academies Elite Championship, assessing the differences between FIR academies (i.e., Torino, Milano, Prato, Remedello, Mogliano Veneto, Rovigo, Roma, Benevento, and Catania academies), regional tournaments (i.e., North, Center, South), and outcomes (i.e., winning, loosing) by means of strong differences ($p \leq 0.05$ with moderate-large effect size [ES]).

Methods

Experimental Approach to the Problem

The University of Torino Review Board approved this study to investigate the rugby technical and tactical aspects of the Italian under-18 academies competing during the 2014–15 season. In particular, this championship has been played according to the international youth rugby rules (31), and consisted of 2 phases. In the first one, 18 matches of 2 halves of 35 minutes were played into 3 different regional tournaments; in the second one, each academy played 2 40-minute games against other academies selected according to the results of the regional tournaments. For the analyses of this study, only the matches of the first competition phase were considered.

In line to previous studies on senior rugby (6,18,19,23,24,29), it seems reasonable to hypothesize that differences would emerge in terms of technical and tactical aspects between winning and losing teams, as well as between different teams and regional tournaments. Nevertheless, common technical and tactical strategies eventually provided by the FIR training staffs working in all 9 Academies to mainly obtain the development of players' performance skills, could minimize the expectations of several strong differences ($p \leq 0.05$ with large ES) between teams.

However, from the data of this study focused on Italian youth rugby matches, differences were expected between teams, regional tournaments and in terms match outcome. For this purpose, the data related to the technical and tactical indicators of these teams have been considered as dependent variables, whereas the outcome, FIR Academies, and regional tournaments have been considered as between factors.

Subjects

The coaches of the Italian under-18 residential rugby academies (age range = 15–17 years) gave their approval for the analyses of the matches, after having received the written parental consent for each player and subject consent to video record the rugby matches, even considering the risks and benefits of the study. Italian Rugby Academies competing into the Elite Championship 2014–15 were split in 3 regional tournaments (i.e., North, Center, South) consisting of 3 academies each one, and each academy played 2 games (against to the other 2 academies of the same regional tournament) which were valid to achieve the best possible ranking position in each tournament, and to access to following national competition phase.

According to the coaches of the Italian Rugby Academies, the Italian under-18 rugby players enrolled in the residential academies usually perform a minimum of 4 to a maximum of

Table 4. Mean values, standard deviations (differences; effects size), and mean differences (95% confidence interval) of all performance indicators, in relation to winning and losing Italian under-18 academies.

#	Performance indicators	Outcome: Winning academies	Outcome: Losing academies
1*	Set pieces won/regained	25.8 ± 1.9 †(0.037; 0.4), 24.7 (23.6, 25.8)	23.6 ± 3.5
2*	Set pieces lost	23.6 ± 3.5	25.8 ± 1.9
3*	Offensive breakdown total	50.0 ± 11.6	48.3 ± 15.6
4*	Offensive breakdown "v++" (%)	27.7 ± 9.8	23.8 ± 10.3
5*	Offensive breakdown "v+" (%)	18.8 ± 7.5	19.9 ± 5.5
6‡	Offensive breakdown "v−" (%)	10.3 ± 6.7	8.7 ± 5.4
7*	Offensive breakdown "l" (%)	33.8 ± 11.5	33.9 ± 8.2
8‡	Offensive breakdown "− −" (%)	9.62 ± 4.7	13.6 ± 7.7
9*	Defensive breakdown total	49 ± 16.5	48 ± 10.8
10‡	Defensive breakdown ">>" (%)	76.6 ± 11.2	77.7 ± 11.3
11‡	Defensive breakdown "=" (%)	18.6 ± 8.7	17.7 ± 7.9
12§	Defensive breakdown "<<" (%)	4.75 ± 3.6	4.5 ± 5.0
13*	Tackles total	81.6 ± 25.2	89.6 ± 22.1
14*	Tackle "++" (%)	6.81 ± 2.6	5.5 ± 2.8
15*	Tackle "+" (%)	25.0 ± 6.0	22.6 ± 4.8
16*	Tackle "−" (%)	38.9 ± 6.2	39.3 ± 8.3
17‡	Tackle "− off" (%)	8.87 ± 3.6 †(0.014; 0.4), 1 (0.92, 1.48)	13.3 ± 6.4
18*	Missed tackle (%)	20.1 ± 4.2	19.0 ± 6.1
19‡	Pass total	102. ± 31.9	85.5 ± 29.6
20*	Pass "+" (%)	84.0 ± 3.2	83.8 ± 6.2
21*	Pass "−" (%)	15.9 ± 3.2	16.1 ± 6.2
22‡	Pass to possession ratio	7.11 ± 1.8	6.3 ± 1.4
23*	P.k. total	14.1 ± 4.8	12.3 ± 4.5
24*	P.k. on set piece (%)	17.5 ± 11.4	20 ± 13.6
25*	P.k. on breakdown (%)	44.7 ± 14.5	44.5 ± 18.6
26§	P.k. on tackle (%)	9.68 ± 10.3	8.1 ± 10.8
27‡	P.k. on offside (%)	26.1 ± 8.9	24.2 ± 14.7
28‡	P.k. unsportsmanlike (%)	1.62 ± 3.3	3.1 ± 4.5
29*	P.k. quick played (%)	35.1 ± 16.7	31.4 ± 14.9
30*	Possession lost total	28 ± 5.6 ‖(0.005; 0.5), 30.8 (28.7, 32.9)	33.5 ± 4.6
31*	Possession lost due to an error (%)	44.3 ± 14.0 ‖(0.005; 0.5), 38.1 (33.3, 42.8)	31.8 ± 8.6
32*	Possession lost on kicks (%)	13.8 ± 6.3	12.5 ± 5.7
33‡	Possession lost on turnover (%)	16 ± 6.1	18.5 ± 8.1
34*	Possession lost on set pieces (%)	25.5 ± 8.7 ¶(<0.001; 0.6), 31.3 (27.7, 35)	37.1 ± 7.9
35§	Ball in play	27.5 ± 2.3	27.5 ± 2.3
36*	Time in possession (%)	52.0 ± 7.0	47.9 ± 7.2
37*	Ball in play in own 22 m area (%)	12.3 ± 6.7 †(0.011; 0.4), 16.1 (13, 19.1)	19.7 ± 8.6
38‡	Ball in play in own 22 m–halfway lines (%)	33.9 ± 8.3	33.8 ± 9.8
39*	Ball in play in opponent halfway–22 m lines (%)	33.8 ± 9.8	33.9 ± 8.3
40‡	Ball in play in opponent 22 m area (%)	19.7 ± 8.6 ‖(0.006; 0.5), 1.15 (1.06, 1.23)	12.3 ± 6.7

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TABLE 4. Mean values, standard deviations (differences; effects size), and mean differences (95% confidence interval) of all performance indicators, in relation to winning and losing Italian under-18 academies.

#	Performance indicators	Outcome	
		Winning academies	Losing academies
1*	Set pieces won/regained	25.8 ± 1.9 †(0.037; 0.4), 24.7 (23.6, 25.8)	23.6 ± 3.5
2*	Set pieces lost	23.6 ± 3.5	25.8 ± 1.9
3*	Offensive breakdown total	50.0 ± 11.6	48.3 ± 15.6
4*	Offensive breakdown "v++" (%)	27.7 ± 9.8	23.8 ± 10.3
5*	Offensive breakdown "v+" (%)	18.8 ± 7.5	19.9 ± 5.5
6‡	Offensive breakdown "v−" (%)	10.3 ± 6.7	8.7 ± 5.4
7*	Offensive breakdown "l" (%)	33.8 ± 11.5	33.9 ± 8.2
8‡	Offensive breakdown "− −" (%)	9.62 ± 4.7	13.6 ± 7.7
9*	Defensive breakdown total	49 ± 16.5	48 ± 10.8
10‡	Defensive breakdown ">>" (%)	76.6 ± 11.2	77.7 ± 11.3
11‡	Defensive breakdown "=" (%)	18.6 ± 8.7	17.7 ± 7.9
12§	Defensive breakdown "<<" (%)	4.75 ± 3.6	4.5 ± 5.0
13*	Tackles total	81.6 ± 25.2	89.6 ± 22.1
14*	Tackle "++" (%)	6.81 ± 2.6	5.5 ± 2.8
15*	Tackle "+" (%)	25.0 ± 6.0	22.6 ± 4.8
16*	Tackle "−" (%)	38.9 ± 6.2	39.3 ± 8.3
17‡	Tackle "− off" (%)	8.87 ± 3.6 †(0.014; 0.4), 1 (0.92, 1.48)	13.3 ± 6.4
18*	Missed tackle (%)	20.1 ± 4.2	19.0 ± 6.1
19‡	Pass total	102. ± 31.9	85.5 ± 29.6
20*	Pass "+" (%)	84.0 ± 3.2	83.8 ± 6.2
21*	Pass "−" (%)	15.9 ± 3.2	16.1 ± 6.2
22‡	Pass to possession ratio	7.11 ± 1.8	6.3 ± 1.4
23*	P.k. total	14.1 ± 4.8	12.3 ± 4.5
24*	P.k. on set piece (%)	17.5 ± 11.4	20 ± 13.6
25*	P.k. on breakdown (%)	44.7 ± 14.5	44.5 ± 18.6
26§	P.k. on tackle (%)	9.68 ± 10.3	8.1 ± 10.8
27‡	P.k. on offside (%)	26.1 ± 8.9	24.2 ± 14.7
28‡	P.k. unsportsmanlike (%)	1.62 ± 3.3	3.1 ± 4.5
29*	P.k. quick played (%)	35.1 ± 16.7	31.4 ± 14.9
30*	Possession lost total	28 ± 5.6 ‖(0.005; 0.5), 30.8 (28.7, 32.9)	33.5 ± 4.6
31*	Possession lost due to an error (%)	44.3 ± 14.0 ‖(0.005; 0.5), 38.1 (33.3, 42.8)	31.8 ± 8.6
32*	Possession lost on kicks (%)	13.8 ± 6.3	12.5 ± 5.7
33‡	Possession lost on turnover (%)	16 ± 6.1	18.5 ± 8.1
34*	Possession lost on set pieces (%)	25.5 ± 8.7 ¶(<0.001; 0.6), 31.3 (27.7, 35)	37.1 ± 7.9
35§	Ball in play	27.5 ± 2.3	27.5 ± 2.3
36*	Time in possession (%)	52.0 ± 7.0	47.9 ± 7.2
37*	Ball in play in own 22 m area (%)	12.3 ± 6.7 †(0.011; 0.4), 16.1 (13, 19.1)	19.7 ± 8.6
38‡	Ball in play in own 22 m–halfway lines (%)	33.9 ± 8.3	33.8 ± 9.8
39*	Ball in play in opponent halfway–22 m lines (%)	33.8 ± 9.8	33.9 ± 8.3
40‡	Ball in play in opponent 22 m area (%)	19.7 ± 8.6 ‖(0.006; 0.5), 1.15 (1.06, 1.23)	12.3 ± 6.7

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only for 10 indicators, differences between academies were reported (Table 2). For the regional tournaments, 8 indicators reported a main effect (i.e., 4, $p = 0.037$; 7, $p = 0.007$; 10, $p = 0.03$; 11, $p = 0.013$; 22, $p = 0.006$; 23, $p = 0.022$; 41, $p = 0.003$; 42, $p = 0.001$) and specific differences between tournaments (Table 3). Finally, for the comparison between winning and losing academies, 7 indicators (i.e., 1, 17, 30, 31, 34, 37, and 40) showed the significant difference (Table 4).

Discussion

Although studies focused on technical and tactical aspects of team sports suffer in terms of replication because of relevant situational nature complexity (12,20,21,27), notational analysis demonstrated to be an effective tool for increasing the knowledge of team sports and for better coaching (17). At present, although several studies on the notational analysis of rugby game have been provided (6,18,19,23,24,29), research on technical and tactical aspects of youth rugby is lacking. Therefore, to our knowledge, this is the first study applying a notational analysis of junior elite (Italian under-18 academy category) rugby performance, with the purpose to analyze technical and tactical parameters in relation to different academies, tournaments, and game outcomes.

The main finding of this study is that youth rugby games has a significant impact on the occurrence of technical and tactical indicators of team performance, highlighting divergences among performances of some academies and regional tournaments. However, the first 2 aims could be partially achieved because strong differences emerged only for 10 and 8 indicators (over the 44 ones analyzed) of the comparisons between different academies and tournaments, respectively. In addition, although 7 indicators reported differences between winning and losing academies, these effects resulted less strong because of their small ESs, limiting the relative interpretations and suggesting the hypothesis that the development of technical and tactical skills of players encouraged by FIR staffs has been mostly promoted with respect to the obtaining of a winning game.

Among the differences emerged from the comparisons between academies, academies 2 and 9 resulted as the worst and best academy during the defensive phases (i.e., indicator 10, 11, and 12), respectively, showing a different number of defenders with respect to that of opponent attackers and providing the opportunities of maintain and getting back the ball possessions, which could potentially influence the game success (24,29). Another success association could be suggested also for the "time in possession" parameter, which showed academy 1 and academy 7 as the worst and best team in maintaining the possession of the ball during games, respectively, thus highlighting a divergent capability to limit opponent ball possession. However, this difference is reported with a small ES, limiting the substance of this interpretation. However, academy 7 and academy 4 played the lowest time in its own 22 m area, and the opposite trend (only for academy 7) emerged for the time of play spent in the opponents 22 m area, suggesting strong divergences in the offensive and defensive team skills, which could be linked directly to a different probability of scoring points. Also, the higher occurrence of tackles (29) performed by academy 1 with respect to that of academy 4 and academy 7 could be associated to success; however, this indicator is able just to highlight the occurrence of total tackle attempts regardless of its efficiency, which actually resulted as the worst in absolute terms (i.e., indicators 14 and 15). In addition, academy 7 reported the highest values of passes, although no success application has been provided for this aspect (29), whereas academy 9 reported the best "pass to possession ratio," which could be considered as a better indicator to evaluate the ball-handling capabilities of a rugby team.

For the comparisons between tournaments, results showed clear differences between technical and tactical aspects between the North and South regional subgroups. In particular, academies of the South and North regional tournaments performed a higher occurrence of quick offensive breakdowns ($\leq$3 seconds) using maximum 2 attacking supports and not quickly offensive breakdowns ($>$3 seconds) regardless the number of attacking supports, respectively, speculating different offensive capabilities. However, similarly to previous studies on other team sports (20) where technical and tactical aspects related to the offensive game phases could be useful also to interpret defensive aspects, the different quickness of the offensive breakdowns could be also determined by the higher and lower opponents' defensive skill levels reported by the North and South academies, respectively. In fact, despite for effect of differences with small ESs, the same interpretation seems to be confirmed in the analysis of the defensive breakdowns (i.e., indicator 10 and 11) where the defending support resulted stronger (according to the number of defenders per each defensive phase) in the North than in South academies. As consequence, the "pass to possession ratio" parameter reported that the South academies have the opportunity to mostly pass the ball among teammates with respect to North ones. Different game styles emerged also for the higher penalty occurrences, which were associated to a successful game profile in senior rugby (29), and were more performed by the North than South academies in the Italian under-18 Academy Rugby Union. Finally, in the North tournament, academies usually play for short periods (0–10 seconds), speculating that defenses are able to promptly face opponent attackers to interrupt their active ball possessions and limit the consequent advancing, whereas for the sequences lasting 11–40 seconds, the academies of the South tournament reported higher number of cases with respect to those of Center and North ones.

The comparisons between winning and losing Italian under-18 rugby teams reported differences with small ESs, determining less strong conclusion and strengthening the intrinsic meaning of the Italian rugby academies for which the development of technical and tactical skills is more important than winning a game. Nevertheless, in line with the winning game profile of senior rugby competitions (19,23,24,29), the high occurrences of "all own and opponents' scrums, lineouts, starts and restarts won or regained, respectively" (i.e., indicator 1) and "ball in play in opponent 22 m area" (i.e., indicator 40), as well as the low occurrences of "possession lost total" (i.e., indicator 31), "possession lost on set pieces" (indicator 34), and "ball in play in own 22 m area" (i.e., indicator 37), are able to confirm the substance of this playing events in terms of game success. In addition, despite the higher occurrence of the losing academies for the "tackles which stops the opponent but not the ball" (i.e., indicator 17) seems as controversial (absolute mean values: winning academies, 12; losing academies, 11); this result represents the percentage balance to the high frequency of the "dominant tackle which stops the opponent and the ball" indicators (i.e., 14 and 15) reported by the winning academies. A possible explanation of this result could be that the players of losing teams were not only less skilled but also less physically prepared. In fact, previous investigations (8,9) documented a significant correlation between tackling proficiency and players' physical characteristics (acceleration and lower body muscular power). In particular, the authors of this study suggested that strength and condition coaches should emphasize on these specific players' characteristics to improve tackling abilities.

However a similar interpretation might be provided also for the higher occurrence of the "possession lost due to an error" reported by winning academies, which emerged for effect of the higher values of the "possession lost on set pieces" reported by losers. As consequence, the winning game profile is more focused on proving a high number of offensive possessions than not committing errors during this game phase, thus speculating a substantial influence of the players' strength and conditioning levels. In fact, the obtaining of more ball possessions can be determined by a higher number of winning set pieces due to a better cognitive (i.e., better players' tactical arrangement) as well as by higher strength capabilities. Similarly, a higher number of ball possessions can be also due to a better repeated sprint capability with and without change of direction.

Youth rugby coaches should be aware that specific technical and tactical aspects of rugby game could be useful to plan and monitor substantial training sessions and workouts. In fact, coherently to the encouragement of Vaz, Van Rooyen, & Sampaio (29) to promote further researcher on northern and southern hemisphere senior teams, this study should be the starting point to provide information on actual technical and tactical demands of youth rugby games, even analyzing different international championships and variables, without remaining approximate and referring to alternative competition profiles. Similarly, from the analysis of the technical and tactical aspects, crucial interpretation on physiological issues can be equally provided, also encouraging future studies to mainly focus on the identification of the rugby players' physical parameters in relation to different FIR academies, regional tournaments and game outcomes.

Practical Applications

This study contributes to the systematic identification of the actual rugby demands occurring during youth games, showing an essential process to define training programs fully designed to meet the demands of competition (6). In fact, the present findings not only offer general information to coaches about technical and tactical rugby aspects but also identify the game aspects that can mostly differ between academies, as well as in relation to different Italian geographic areas, and winning and losing outcomes, also from a strength and conditioning point of view.

In conclusion, this study has demonstrated that only a few indicators (over the 44 considered) were able to discriminate the technical and tactical performances of Italian under-18 rugby players in relation to different academies, tournaments, and game outcomes. Therefore, it could be also speculated that same effects reported for these indicators probably emerged because of heterogeneous coaches' teaching and players' learning capabilities and were quite limited by a common technical and tactical training strategy of the FIR academy staffs, which operated more toward the development of players' skills than the obtaining of success in single games. For example, regarding the attacking phase, the attitude to always attack, obtaining the "ball in play in opponent 22 m area" (i.e., indicator 40) represents a game aspect directly linked to the winning performance, even in the case that players' technical skills are quite poor. As consequence, according to the Italian rugby academies tactical objective to prepare athletes to play at the international level, strength and conditioning coaches should stimulate this capability. In particular, for the conditional training, the players' enhancing of the repeated sprint ability with and without the ball possession can favor substantial improvements in getting the opponent 22 m area, especially enhancing the capability to first resist against opponent tackles or during set pieces and then sprinting forward. Therefore, training sessions aiming to improve the players' strength level and the running speed could crucially improve the outcome of the game phases highlighted in the findings of this study. In particular, enhancing the difficulty of the exercises, focusing on unplanned and reactive drills, and reinforcing the proper execution of the acceleration and deceleration phases should be considered as the main training objectives by strength and conditioning coaches (2). In fact, a sharp execution of changes of direction should be emphasized because, at this stage of youth development, players are more able to perform sharper executions than rounded ones (2). However, in line to American football players (3), straight sprinting speed firstly requires to increase the linear acceleration. Therefore, strength and conditioning coaches should consider the enhancement of this ability by performing explosive movements, footwork, and repeated short-distance accelerations, highlighting elastic band, down, and uphill, and sled as effective methods to obtain these performance improvements.

In line to this playing scenario, the "possession lost on set pieces" data, tactical, and strength and conditioning coaches should focus training on the development of skills to quickly regain the ball, also to improve the effectiveness of counterattacks. For example, the combination of cognitive (i.e., capability to "read" the playing situation before the opponents) and strength (i.e., capability to get ball during the set pieces) workouts could crucially stimulate players in effectively performing this particular phase of matches. Practically, a progression from simple (i.e., low number of involved offensive and defensive players) to complex (i.e., high number of players) set pieces where the aim is getting the ball to perform a quick offensive action could stimulate players both for tactical capabilities and the above-mentioned physical aspects (i.e., cognitive, strength, and repeated sprint abilities with and without change of direction).

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1.2.2 Paper #2

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"How" is more important than "how much" for game possession in elite northern hemisphere rugby union

AUTHORS: Alexandru Nicolae Ungureanu[1], Paolo Ricardo Brustio[1], Luca Mattina[2], Corrado Lupo[1]

[1] Neuromuscular Function Research Group, School of Exercise & Sport Sciences (SUISM), Department of Medical Sciences, University of Torino, Turin, Italy
[2] School of Exercise & Sport Sciences (SUISM), University of Torino, Turin, Italy

ABSTRACT: The present study aimed to analyse technical and tactical aspects of rugby teams competing in the 2016/17 PRO12 Championship (12 professional club teams from Wales, Scotland, Italy, and Ireland) according to: margin of victory (close and balanced games, 1–9 and 10–26 points of difference in final score, respectively), ranking position [the four best placed clubs from each nation (the 1^{st}–4^{th} team) and the three following ranked clubs (the 5^{th}–7^{th} team)], and game outcome and ranking combined (winning and losing performances in the 1^{st}–4^{th} and 5^{th}–7^{th} team subgroups). One hundred and thirty-two games were analyzed according to 20 key performance indicators. A non-parametric approach was applied to evaluate differences ($p \leq 0.05$) between teams. In close games, winning teams reported less possession (p=0.039), defended more (tackles made, p=0.039), and carried the ball less than losing counterparts (p=0.05), whereas in balanced games, winning teams were found to be much better than losers in "tries for" (p<0.0001) as well as "tries against" (p<0.0001), and "clear breaks" (p=0.0003). The teams of the 1^{st}–4^{th} subgroups were found to be more oriented to provide a solid defence than the 5^{th}–7^{th} winning teams, which were more offensive oriented (possession, p=0.01; gain line carries, p=0.001; passes, p<0.0001). Finally, a similar scenario to that of balanced games emerged for winning and losing performances in the 1^{st}–4^{th} and 5^{th}–7^{th} team subgroups. Coaches and physical trainers of elite northern hemisphere rugby union teams should be aware that successful performances mainly consist of a strong defence, tackling, scrumming, breaking the defensive line and high occurrences of possessions during the attacking phase.

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Corresponding author:
Corrado Lupo
Neuromuscular Function Research Group, School of Exercise & Sport Sciences (SUISM), Department of Medical Sciences, University of Torino
Turin, Italy
Piazza Bernini 12
10143 – Turin, Italy.
Phone: Int+39 3490728200
Fax: Int+39 011 748251
E-Mail: corrado.lupo@unito.it

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INTRODUCTION

The current improvement of professionalism in rugby union is characterized by technological progression, which makes training more individualized and effective in terms of physical performance, even minimizing the risk of overtraining [1]. At present, the use of technology is focused on the analysis of technical and tactical patterns oriented to the game success [2, 3, 4, 5, 6], as well as on the physiological demands occurring during the game [7].

In rugby union, key performance indicators (KPIs) have been selected and combined with the aim of discriminating winning and losing performances in national [2, 8] and international [4, 9, 10, 11] games. Among the latter category of studies, Ortega et al. [4] reported interesting findings about the 2003–06 Six Nations editions, where the success of games was principally associated with loss of fewer balls in the scrummage and line-out phases; playing more with their feet; using the maul and breaking the defensive line; and recovering more balls and completing more tackles. Moreover, for the same Championship, Vaz et al. [12] also demonstrated that home teams benefit from the advantage in terms of penalty goals overall, successful penalty goals, rucks/mauls won, and passes completed. In another study on World Cup Rugby [9], the winning outcome of games was especially characterized by the possession retained, number of points scored in the second half, and the propensity to lose possession in areas of the field from which the opposition is likely to score. In contrast, Vaz et al. [10, 11] have investigated successful performances in international championships, including northern and southern hemisphere national teams (i.e., Six Nations, Tri Nations and World Cup), and in international club competitions exclusively including southern hemisphere teams (i.e., Super 12 Championship). The studies showed for the first subgroup of games that no difference between winning and losing teams emerged in close games (i.e., when the final score difference between teams is 15 points or less), highlighting that national teams of the northern and southern hemisphere used to play with no particular playing tendency. Conversely, a different scenario is associated with club competitions, which tends to link a kicking based game plan to success, even in close games [11].

Therefore, it is difficult to recognize a common playing style in rugby, confirming the fact that team games have to be analysed in relation to specific conditions [13]. In line with this perspective, Jones et al. [2, 8] provided two studies on the analysis of technical and tactical aspects exclusively related to a professional European rugby union team.

In one of these studies [8], specific long-term performance standards were highlighted in order to provide useful information when a single game is compared to others (i.e., the average level of the previous performances). In another study [2], technical and tactical analyses of teams were considered according to a balanced number of home and away games, reporting effects only for two team performance indicators (i.e., lineouts won on opposition's throw and tries scored) among the twenty-two considered in the study. Therefore, these findings confirm the hypothesis for which a model to predict future performances in rugby union should be structured only considering a specific competitive level.

Although Vaz et al. [11] reported data about a club international championship exclusively related to the southern hemisphere (i.e., S12), no investigation was provided for the same competition level in the northern hemisphere. Top 14 (France), Premiership Rugby (England), and PRO12 (Wales, Scotland, Italy and Ireland) represent the three main championships. However, only the PRO12, named PRO14 after the involvement of two South African teams in the 2017–18 edition, championship is characterized by the involvement of professional teams from four European countries. Based on the final ranking (i.e., the four best placed clubs from each nation plus the three highest ranked clubs not qualified thereafter), the best seven teams of this championship can access the European Rugby Champions Cup (ERCC) with thirteen other teams from French and English leagues.

It seems reasonable to hypothesize that the technical and tactical aspects are influenced by the final outcome, but the margin of victory can provide deeper information on the game. At present, elite men's club rugby competing in the northern hemisphere has not been investigated according to this rationale, and the above-mentioned game variables can only be inferred from the analyses of previous studies [11].

Therefore, considering the lack of research on technical and tactical aspects on international club competition related to the northern hemisphere, the aim of the present study was to analyse team performance in the PRO12 Championship verifying: i) the difference between winning and losing teams in close games (1–9 points in the final score) and in balanced games (10–26 points between teams in the final score); ii) the difference between the four best placed clubs from each nation (1^{st}–4^{th} team) and those of the three highest ranked clubs not qualified thereafter (the 5^{th}–7^{th} team); and iii) the combination of game outcome and ranking position (i.e., comparison between winning and losing performances in the 1^{st}–4^{th} team subgroup and in the 5^{th}–7^{th} teams).

MATERIALS AND METHODS

Design

This study comprised all 132 games (22 rounds per 6 games each) played during the 2016/17 PRO12 regular season by 12 professional teams from four countries (Wales, Scotland, Italy, Ireland). In particular, archival data were obtained from the Ultimate Rugby web domain (https://www.ultimaterugby.com/#). According to the literature [14], all data reported in this Web domain were collected by professional analysts, who applied a reliability test (kappa coefficients) on 12 games of the above-mentioned sample of games. The results of this test showed coefficients of agreement of 1.0 for passes and tackles made for both teams in each game. The local institutional review board approved this study.

Procedure

Each of the 132 considered games types was divided according to the final score difference as previously suggested [15, 16]. Specifically, according to Sampaio et al. [17] and Vaz et al. [11] the final score difference in each game was clustered by the k-means clustering method. This method produced 3 different category clusters of the greatest possible distinction according to game final score differences [17]: 1–9 points of difference in the final score (close game); 10–26 points of difference in the final score (balanced game); more than 26 points of difference in the final score (unbalanced games). Thus, to provide a first reference on technical and tactical aspects classified according to specific margins of victory for PRO12 teams only the close games and the balanced game clusters were selected for the final analysis. In particular, the exclusion of draw games is due to the impossibility of establishing winning and losing teams, whereas unbalanced games were not considered because no surprising results were expected for this type of competitive condition.

Moreover, since the final ranking in the regular PRO12 Championship season leads to the qualification for the ERCC in accordance with two conditions (i.e., the first best ranked 4 teams from each country then the 3 highest ranked clubs not qualified thereafter), technical and tactical differences between teams were also expected in relation to the final ranking. Therefore, a comparison between winning teams' technical and tactical performances related to the 1^{st}–4^{th} and the 5^{th}–7^{th} teams were also compared, as well as between winning and losing performances (regardless of margin of victory) in the 1^{st}–4^{th} and the 5^{th}–7^{th} team subgroups.

According to previous studies [10, 11, 12], the KPIs presented in Table 1 were considered for the analysis. A further three KPIs (i.e., points scored over clean break, defenders beaten over try and offloads over defenders beaten), which were expressed as ratios (following a combination of two KPIs), were added to the analysis to provide additional and more accurate information of the performance.

TABLE 1. Description of all key performance indicators (KPIs) used for analyzing rugby games

#	KPI	Description
1	Possession (%)	Percentage ratio expressed by playing time handling the ball over total time
2	Territory (%)	Percentage ratio expressed by playing time in the opponent half of the pitch over total time
3	Tries for (n)	Occurrence of tries scored during a game (penalty tries included)
4	Tries against (n)	Occurrence of tries received (by the opponent team) during a game (penalty tries included)
5	Distance gained on possession (m)	Amount of metres covered by each player carrying the ball in the direction of the try line
6	Defenders beaten (n)	Occurrence of evasive ball carried by acting a side step or even pushing away the tackler resulting in missed tackle for the defence
7	Clean breaks (n)	Occurrence of offensive carries leading to a break in the first defensive line and to engage a defender from the second defensive line
8	Gain line carries (n)	Occurrence of ball carries leading to gain the advantage line
9	Passes (n)	Occurrence of completed (i.e., performed from a player to another team mate) passes
10	Offloads (n)	Occurrence of completed passes performed from the ball carriers, after being in contact with the tackler
11	Turnovers won (n)	Occurrence of possessions regained from the opponents
12	Kicks from hand (n)	Occurrence of possessions kicked during the ball in play time
13	Tackles made (n)	Occurrence of tackles completed
14	Tackles missed (%)	Percentage ratio expressed by missed tackles (i.e., without stopping of the ball carriers advancing) over total tackles performed
15	Ruck success (%)	Percentage ratio expressed by possession retained by means of the offenders intervention on the ruck situation over total rucks
16	Lineout success (%)	Percentage ratio expressed by the possession retained by means of the offenders on the lineout situation over total occurrence of lineout
17	Scrum success (%)	Percentage ratio expressed by the possessions retained by the offenders on the scrum situation over total occurrence of scrum
18	Points scored over clean break (n)	Ratio expressed by points scored during a clean break and total occurrence of clean break (which represents the offensive effectiveness because it consists into a clear attacking advantage which potentially leads to score points by performing a try or even gaining a penalty)
19	Defenders beaten over try (n)	Ratio expressed by the defenders beaten (i.e., evasive ball carries by acting a side step or even pushing away the tackler resulting in missed tackle for the defence) and tries for (i.e., tries scored during a game; penalty tries included)
20	Offloads over defenders beaten (n)	Ratio expressed by the offloads (i.e., completed passes performed by ball carriers, after being in contact with the tackler) and the defenders beaten (i.e., evasive ball carries by acting a side step or even pushing away the tackler determining a missed tackle of defence)

Data Analysis

For each KPI, medians (Mdn) and 95% confidence limits were calculated for winning and losing teams. After applying the Shapiro-Wilk normality test for each KPI and assuming that normality was not confirmed ($p \leq 0.05$), the non-parametric Mann-Whitney U test was used for all 20 KPIs to evaluate the differences between winning and losing teams in close and balanced games, the 1st–4th and 5th–7th winning teams, and all (i.e., regardless of game outcome) the 1st–4th and the 5th–7th teams. Finally, to provide meaningful analysis for significant comparisons from small groups, the *phi* (φ) value was calculated for significant differences considering 0.1, 0.3, and 0.5 as small, medium, and large effect sizes, respectively [18]. The difference between medians (95% confidence interval) was reported only for those significantly different. Statistical analysis was conducted using GraphPad Prism (V6.0, GraphPad Software) and the criterion for significance was set at $p \leq 0.05$.

RESULTS

From the whole sample of games, 100 (38%, mean score difference = 4), 120 (45%, mean score difference = 15), and 44 (18%, mean score difference = 40) were close, balanced, and unbalanced, respectively. No game reported a draw final score.

Winning and losing teams in close and balanced games

Table 2 shows the descriptive statistics (i.e., medians and 95% confidence limits) of the 20 KPIs in relation to winning and losing games specifically related to close and balanced games.

Considering close games, a significant difference was observed in possession, gain line carries, and tackles made between winning and losing. Specifically, the winning team presented a higher score in tackles made [Mdn difference = 14, 95%CI (1–31), p=0.039, φ=0.2] and a lower score in possession [Mdn difference = -4, 95%CI (-6 to -1), p=0.0039, φ=0.2] and gain line carries [Mdn difference = -14, 95%CI (-23 to -1), p=0.05, φ=0.2] compared to the losing team. In contrast, in balanced games the winning team presented a higher score in tries for [Mdn difference = 3, 95%CI (2–3) p<0.0001, φ=0.7], metres gained in possession [Mdn difference = 36, 95%CI (9–92), p=0.016, φ=0.2], clean breaks [Mdn difference = 2, 95%CI (1–4), p=0.0003, φ=0.3], offloads [Mdn difference = 2, 95%CI (1–4), p=0.05, φ=0.2], turnovers won [Mdn difference = 1, 95%CI (1–2), p=0.05, φ=0.2], kicks from hands [Mdn difference = 3, 95%CI (1–6), p=0.03, φ=0.2], scrum success [Mdn difference = 7, 95%CI (1–9), p=0.03, φ=0.2], points scored over clean break [Mdn difference = 1, 95%CI (1–2), p<0.0001, φ=0.1], and lower score in tries against [Mdn difference = -3, 95%CI (-3 to -2), p<0.0001, φ=0.7], tackles missed [Mdn difference = -4, 95%CI (-4 to -1), p<0.009, φ=0.2] and defenders beaten over try [Mdn difference = -4, 95%CI (-5 to -3), p<0.001, φ=0.2] compared to the losing team.

Difference between the 1^{st}–4^{th} and 5^{th}–7^{th} winning teams

Possession [Mdn difference = -6, 95%CI (-10 to -1), p=0.001, φ=0.3], gain line carries [Mdn difference = -25, 95%CI (-33 to -12), p=0.001, φ=0.4] and passes [Mdn difference = -38, 95%CI (-57 to -26), p<0.0001, φ=0.5] were lower in the 1^{st}–4^{th} compared to the 5^{th}–7^{th} team subgroup.

TABLE 2. Medians (95% confidence limits) of all performance indicators in relation to winning and losing performances in close (0–9 score difference) and balanced (10–26 score difference) games.

#	Performance indicators	Close games (1–9 points)		Balanced games (10–26 points)	
		Winning	Losing	Winning	Losing
1	Possession (%)	48 (45, 52)	52 (48, 55)*	53 (47, 54)	47 (46, 53)
2	Territory (%)	49 (45, 51)	52 (49, 55)	50 (46, 57)	48 (43, 53)
3	Tries for	2 (2, 3)	2 (2, 3)	4 (3, 4)	1 (1, 2)****
4	Tries against	2 (2, 3)	2 (2, 3)	1 (1, 2)	4 (3, 4)****
5	Metres gained on possession	390 (366, 460)	363 (341, 443)	401 (393, 450)	365 (324, 403)*
6	Defenders beaten	16 (13, 18)	15 (15, 17)	17 (14, 18)	14 (12, 17)
7	Clean breaks	7 (5, 8)	7 (5, 8)	8 (7, 10)	6 (5, 7)***
8	Gain line carries	115 (103, 129)	129 (118, 137)*	121 (107, 133)	120 (108, 141)
9	Passes	147 (131, 169)	153 (136, 163)	150 (136, 169)	162 (146, 173)
10	Offloads	9 (7, 10)	10 (7, 11)	10 (9, 12)	8 (7, 11)*
11	Turnovers won	6 (6, 7)	6 (5, 7)	7 (6, 8)	6 (5, 7)*
12	Kicks from hands	25 (21, 28)	25 (20, 27)	24 (21, 27)	21 (18, 23)*
13	Tackles made	137 (125, 145)	123 (104, 132)*	130 (106, 152)	121 (113, 139)
14	Tackles missed (%)	12 (11, 13)	13 (11, 14)	10 (9, 12)	14 (11, 15)**
15	Ruck success (%)	96 (96, 97)	96 (95, 96)	96 (96, 97)	96 (95, 97)
16	Lineout success (%)	92 (89, 94)	91 (85, 95)	90 (85, 94)	88 (86, 90)
17	Scrum success (%)	100 (100, 100)	100 (100, 100)	100 (100, 100)	93 (85, 100)**
18	Points scored over clean break	3.3 (2.5, 4.3)	3 (2.3, 3.6)	3.3 (2.9, 4.1)	2.2 (1.7, 2.7)****
19	Defenders beaten over try	6 (5.2, 7)	7.5 (5.5, 9.5)	4.5 (4, 5.4)	8 (7, 9.5)****
20	Offloads over defenders beaten	0.58 (0.5, 0.63)	0.6 (0.44, 0.74)	0.68 (0.54, 0.72)	0.64 (0.56, 0.74)

Note: * (p ≤ 0.05), ** (p ≤ 0.01), *** (p ≤ 0.001), **** (p ≤ 0.0001) differences with respect to winning performances.

TABLE 3. Medians (95% confidence limits) of all performance indicators in relation to the 1st–4th and 5th–7th winning team subgroups, and winning and losing teams in the 1st–4th and 5th–7th subgroups.

#	Performance indicators	Winning 1st–4th team	Winning 5th–7th team	1st–4th team Winning	1st–4th team Losing	5th–7th team Winning	5th–7th team Losing
1	Possession (%)	47 (43, 51)	53 (47, 54)*	47 (43, 51)	51 (46, 56)	53 (47, 54)	53 (47, 56)
2	Territory (%)	48 (43, 53)	51 (46, 57)	48 (43, 53)	53 (45, 60)	51 (46, 57)	51 (46, 53)
3	Tries for	3 (2, 4)	3.5 (3, 4)	3 (2, 4)	2 (1, 2)***	3.5 (3, 4)	2 (1, 2)****
4	Tries against	2 (1, 2)	1 (1, 2)	2 (1, 2)	3 (3, 4)****	1 (1, 2)	3 (2, 4)***
5	Metres gained on possession	389 (341, 442)	439 (396, 470)	389 (341, 442)	359 (312, 454)	439 (396, 470)	383 (329, 445)
6	Defenders beaten	16 (13,18)	16 (13, 20)	16 (13,18)	15 (12, 18)	16 (13, 20)	17 (15, 21)
7	Clean breaks	7 (6, 9)	8 (7, 10)	7 (6, 9)	6 (4, 8)	8 (7, 10)	7 (7, 8)
8	Gain line carries	105 (98, 114)	130 (121, 139)***	105 (98, 114)	124 (108, 146)*	130 (121, 139)	136 (126, 154)
9	Passes	135 (119, 143)	173 (155, 189)***	135 (119, 143)	153 (124, 172)	173 (155, 189)	173 (158, 198)
10	Offloads	9 (7, 10)	10 (8, 12)	9 (7, 10)	9 (7, 12)	10 (8, 12)	11 (7, 12)
11	Turnovers won	7 (6, 8)	7 (6, 7)	7 (6, 8)	6 (5, 8)	7 (6, 7)	7 (5, 8)
12	Kicks from hands	27 (22,30)	23 (21, 24)	27 (22,30)	23 (18, 27)	23 (21, 24)	23 (16, 27)
13	Tackles made	143 (122, 151)	131 (119, 153)	143 (122, 151)	115 (96, 141)*	131 (119, 153)	131 (112, 164)
14	Tackles missed (%)	11 (10, 14)	11 (8, 13)	11 (10, 14)	15 (12, 16)*	11 (8, 13)	12 (7, 16)
15	Ruck success (%)	96 (95, 97)	96 (96, 97)	96 (95, 97)	96 (95, 97)	96 (96, 97)	96 (95, 98)
16	Lineout success (%)	92 (86, 93)	93 (85, 100)	92 (86, 93)	90 (85, 92)	93 (85, 100)	88 (83, 90)
17	Scrum success (%)	100 (100, 100)	100 (100, 100)	100 (100, 100)	100 (86, 100)	100 (100, 100)	100 (80, 100)*
18	Points scored over clean break	3.1 (2.7, 4.1)	3.3 (2.7, 4.1)	3.1 (2.7, 4.1)	2.8 (2, 3.8)	3.3 (2.7, 4.1)	2.1 (1.5, 2.9)**
19	Defenders beaten over try	5 (4.5, 6)	5.5 (4.3, 6.7)	5.2 (4.5, 6.5)	8 (7, 10)***	5.5 (4.3, 6.7)	8.5 (7, 16)****
20	Offloads over defenders beaten	0.58 (0.44, 0.68)	0.65 (0.54, 0.71)	0.58 (0.44, 0.68)	0.67 (0.47, 0.8)	0.65 (0.54, 0.71)	0.57 (0.38, 0.65)

Note: * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$), **** ($p \leq 0.0001$) differences with respect to the 1st–4th team subgroup (in the 1st–4th vs 5th–7th winning performance comparison), and with respect to winning performances (in winning and losing performance comparison singularly related to the 1st–4th and 5th–7th team subgroups).

Difference between winning and losing performance in the 1st–4th and 5th–7th team subgroups

Considering the 1st–4th teams, winning performances presented a higher score in tries for [Mdn difference = -1, 95%CI (-2 to -1), p<0.0001, φ=0.5] and tackles made [Mdn difference = -29, 95%CI (-35 to -1), p=0.05, φ=0.2] and a lower score in tries against [Mdn difference = 1, 95%CI (1–2), p<0.0001, φ=0.6], gain line carries [Mdn difference = 19, 95%CI (3–32), p=0.016, φ=0.3], tackles missed [Mdn difference = 4, 95%CI (1–5), p=0.02, φ=0.3] and defenders beaten over try [Mdn difference = 3, 95%CI (1–4), p=0.0009, φ=0.4]. For more details see Tables 3.

Considering the 5th–7th teams, winning performances showed a higher score in tries for [Mdn difference = 2, 95%CI (1–2), p<0.0001, φ=0.5], scrum success [Mdn difference = 1, 95%CI (1–13), p=0.04, φ=0.2], and points scored over clean break [Mdn difference = 1, 95%CI (1–2), p=0.006, φ=0.2], and a lower score in tries against [Mdn difference = -2, 95%CI (-2 to -1), p=0.0002, φ=0.5] and defenders beaten over try [Mdn difference = -3, 95%CI (-7 to -2), p<0.0001, φ=0.1]. For more details see Tables 3.

DISCUSSION

The aim of this study was to identify differences between winning and losing teams according to final game scores (i.e., margin of victory) and ranking position (i.e., the 1st–4th, the 5th–7th teams) in the northern hemisphere international club competition PRO12. As the main findings, PRO12 winning teams performing close games showed a restricted number of KPI differences (i.e., possession, gain line carries, and tackles made) in comparison with losing teams, whereas several aspects can be considered to show the successful performance in balanced games. In addition, the three parameters that discriminate winning and losing teams in close games are characterized by a small effect size (which is regularly 0.2), partially confirming the first hypothesis for this specific game subgroup. In fact, despite the victory, the technical and tactical performance of winning teams is characterized by lower possession, defending more, and carrying the ball less than losing counterparts, even reporting similar occurrence of tries.

By contrast, in balanced games, winning teams were found to be clearly better than losing teams (due to large effect sizes) for the KPIs "tries for", and consequently for "tries against", and "clean breaks" (whereas "points scored over clean break", and "defenders beaten over try" did not show strong significance or large effect sizes). The higher number of KPIs discriminating winning and losing teams in balanced games shows more similarities to the results reported in previous studies [4, 11], where kicking away possession and defending more effectively make winning teams able to prevent opponents from scoring tries, completing successful tackles, and obtaining more turnovers. In addition, these findings are in line with those reported by Jones et al. [2], who found that successful performances are systematically characterized by the winning of more turnovers. Nevertheless, an opposite scenario was reported in Super 12 [11], for which winners actually won fewer turnovers than losers, thus suggesting how technical and tactical analyses should regularly be conducted in relation to specific performance contests.

For the attacking side, it could be supposed that winners of balanced games are more skilled in running and decision making, considering the better performances in terms of tries for, clean breaks, and points scored over clean break. Therefore, this scenario could be related to the evidence reported by Wheeler and colleagues [19], for whom effective attacking strategies consisted of a specific side-stepping pattern for the straightening of the running line. In addition, ball carriers' ability, tackle-breaks, line-breaks, and offloading in the tackle were reported to promote try-scoring ability and positive phase outcomes as well [6, 20, 21, 22]. Finally, winning teams made less effort in beating defenders per action and obtained a better score point each break-line. Therefore it could be speculated that the higher values regarding tries for and clean breaks reported by winning teams during balanced games can be associated with a more efficient tactical plan which allows one to avoid contact, to break the line, to offload the ball, and therefore to score more points [23]. As a consequence, differently from close games, the first hypothesis can be accepted in consideration of the balanced game subgroup.

Since the final ranking in the regular PRO12 Championship season affects the qualification for ERCC, performances in the 1^{st}–4^{th} and the 5^{th}–7^{th} team subcategories were compared as well. In particular, the winning performances of the 5^{th}–7^{th} teams showed higher possession (φ= 0.3), gain line carries (φ=0.4), and passes scores (φ=0.5) compared to 1^{st}–4^{th} teams. In other words, the 1^{st}–4^{th} team subgroup is more oriented to providing a solid defence (also due to a lower value of possession) than the 5^{th}–7^{th} teams winning counterparts, which proved to be more offensive oriented. However, in general, the winning performances of the 1^{st}–4^{th} and 5^{th}–7^{th} team subgroups were quite homogeneous, leading to the rejection of the second experimental hypothesis.

In this study, a combination of game outcomes and ranking positions has also been provided, analyzing winning and losing performances in the 1^{st}–4^{th} and 5^{th}–7^{th} team subgroups. Main effects (medium ESs) emerged for the tries for (more in winning), and tries against (more in losers) KPIs, as well as for defenders beaten over try and tackles missed (more in losers) only in the 1^{st}–4^{th} teams. Therefore, a similar scenario with respect to the balanced game samples emerged (the same three large differences in the 1^{st}–4^{th} and 5^{th}–7^{th} team subgroups of the four ones that emerged for balanced games), thus supporting the third hypothesis of the study.

In conclusion, the present study revealed that in the PRO12 Championship: i) although only small differences can be identified between winning and losing performances in close games, the same comparison in balanced games seems to be based on scrum success, higher evasion skills that leads to more offloads, more breaklines and more metres gained in possession, a kicking based game plan and higher attacking efficiency (more points scored per each breakline and less technical individual work rate per try); ii) the 1^{st}–4^{th} winning teams are more oriented to a defensive game plan (less possession, fewer passes and carries) than those of the 5^{th}–7^{th} subgroup; and iii) winning and losing teams in the 1^{st}–4^{th} and 5^{th}–7^{th} team subgroups reported quite similar technical and tactical differences, which were similar to those of the balanced subgroup.

However, the exclusive consideration of the final ranking of teams instead of considering the progressive ranking at the time of games can represent a limitation for the present study. In fact, possible fluctuations during the competition could crucially alter the playing styles of teams throughout the season. As a consequence, further studies should be focused on the influence of current team ranking on playing style as well as concurrent physiological factors (i.e., heart rate responses), time motion parameters (i.e., indicators editable from global positioning systems), neuromuscular effects (i.e., strength and power of upper and lower limbs), psychometric questionnaire (i.e., rating of perceived exertion), tending to promote an integrated approach, which is able to more deeply investigate the real effect of the rugby union performance.

CONCLUSIONS

The present study demonstrated how technical and tactical aspects are influenced in relation to the game outcome and ranking position. In consequence, coaches and physical trainers should be aware that the effectiveness of international winning teams depends on a strong defence, tackling, scrumming, breaking the defensive line and performing more possessions during the attacking phase. Nevertheless, according to van Rooyen and colleagues [24], the amount of attacking possession does not absolutely predict success in rugby union. Therefore, the effective training strategy should be oriented on "how" to effectively use possession instead of "how much" possession a team should gain. In line with this point of view, strength and conditioning training should be focused on enhancing isometric strength to support effective scrumming. In addition, improvements in dynamic strength could primarily favour explosive movements and repeated sprint ability with and without change of direction, and consequently improve the capability to gain distance (meters) during possessions as well as to perform effective tackles during defending phases.

In line with the findings of this study, coaches could train the offensive game actions with the aim of scoring a try or obtaining a penalty kick for every single line break performed. Consistently with this training scenario, coaches could also practise training skills to quickly offload the ball once the line break is achieved, arranging both the ball carriers and the closest carriers' supporters to maintain the momentum and tend to score a try. For example, the combination of cognitive (i.e., the ability to quickly recognize the defensive setting and to identify the gaps to attack) and conditioning (i.e., by delaying the supporters' action once the ball carriers start to play) workouts could effectively stimulate players in performing offensive actions, which could determine line breaks.

Practically, a progression from simple to complex tasks (i.e., from a low to high number of involved players) to quickly create the breakline and keep the momentum could stimulate players from a technical and tactical point of view as well as in terms of physical conditioning (i.e., strength, repeated sprint ability with and without the ball, cognitive exercises).

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1.2.3 Paper #3

Technical and tactical effectiveness is related to time-motion performance in elite rugby

Alexandru N. Ungureanu[1], Paolo R. Brustio[1*], Corrado Lupo[1]

[1]NeuroMuscularFunction Research Group, School of Exercise & Sport Sciences, Department of Medical Sciences, University of Turin, Turin, Italy.

***Corresponding author:**
Paolo R. Brustio, PhD
NeuroMuscularFunction Research Group, School of Exercise & Sport Sciences, Department of Medical Sciences, University of Turin, Turin, Italy.
Phone: +39 0116708084
Email: paoloriccardo.brustio@unito.it

Technical and tactical effectiveness is related to time-motion performance in elite rugby

Abstract

BACKGROUND: Performance during a rugby union game is based on technical and tactical performance and running activity. Notational and time-motion analyses may be useful to better understand the mutual influence of both factors. Thus, this study investigated the relationship between technical and tactical performance and running activity for both forwards and backs during official games of under 20 Six Nations Championship.

METHODS: Technical and tactical performance and running activity of thirty under-20 elite players (age range=18-20 years; total games=98) were assessed in relation to 20 key performance indicators (KPIs) and analysed separately for forwards and backs. General linear mixed models were performed to evaluate the relationship between KPIs, including subjects and games as random effect.

RESULTS: Different technical and tactical KPIs influenced the running activities for forwards and backs, while tackles, passes, and positive work rate influenced running activity (i.e., total distance, metres/minute, %high speed running, and explosive distance) in forwards. Only passes and possession influenced running activity (i.e., %high-speed running and distance covered above 14km/h, 17km/h, and 24km/h speed) in backs.

CONCLUSIONS: Technical and tactical performance affects running activities differently for forwards and backs. During training sessions, coaches should stimulate forwards to be more active (i.e. to complete more metres/minute, more explosive distance) and backs to control more the defensive structure (i.e., less %high-speed running and less distance covered above 14km/h and 17km/h speed). A progression from short to long game sequences, that quickly recreate the game plan and keep the momentum, could stimulate technical and tactical performance, as well as physical conditioning.

Key words: match analysis; GPS technology; rugby union; integrated analysis; notational analysis

Introduction

Rugby union is a high demanding collision sport requiring high-intensity running activities separated by periods of low-intensity activities and influenced by several factors, such as physical fitness level, players' technique, and team tactics. It is well established that over time, the game becomes faster, with more intensive and aggressive play.[1] As consequence, the technical and tactical factors and players' physical and anthropometric profiles change.[1, 2] Specifically, tackles, passes, rucks, and ball-in-play time increase, while scrums, lineouts, and mauls decrease.[1, 2] As the consequence, players' characteristics change as well, according to their positional roles (i.e., forwards and backs). In particular, backs are more involved in rucks and mauls that are traditionally the domain of the forwards.[1] In this scenario, new game-related tactics, along with different conditioning and recovery strategies, are required to effectively manage performance, training load and recovery.[1]

In sport sciences, performance analysis is usually investigated by means of the notational analysis (e.g., using video based systems) and the time-motion analysis (e.g., using Global Positioning System, GPS), that code athletes' relevant technical and tactical behaviors and running activities respectively during ecological situations (i.e., game match or training sessions).[3-7] Additionally, the performance analysis may be informative to program training exercises and tailored loads, to optimize physical performance and to prevent overtraining.[8]

In particular, notational analysis is focused on studying the interaction between players and the technical and tactical key performance indicators (KPIs), as a measure of positive and negative aspects of the performance.[9] Tackles, passes, turnovers, possession, scrums, lineouts, kicks, possession lost and regained are some of the principal KPIs used in rugby union notational analysis process.[4, 5, 10] However, reliability in video-based notational analysis process is limited by the time taken to complete analyses, the definition of movement categories, and the parallax error.[11]

On the other hand, during the time-motion analysis process, GPS technology is used since it is lightweight and non-intrusive, and provides real-time information of running activities during the game, (i.e., total distance, high speed running, explosive distance, accelerations, sprints),[3, 12-19] despite its reliability decreases with speed increasing of movement and the presence of change of direction movements.[20, 21]

Several studies[17, 22, 23] used both approaches to analyze technical and tactical performance, and running activity in rugby, although no relationship between them was investigated. The running activity (i.e., sprinting, striding, accelerating, changing of direction) seems to decline at the end of the game when it is separately analyzed from the technical and tactical performance.[20-21] At the same time, technical and tactical performance remains unchanged over the whole game both for backs and forwards.[20] In fact, professional rugby players seem to maintain their ability in performing key actions through the whole competition, probably changing the game plan from an expansive to a conservative one, as already highlighted in rugby league.[22, 23] Greater physical demands are elicited in the early phases of the game, in association with a greater number of defensive collisions compared to the attacking ones, probably due to the higher cost of the defending gameplay.

Moreover, low to moderate relationship between technical and tactical KPIs (i.e., passes, tackles, line breaks, handling errors, set pieces, turnovers, possession lost and regained) and field-based fitness tests (i.e., repeated sprint ability, strength and power, speed, body composition) were found.[24] In particular, the large relationships between both 10 and 40 m sprint times and the number of line breaks and defenders beaten per game suggest that accelerations and maximal speed are likely to be important in rugby sevens. Evaded and carried tackles were also strongly correlated to a greater performance in horizontal and vertical jumps and peak power in body weight, and weighted counter movement vertical jumps were strongly related to the effectiveness in attacking and defensive rucks.[24]

However, to our knowledge, no study explains the relationship between technical and tactical game-related statistics and running activities during a match. Using technical and tactical and time-motion analysis could be relevant to analyze the mutual influence of both playing performance and running activities. Therefore, the aim of this study was to investigate the relationship between specific game-related technical and tactical KPIs (i.e., passes, tackles, kicks, possession lost, possession regained) and running activities (i.e., sprinting, striding, accelerating, changing of direction), in order to improve training plans specifically for forwards and backs.

Material and methods

Participants

Thirty (scrum halves excluded) under 20 elite players (age range = 18-20 years) including 15 backs and 15 forwards participated in the study. All players were recruited from the same elite under 20 Italian National team and had at least 6 years of experience in rugby trainings and competitions. A total of 5 games, performed during the under 20 Six Nations Championship (2018 edition), was considered for the purpose of the study. Informed consent was obtained, and the Italian Rugby Federation management approved the study.

Measures

Data from technical and tactical, and time-motion KPIs were recorded from 5 games and included 98 players' performance. Due to the different game patterns, all the analysis was separately performed for forwards (game performances n=62) and backs (game performances n=36). Scrum halves players were excluded because they usually represent an outlier performance.[5, 13-15] Indeed, scrum-halves are highly specialized in roles where technical and tactical KPIs differ from those of the forwards and any other backs (i.e., 31 vs. 9 pass/match average for a common back role). The mean (±SD) number of observations for each player was 3 ± 1 (range 1–5).

Design and Procedures

Integral match video recordings were provided live by the World Rugby broadcast and stored as a mp4 file on a MacBook Pro 15© (Apple Inc). Notational analysis was performed at the end of each game by means of SportsCode Gamebreaker software (Sportstec, Sydney, Australia). According to Quarrie et al.,[15] the player's actions in possession of or close to the ball were coded. Examples of actions 'close to the ball' – tackles made and joining rucks and mauls – would typically be within one-man length radius of the location of the ball. Video analysis was carried out in relationship to ten technical and tactical KPIs (Table I, item 1-10), which were structured according to a previous study[25] and coaches' expertise (>10 years international experience). The same senior match analyst coded all the technical and tactical KPIs (>6 years of experience) for all 5 games. According to a previous study, the intracoder reliability was determined by randomly selecting 1 games and analyzing it twice 14 days apart.[26]

GPS-based time-motion analysis was carried out by means of 23 GPS units (K-Gps 10Hz, K-Sport®, Montelabate, Pesaro-Urbino, Italy). Thirty minutes before kick-off, GPS units were fixed on the torso of each player in a vest under the official competitive t-shirt and turned on. At the end of the game, devices were turned off and data were downloaded through the K-Fitness software (K-Sport®, Montelabate, Pesaro-Urbino, Italy). Ten time-motion KPIs from kick-off to the end of the game were analyzed. For more details about the time-motion KPIs see Table I (item a-j).

[Table I near here]

Statistical Analysis

For each KPI, medians (Mdn) and 95% confidence limits were separately calculated for the forwards and the backs. Technical and tactical KPIs were normalized to the total frequencies.[27] Consistency of both physical and technical and tactical performances over the 5 games was evaluated by performing the Kruskal-Wallis and Dunn's post-hoc test. ROUT method at 1%[28] was performed to detect outliers for the "time in play" indicator, in order to eliminate compromised GPS data recordings due to failed powering on or other technical issues.

General linear mixed models were performed to evaluate the relationship between technical and tactical and time-motion KPIs. Specifically, the technical and tactical KPIs entered the model as fixed effects, while the ten time-motion KPIs were used as separate dependent variables. Subjects and play were included as random effect within the model. All the above model was performed for forwards and backs subcategories separately. Due to total kicks in play or in touch and to conversion attempts that are a peculiarity of backs role, we decided to exclude this variable when analyzing forwards subcategories. The level of significance was set at P=0.05. The Statistical Package R (version 3.6.2 R Foundation for Statistical Computing, Vienna, Austria) with the packages lme4[29] were used for all statistical analyses.

Results

Descriptive statistic (Mdn; 95% CI) of the twenty KPIs are displayed in Table II, both for forwards and backs. No outlier was detected for the “time in play” indicator. Thus, all the 98 game performances were considered for the statistical analysis.

[Table II near here]

The Table III reports the result for the significant model in general linear mixed analysis for the forwards' time-motion performance expressed according to the technical and tactical KPIs.

The main effects of Total Tackles were significant considering as dependent variable Total Distance [B = 98.99, 95% CI (13.37; 184.61); SE = 46.85; t-ratio = 2.113; p = 0.039], Explosive distance [B = 6.65, 95% CI (1.69; 11.60); SE = 2.74; t-ratio = 2.424; p = 0.019] and Average Peak Speed [B = 0.08; 95% CI (0.02; 0.15); SE = 0.04; t-ratio = 2.258; p = 0.029]. Main effects of Positive Work Rate were significant for Meters/Minute [B = 27.54 95% CI (17.40; 37.68); SE = 5.55; t-ratio = 4.965; p < 0.001], High Speed Running [B = 6.85, 95% CI (1.98; 11.58); SE = 2.58; t-ratio = 2.651; p = 0.012] and Average Peak Speed [B = 1.47, 95% CI (0.53; 2.41); SE = 0.51; t-ratio = 2.907; p = 0.006]. Moreover, as Average Peak Speed as dependent variable Possession Regained was significant [B = 0.59, 95% CI (0.15; 1.07); SE = 0.24; t-ratio = 2.495; p = 0.016]. No significant effect was observed for the other technical and tactical KPI.

[Table III near here]

The Table IV reports the results for the significant model in general linear mixed analysis for the backs' time-motion performance expressed according to the technical and tactical KPIs.

The main effects of Possession Regained were significant for % High Speed Running [B = 1.52 95% CI (-2.31; -0.23); SE = 0.56, df = 14.60; t-ratio = -2.689; p = 0.017], Distance > 14 km/h [B = - 42.56, 95% CI (-73.55; -10.12); SE = 18.6; t-ratio = -2.768; p = 0.022] and Distance > 17 km/h (B = -42.56 95% CI (-75.59; -14.68); SE = 18.61; t-ratio = -2.482; p = 0.035). Differently, for Distance > 24 km/h as dependent variable both Total Pass (B = -12.16 95% CI (5.01 ; 24.34); SE = 5.01; t-ratio = -2.429; p = 0.023) and Total Work Rate (B = 7.66, 95% CI (3.65 ; 24.34); SE= 3.65; t-ratio = 2.098; p = 0.0465) showed a significance. Differently no significant effect was observed for the other technical and tactical KPIs.

[Table IV near here]

Discussion

This study investigated the relationship between specific game-related technical and tactical KPIs (i.e., passes, tackles, kicks, possession lost, possession regained) and running activities (i.e., sprinting, striding, accelerating, changing of direction) in national elite Under 20 rugby players. For this purpose, we investigated the mutual influence of both factors during 5 international games (i.e., Six Nations Championship) using notational analysis (for technical and tactical indicators) and time-motion analysis. Due to the little evidences of the relationship between technical and tactical performance and running activities during games in rugby union, we think that using this ecological approach may be useful to improve training plans, specifically for forwards and backs. The main finding of our study was that game actions affected running activities differently for backs and forwards players' position. As a consequence, coaches and physical practitioners should plan and implement different training sessions according to players' position.

Since forwards and backs show different physical demands in rugby union,[3, 12, 14] correlations between different KPIs were expected for the two tactical roles. Total distance, explosive distance, and Average Peak Speed significantly affected the workload on the tackling area for the forwards. Indeed, according to Duthie et al.,[3] who quantified the movement patterns of rugby players and examined differences between positional groups, forwards were involved more in standing and fighting actions in possession of the ball or near the ball (i.e., scrumming, rucking, mauling) even though no trend to perform more tackles was reported with respect to backs. Moreover, forwards covered long distances at a relatively medium speed for moving from a breakdown to another, since they covered a unique role in forming the platform for offence and defense.[3] From the offensive point of view, higher density (i.e., meters/minute) in running patterns led to a higher involvement of the forwards in the open game (i.e., total passes completed and WR + (%)). According to Baker and Nance,[32] speed and acceleration represent the most important qualities in rugby players, especially for the forwards when tackling and regaining possession. These qualities are related to strength and power capabilities, as well as to specific game activities (i.e., number of line breaks and defenders beaten per match).[24]

From the defensive prospective, once the defensive line is organized, speed and acceleration (i.e., explosive running) allow defenders to prevent successful attacks. Indeed, the reducing of time and space for attackers will increase the probability to effectively perform a successful defense with a consequent turnover.[33] According to Hendricks et al.,[33] defending teams are more likely to win the breakdown and to regain possession when approaching attackers at a moderate or fast speed movement. An effective defensive organization combining several factors (i.e., direction, shape, and speed) may allow defenders to perform more tackles, even doubling them within a single action. Thus, as highlighted in this study, a higher average peak speed along with an appropriate defensive strategy could be more likely to increase regained possession.

However, referring to high speed running for backs, the regained possession was inversely correlated to the % high-speed running and the distance covered above 14 and 17 km/h speed. Unlike the forwards, the backs spend approximately two to three times more time in high-intensity running and are more involved in off-the-ball utility movements (i.e., shuffling sideways or backwards to change field position).[3] It may be speculated that an effective, collective arrangement during the defensive phases is more important than the high-speed running ability of the single player. However, once the defensive line is organized, by shuffling sideways or backwards at low or medium speed, acceleration and high speed should be acted to attack the opponents' possession.

Consequently, coaches and physical trainers should consider these aspects when planning the defense-based training sessions. In other words, during training session they should not focus only on high speed running, but rather on high-pace organization and reorganization of the defense system, that is composed both by the defenders' distribution on the field and the effectiveness on impacts.

Since these events are processed at high pace in international level games, the probability to regain the possession is higher if defenders are quickly well organized in the defensive line and highly skilled in tackling. As reported for the senior level,[10] defensive skills are crucial for reaching success and coaching staff should focus on training tackling skills at high pace, in order to achieve defensive effectiveness in international competitions. Thus, when planning an exercise, coaches should decide to manipulate defensive constrains (i.e., direction and shape) to improve decision making in relation to the opponent side (e.g., drift defense practice task, where the defenders are outnumbered by the attackers or the rush defense practice task, where the defenders are equal or numerically superior to the attackers).[34, 35] Manipulating task constraints (i.e., changing rules, field dimensions, numbers of players) according to the desirable outcome could promote a more effective learning and transfer for game performance.

In addition, coaches and physical trainers should monitor running activities in small side games or full squad (15 vs. 15) during training sessions. In particular, during tactical training based on turnover balls (*regained possession*), trainers should stimulate forwards to be more active (i.e. to complete more distance, more meters/minute,) and backs to control more the defensive structure (i.e., less % high-speed running and less distance covered above 14 and 17 km/h speed) and to act high speed running once the structure is completed. Moreover, to act the game plan at the highest intensity level without downgrading the technical and tactical skills, they should train both cognitive (i.e., the ability to quickly recognize the opponents' setting and to make a good decision making) and conditioning abilities (i.e., by repeating game skills at high-pace level). Practically, a progression from short to long game sequences (i.e., from a low to high number of phases) to quickly recreate the game plan and keep the momentum could stimulate players from a technical and tactical point of view, as well as in terms of physical conditioning (i.e., strength, repeated sprint ability with and without the ball, cognitive exercises).

Despite these results, caution is needed when interpreting our results. Both notational analysis (e.g., video-based systems) and time-motion analysis (e.g., GPS) are considered effective tools for studying team sports and better coaching, as well as a convenient and popular method to quantify movement patterns and physical demands in sport[9, 16] However, the dynamic nature of team sport and the consequent difficulty to interpret the data in term of replication may affect the results.

Conclusions

In conclusion, the present study demonstrates that the more the forwards are involved in game situations with or close to the ball the more their physical load increases. Moreover, from a technical and tactical point of view, regaining possession seems to be a matter of organization more than individual high-speed ability. Based on this finding, coaches and physical trainers could couple technical and tactical and physical aims during field-based training sessions. They should manipulate environmental constrains (e.g., changing field dimensions, manipulate players' starting position, the number of players involved in a training task) to enhance players' decision-making skills along with strength and conditioning capabilities. Further studies or coaching strategies could consider this analysis as a low-cost method with high benefits to gather crucial interpretation on the physiological demands related to the technical and tactical parameters.

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NOTES

Conflict of interest statement:
The authors have no conflicts of interest.

Authors' contributions
Alexandru N. Ungureanu : Conceptualization; Investigation and data collection; Writing—original draft; Writing—review and editing
Paolo R. Brustio: Formal Analysis; Writing—review and editing
Corrado Lupo: Supervision; Writing—review and editing
All authors read and approved the final version of the manuscript.

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Table I. Technical and tactical and time-motion performance indicators description.

#	Technical and tactical indicators	Description
1	Total tackles	Times a player tackled an opponent (all dominant, non-dominant, missed and assisted/doubled tackles).
2	Total tackle&jackal	Times a tackler contested the ball after the tackle by standing up, counter-rucking or returning in the defensive line.
3	Total jackal	Player contesting the ball on breakdown in both effective (regaining or slowing down the ball) and non-effective (without regaining or slowing down the ball).
4	Possession regained	Possession regained on breakdown, on the opponents' kick or loss.
5	Total ball carrier	Times a player carried the ball in both dominant (gains the collision with the defender and once he is brought to ground he acts properly in order to quickly release the ball) and non-dominant manner (loses the ball).
6	Total support	Times a player supported the ball carrier in order to quickly release the ball on breakdown
7	Total pass	Total passes completed by a player, both positive (which centers the target (receiver's hands) and allows receiver to maintain speed and acceleration) and negative (doesn't centers the receiver's hands)
8	Total kick	Total kicks in play or in touch conversion attempts
9	Total work-rate	Sum of KPIs from 1 to 8
10	Positive work-rate (%)	Ratio between the effective and non-effective KPIs
#	**Time-motion indicators**	**Description**
a	Total distance (m)	Total distance (m) covered since the unit turned on
b	Metres /Minute	Ratio between the distance covered and the time since the unit turned on
c	% High Speed Running	Ratio between distance covered at speed covered above 14km/h and the overall distance
d	Explosive Distance (m)	Distance (m) by a player when his speed is above 17 km/h and the acceleration is above 2.5 m/s^2
e	Accelerations	Counts of accelerations above 2.5 m/s^2
f	Sprints	Counts of crossed speed > 25km/h threshold
g	Dist > 14 km/h (m)	Distance covered (m) above 14 km/h speed
h	Dist > 17 km/h (m)	Distance covered (m) above 17 km/h speed
i	Dist > 24 km/h (m)	Distance covered (m) above 24 km/h speed
j	AveragePeak Speed (m/s)	Average of all peaks reached within the performance

Table II. Descriptive statistics (Mdn; 95% CI) of the twenty KPIs.

#	Technical and tactical indicators	Forwards	Backs
1	Total tackles	7 (6.21, 9.32)	6 (4.67, 8.27)
2	Total tackle&jackal	0 (0.44, 0.90)	0 (0.31, 1.13)
3	Total jackal	1 (0.62, 1.13)	0 (-0.4, 0.4)
4	Possession regained	0 (0.14, 0.43)	1 (0.74 , 1.81)
5	Total ball carrier	3 (2.78, 4.34)	3 (2.55, 4.45)
6	Total support	6 (5.31, 7.82)	3 (2.77, 5.06)
7	Total pass	0.83 (0.55, 1.11)	2 (1.60, 6.07)
8	Total kick	-	1 (0.80, 5.43)
9	Total work-rate	21 (17.38, 25.15)	22.5 (18.57,30.76)
10	Positive work-rate (%)	0.75 (0.61, 0.47)	0.64 (0.57, 0.70)
#	**Time-motion indicators**		
a	Total distance (m)	1077 (1154, 1854)	3150 (2678, 3621)
b	Metres/Minute	37 (31.33, 37.39)	40 (38.11, 43.94)
c	% High Speed Running	5.8 (5.64, 8.02)	15.55 (14.33, 17.82)
d	Explosive Distance (m)	32 (37, 76)	332 (296, 478)
e	Accelerations	9 (9.99, 25.57)	36.5 (32.23, 56.16)
f	Sprints	1 (1, 1)	2 (1.39, 3.28)
g	Dist > 14 km/h (m)	120 (129, 223)	523 (432, 652)
h	Dist > 17 km/h (m)	28 (41,87)	253 (225, 355)
i	Dist > 24 km/h (m)	7 (-13, 60)	26 (19, 44)
j	AveragePeak Speed (m/s)	5.4 (4.9, 5.6)	7.2 (6.8, 7.5)

Table III. General linear mixed model parameter estimates for the forwards' time-motion performance expressed according to the technical and tactical KPIs

	Total Distance (m)			Metres/min			% High Speed Running			Explosive Distance			AveragePeak Speed		
	B (95% CI)	SE	p value	B (95% CI)	SE	p value	B (95% CI)	SE	p value	B (95% CI)	SE	p value	B (95% CI)	SE	p value
Total tackles	98.99 (13.37, 184.61)	46.85	0.039*	-0.51 (-1.18, 0.16)	0 .37	0 .170	0.1 (-0.18, 0.36)	0 .15	0 .512	6.65 (1.69, 11.6)	2 .74	0 .019*	0.08 (0.02, 0.15)	0 .04	0 .029*
Total tackle&jackal	-380.74 (-800.72, 39.24)	229.79	0.103	2.12 (-1.16, 5.39)	1 .79	0 .243	1.05 (-0.17, 2.29)	0 .68	0 .129	-11.06 (-34.85, 12.35)	12 .95	0 .397	0 (-0.32, 0.31)	0 .17	0 .978
Total jackal	32.37 (-332.77, 397.52)	199.78	0.872	1.39 (-1.46, 4.23)	1 .56	0 .377	-0.16 (-1.34, 0.99)	0 .63	0 .800	-14.38 (-35.74, 5.94)	11 .3	0 .209	0.18 (-0.12, 0.49)	0 .16	0 .271
Possession regained	-249.18 (-796.56, 298.21)	299.49	0.409	-1.27 (-5.54, 3.00)	2 .34	0 .589	0.64 (-1.05, 2.43)	0 .93	0 .495	6.42 (-23.03, 37.46)	16 .31	0 .696	0.59 (0.15, 1.07)	0 .24	0 .016*
Total ball carrier	97.81 (-30.81, 226.44)	70.38	0.170	-0.04 (-1.04, 0.97)	0 .55	0 .949	-0.29 (-0.73, 0.15)	0 .24	0 .219	-2.28 (-9.57, 4.89)	3 .95	0 .567	0.03 (-0.08, 0.15)	0 .06	0 .630
Total support	43.73 (-44.7, 132.16)	48.38	0.370	-0.49 (-1.18, 0.20)	0 .38	0 .202	-0.04 (-0.30, 0.23)	0 .15	0 .788	1.38 (-3.65, 6.46)	2 .78	0 .622	0.02 (-0.04, 0.09)	0 .04	0 .506
Total pass	26.22 (-300.58, 353.03)	178.81	0.884	4.02 (1.47, 6.57)	1 .39	0 .006*	0.16 (-0.81, 1.15)	0 .54	0 .765	-3.78 (-21.59, 14.63)	9 .86	0 .703	0.12 (-0.13, 0.38)	0 .14	0 .377
Total work-rate	-6.01 (-46.24, 34.23)	22.01	0.786	0.04 (-0.27, 0.36)	0 .17	0 .798	0.02 (-0.10, 0.14)	0 .06	0 .724	0.29 (-1.93, 2.49)	1 .21	0 .81	-0.01 (-0.04, 0.02)	0 .02	0 .592
Positive work-rate (%)	501.03 (-799.28, 1801.34)	711.45	0.484	27.54 (17.4, 37.68)	5 .55	p<0.001*	6.85 (1.98, 11.58)	2 .58	0 .012*	-3.21 (-90.74, 77.25)	44 .56	0 .943	1.47 (0.53, 2.41)	0 .51	0 .006*
$R^2_{GLMM(c)}$	0.29			0.43			0.70			0.33			0.81		

Notes: B, Beta; 95% CI, 95% confidence interval; SE, Standard error; p, p value; $R^2_{GLMM(c)}$, conditional variance explained by the entire model.

Table IV. General linear mixed model parameter estimates (Beta, B (95% CI); Standard error, SE; significance, p value; conditional variance explained by the entire model, R^2GLMM(c)) for the backs' time-motion performance expressed according to the technical and tactical KPIs.

	% High Speed Running			Dist > 14 km/h (m)			Dist > 17 km/h (m)			Dist > 24 km/h (m)		
	B (95% CI)	SE	p value	B (95% CI)	SE	p value	B (95% CI)	SE	p value	B (95% CI)	SE	p value
Total tackles	-0.49 (-1.47, 0.05)	0.45	0.285	-18.59 (-56.22, 22.29)	22.5	0.418	-15.95 (-43.91, 12.04)	15.26	0.307	-5.65 (3.45, 22.66)	3.45	0.115
Total tackle&jackal	0.84 (-5.07, 4.35)	2.72	0.759	-9.95 (-229.39, 189.99)	126.5	0.938	26.15 (-119.89, 172.07)	87.73	0.769	3.81 (21.17, 23.58)	21.17	0.859
Total jackal	-1.01 (-3.26, 0.43)	0.99	0.325	-26.5 (-101.64, 51.31)	44.92	0.564	-23.56 (-83.78, 33.27)	31.92	0.470	-11.21 (7.92, 23.94)	7.92	0.170
Possession regained	-1.52 (-2.31, -0.23)	0.56	0.017*	-69.93 (-110.59, -29.88)	25.26	0.015*	-45.28 (-75.59, -14.68)	18.24	0.024*	-7.88 (4.57, 22.9)	4.57	0.098
Total ball carrier	-0.38 (-1.56, 0.73)	0.65	0.561	-13.72 (-68.76, 40.77)	32.34	0.676	-8.37 (-46.38, 30.2)	22.15	0.709	-5.39 (5.07, 22.85)	5.07	0.299
Total support	-0.54 (-2.1, 0.25)	0.67	0.423	-16.98 (-68.47, 33.94)	31.22	0.594	-11.56 (-49.07, 25.99)	22.03	0.606	-9.1 (5.27, 24.2)	5.27	0.097
Total pass	-0.95 (-2.45, -0.19)	0.64	0.153	-45.6 (-97.15, 10.48)	31.51	0.162	-30.97 (-69.87, 7.99)	21.51	0.164	-12.16 (5.01, 24.34)	5.01	0.023*
Total kick	-0.52 (-1,79, 0.11)	0.54	0.346	-15.16 (-58.02, 31.93)	26.25	0.570	-13.98 (-46.56, 18.7)	17.85	0.442	-6.02 (4.21, 24.76)	4.21	0.165
Total work-rate	0.63 (0.03, 1.7)	0.46	0.190	31.39 (-7.87, 68.15)	22.32	0.175	21.65 (-6.03, 49.69)	15.4	0.174	7.66 (3.65, 24.34)	3.65	0.047*
Positive work-rate (%)	-2.91 (-12.91, 8.29)	6.29	0.647	39.27 (-333.58, 426.84)	219.47	0.860	33.65 (-258.65, 312.56)	154.39	0.830	-27.05 (36.58, 22.27)	36.58	0.467
$R^2_{GLMM(c)}$		0.62			0.88			0.80			0.43	

Notes: B, Beta; 95% CI, 95% confidence interval; SE, Standard error; p, p value; $R^2_{GLMM(c)}$, conditional variance explained by the entire model.

1.2.4 Paper #4

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Padel Match Analysis: Notational and Time-Motion Analysis during Official Italian Sub-Elite Competitions

Alexandru Nicolae Ungureanu [1,2], Corrado Lupo [1,2,*] and Paolo Riccardo Brustio [2,3,4]

1 Department of Medical Science, University of Turin, 10126 Turin, Italy; alexandru.ungureanu@unito.it
2 NeuroMuscular Function Research Group, School of Exercise & Sport Sciences, University of Turin, 10126 Turin, Italy; paoloriccardo.brustio@unito.it
3 Department of Neuroscience, Biomedicine and Movement, University of Verona, 37129 Verona, Italy
4 Department of Clinical and Biological Sciences, University of Turin, 10126 Turin, Italy
* Correspondence: corrado.lupo@unito.it; Tel.: +39-01-1670-8083

Abstract: Although performance analysis in padel represents a useful process to gain references about players' technical and tactical behavior, most of the research was conducted in elite compared to the sub-elite competitions. Therefore, this study aimed to describe sub-elite competitions in order to enhance scientific knowledge for sub-elite athletes and technical staff. 4287 shots were analyzed within five areas (time-motion analysis, shots characteristics, errors, serve and points won). Effective playing time and work-to-rest ratio were lower than in elite competitions, while strokes per minute and total match duration were in line with it. Shots were mainly forehand volleys performed under the head, while volleys and smashes were more likely to end with a point in comparison with ground or wall shots. However, sub-elite winning pairs performed fewer volleys than the losing side and fewer errors on volleys. One serve out of five ended in errors (almost half were net errors); fewer errors during serve return shots represented an advantage for the winning pairs. Finally, 65% of the points scored were caused by unforced errors of opponents. This knowledge should help technical staff design specific training programs for sub-elite padel players.

Keywords: notational analysis; time-motion analysis; training load; padel tennis; key performance indicators; racket sports

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1. Introduction

Padel is a doubles racket sport that was born in 1969 in Acapulco (Mexico), and spread in Argentina and Spain to become very widespread across Europe in the present day [1]. Due to the great popularity of this sport across Europe, the major European stakeholders (i.e., Spanish, Finnish, British, Swiss, Polish, Danish, Portuguese, Austrian, Czech, Belgium, Deutscher, Nederlandse, Svenska and Estonian Federations) created the European Padel Association [2]. In particular, the Italian Olympic Committee recognized padel as a stand-alone discipline, and consequently, the participation of the athletes in national and international competitions. Moreover, the ongoing development of padel increased amateur and competitive level practitioners' participation while decreasing tennis practitioners' participation, especially in Spain [3].

Padel is a netball and racquet game similar to tennis, in terms of its scoring system, but with some changes, such as the underhand serve and the characteristics of the court [4]. Padel is played on a 20 m × 10 m (length × width) enclosed synthetic glass and metal court divided by a standard tennis net (0.88 m at the center strap and 0.92 m at the post) in the middle [4]. The back (3 m height × 10 m length) and the side walls (3 m × 2 m) end on another 2 m × 2 m wall, while the rest of the court consists of two metallic panels of equal dimensions (3 m × 2.59 m) and one gate (2 m × 0.82 m) for each half [4]. This setting allows the ball to bounce on lateral and back walls [4], and leads to longer rallies than other racket sports such as tennis or badminton [5]. However, substantial differences in rally durations exist according to age, competition level or type [5]. Performance in padel was widely investigated in elite competitions [6–10], and scientific research has arisen to better understand the characteristics of padel in terms of anthropometrics, biomechanics, epidemiology, physiological requirements and match analysis [10]. In this regard, the literature shows controversial results about time-motion (TMA) and notational analysis (NA). The effective playing time is around 56 min [11], and it varies between 38% [12] and 46% [13] of the total match duration, while ball in play and break time per rally are roughly 13 and 15 s, respectively, with a work-to-rest ratio (WRR) of 0.84 on average [13]. The main distribution of rallies duration is commonly between 3 to 6 s (23.2%), 6 to 9 s (29.3%), 9 to 12 s (19.6%) and 12 to 15 s (13.3%) [5]. Nevertheless, when comparing male and female athletes, controversial results exist. In particular, Lupo et al. [6] reported significant and considerable differences in the rallies' duration between men and women (i.e., 12.6 s vs. 16.8 s), while Torres-Luque et al. [5] did not (i.e., 9.3 s vs. 9.7 s). Similarly, the number of strokes per rally was 9.3 and 9.5 for men and women, respectively, with no differences for gender [5]. On the contrary, Lupo et al. reported large differences between men and women, of 9.6 vs. 12.2, respectively. These divergences in literature can be due to the competition level, as performance is level-dependent in padel [14,15]. In fact, when comparing final or semi-final matches (such as Torres-Luque et al. [5]) to other high levels, even professional matches (such as Lupo et al. [6]), discrepancies may emerge, and this evidence stresses the need for comparing the same level of competition, even within professional tournaments. From a technical and tactical perspective, NA highlighted volley, smash and backhand strokes as the most common strokes among elite players [5,6,16,17]. However, the stroke distribution varies with age and gender, showing more strokes and lobs per rally in under-18 compared to younger male players (i.e., under-16) and vice-versa in under-16 female players [18]. Volleys, smashes and the low number of wall shots (e.g., side and back wall) represent an effective strategy in gaining an advantage when comparing shot effectiveness between winning and losing performances in elite players [19,20]. Indeed, these types of strokes may be advantageous, as they are executed in response to the opponent's errors (e.g., shorter lobs to the opponent's playing position) [6,21]. In fact, the smash after a lob is the most effective action to solve the point, although it is highly probable to end with an error [7]. From the defensive perspective, responding to smashes using an aggressive backwall defense could represent an effective and surprising counter-offensive strategy [7]. Moreover, smashes determining ball out could represent an effective strategy in scoring points for men more than for women, probably due to different strength levels between the genders [6].

Despite this important and growing information about performances in elite padel representing useful references for elite coaches and athletes, little is known about sub-elite or domestic competitions across Europe. From the match analysis perspective, which is the primary area of scientific interest from 2013 to date (i.e., 38 papers out of 72 reviewed), most (25 out of 38) focused on elite performance [10]. As a consequence, specific analyses for sub-elite competitions are needed. Performance is well known as level-dependent in padel [14,15], as in other sports [22,23], so specific research is needed to enhance scientific knowledge for athletes and technical staff. Therefore, this study aimed to describe sub-elite level padel competitions (i.e., the Italian second division "Serie B") through technical, tactical and time-motion key performance indicators.

2. Materials and Methods

2.1. Design and Instruments

A descriptive-comparative study analyzed 4287 shots of 12 teams within 6 outdoor matches valid for the Italian Serie B male national league. Data were recorded from 10:00 15:00 local time (UTC+2) over a period of 2 days through a video camera (GoPro, Hero 4 Silver, GoPro Inc., San Mateo, CA, USA). The camera was located longitudinally with reference to the court, at a height of 4 m. The matches were recorded for their duration, and videos were saved in mp4 format. The software Longomatch Open Source version 1.3.2

installed on a MacBook Pro 15″ (Apple, Cupertino, CA, USA) was utilized to analyze the matches. The local institutional review board approved this study (ID. 25831), and an informed consent form was obtained from the participants regarding the use of the video recordings for scientific purposes.

2.2. Methodology

According to previous research [10], 61 key performance indicators (KPIs)—9 for time-motion analysis (TMA) and 52 for notational analysis (NA)—were analyzed. They were clustered within five areas [time-motion analysis (TMA), shots characteristics (SC), errors (E), serve (S) and points won (PW)], and described as follows in Table 1. Since the measures in this study were mainly based on human perceptions, their reliability and objectivity represented an issue [24]. Therefore, a single match analyst (with more than three years of specific experience in notational analysis) analyzed all the matches to avoid any inter-observer variability. However, the match analyst and an expert padel coach examined an entire match randomly selected to assess reliability, reporting high inter-observer reliability for all KPIs (ICC range = 0.95 to 0.97). Finally, the intra-observer agreement was assessed by the match analyst, who analyzed 3 sets randomly chosen twice with an interval of 14 days, reporting a high intra-observer test-retest reliability (Intraclass Correlations, ICC = 0.99).

Table 1. Description of the KPIs according to the 5 areas of investigation: time-motion analysis (TMA), shots characteristics (SC), errors (E), serve (S) and points won (PW).

Area	Performance Indicators	Description
Time-motion Analysis (TMA)	Total playing time	Effective playing time + total recovery time (min)
	Effective playing time	Effective playing time from the serve to the point scored (min)
	Total recovery time	Total recovery time from the point scored to the next serve (min)
	Average rally duration	Average duration of the time intervals from the serve to the point(s) scored
	Maximum rally duration	Maximum duration of the longest time interval from the serve to the point(s) scored
	Average recovery between rallies	Average duration of the time intervals from the point scored to the next serve(s)
	Maximum recovery between rallies	Maximum duration of the time interval from the point scored to the next serve(s)
	Work-to-rest ratio (WRR)	Average of the ratios between rally duration and the following recovery time
	Shots per minute	Ratio between the total number of shots performed by both the teams and the effective playing time
Shot characteristics (SC)		
Origin	Bounce	Shot performed after a bounce of the ball
	Board	Shot performed after the ball touches against the sidewall and/or backwall
	Air (volley)	Shot performed without any previous bounces of the ball
	Serve	Shot to start a point
	Serve return	Shot performed after the serve of the counterpart
Type of shot	Forehand	Shot performed with the forehand
	Backhand	Shot performed with the backhand
	Smash	Shot performed with the smash (including flat, topspin, tray)
Height of shot	Overhead	Shot in which the ball is at the level of the ear or above it when impacted by the racket
	Underhead	Shot in which the ball is at the level of the ear or below it when impacted by the racket

Table 1. *Cont.*

Area	Performance Indicators	Description
Board	Yes	Shot arrived in the counterpart's court after touching the board in their own court
	No	Shot arrived in the counterpart's court without touching the board in their own court
	Average number of shots per rally	Average number of shots performed by both teams each rally
	Maximum number of shots per rally	Maximum number of shots performed by both teams in one rally
Total		Total number of shots performed
Errors (E)		
Type of error	Out	Shot ending with a point for the opponent because of the ball sent out of the court
	Length	Shot ending with a point for the opponent because the ball was sent directly on the backwall
	Width	Shot ending with a point for the opponent because the ball was sent directly on the sidewall or side fences
	Net	Shot ending with a point for the opponent because the ball was blocked by the net
	Errors at the serve	Total number of wrong serves
Origin	Bounce	Shot ending with a point for the opponent performed after a bounce of the ball
	Board	Shot ending with a point for the opponent performed after the ball touched against the sidewall or backwall
	Air (volley)	Shot ending with a point for the opponent performed before any bounces of the ball
	Serve return	Shot ending with a point for the opponent performed after the serve of the counterpart
Type of shot	Forehand	Shot ending with a point for the opponent performed with the forehand
	Backhand	Shot ending with a point for the opponent performed with the backhand
	Smash	Shot ending with a point for the opponent performed with the smash (including flat, topspin, tray)
Height of shot	Overhead	Shot ending with a point for the opponent in which the ball is at the level of the ear or above it when impacted by the racket
	Underhead	Shot ending with a point for the opponent in which the ball is below the level of the ear when impacted by the racket
Board	Yes	Shot ending with a point for the opponent sent in the counterpart's court after having touched one board in the own court
	No	Shot ending with a point for the opponent sent in the counterpart's court without having touched one board in the own court
Total errors/total shots		Ratio between the total number of errors and the total number of shots performed
Serve (S)		
Type of shot	Forehand	Serve performed with the forehand
	Backhand	Serve performed with the backhand

Table 1. *Cont.*

Area	Performance Indicators	Description
Serve number	First	First shot starting the rally (according to the Rule n.6 of the International Padel Federation) [4]
	Second	Second shot if the first was not valid
Type of error	Out	Serve not valid because of the ball sent out of the court
	Length	Serve not valid because of the ball touching directly the backwall
	Width	Serve not valid because of the ball touching directly the sidewall or touching the side fence after the bounce
	Net	Serve not valid because of the ball blocked by the net
Total serves/error during serve		Ratio between the total number of errors during serve and the total number of serves performed by a player
Points won (PW)		
Origin	Bounce	Shot performed after a bounce of the ball
	Board	Shot performed on a ball returning from a touch against the sidewall or backwall
	Air (volley)	Shot performed before any bounces of the ball
	Ace	Serve to allow for scoring the point before the counterpart touches the ball
	Serve return	Shot performed after the serve of the counterpart
Type of shot	Forehand	Shot performed with the forehand that ends with a point scored
	Backhand	Shot performed with the backhand that ends with a point scored
	Smash	Shot performed with the smash (including flat, topspin, tray) that ends with a point scored
Height of shot	Overhead	Shot ending with a point scored in which the ball is at the level of the ear or above it when impacted by the racket
	Underhead	Shot ending with a point scored in which the ball is below the level of the ear when impacted by the racket
Board	Yes	Shot ending with a point scored that arrives in the counterpart's court after having touched one board in the own court
	No	Shot ending with a point scored that arrives in the counterpart's court without having touched one board in the own court
Points won by means of the opponents' mistakes		Total number of points won following an opponent's mistake (i.e., opponents' unforced errors), in a technical and tactical situation where the opponent was not constricted to respond after a high effective shot (e.g., high-speed ball, very close to the wall ball).
Total		Total number of points won by means of winners + total number of points won by means of opponents' mistakes

2.3. Data Analysis

Descriptive statistics was applied for the 11 TMA variables, and the data are presented as mean ± standard deviation. Due to the violation of normality, a non-parametric statistic was applied for the 48 NA variables. In particular, the Kruskall-Wallis test with Dunn's post hoc was applied to analyze (i) the origin, (ii) the type of shots, (iii) winners, (iv) errors, and (v) the type of error in the serve. Differences among the type of the serve (forehand or backhand) and the biomechanics (overhead or under the head) of shots, errors and winners were investigated through the Mann-Whitney test. The significance level has been set at $p < 0.05$, and the effect size (ES) was calculated and interpreted accordingly: 0.2 to <0.6, small; 0.6 to <1.2, medium; 1.2 to <2.0, large; 2.0 to <4.0, very large; and ≥4.0, extremely large [25]. ICC was computed to determine intra- and inter-observer agreement.

3. Results

3.1. Time-Motion Analysis—(TMA)

The average match duration was 53.7 ± 1 min, divided into 16.8 ± 4 min effective playing time and 36.9 ± 11 min resting time. The effective playing time corresponded to 31.3% of the total match duration. The longest rally lasted 29.4 s. The average rally duration was 6.7 ± 1 s, while the recovery periods between rallies lasted 14.8 ± 2 s. On average, 42.6 ± 2.1 shots were played per minute of match. The WRR was 1:3.4 ± 0.8.

3.2. Notational Analysis—(NA)

Data in Table 2 reports all the significant differences, while shot characteristics (SC) are presented in Figure 1. On average, 4.7 ± 0.7 shots per rally were performed, while the average number of maximum shots played in a rally was 19.7 ± 4.

Table 2. Results of the inferential statistics applied to the notational analysis KPIs.

Areas	Performance Indicators	*p*	ES	diff %
Shot characteristics				
Origin	volley vs. bounce	****	4.4	34.9 ± 5.9 vs. 13.4 ± 4.2
	volley vs. service return	***	4.4	34.9 ± 5.9 vs. 15.5 ± 2.9
	volley vs. board	***	3.9	34.9 ± 5.9 vs. 14.9 ± 4.7
Type of shot	forehand vs. backhand	*	3.0	55.2 ± 8.3 vs. 32.8 ± 7.4
	forehand vs. smash	***	7.4	55.2 ± 8.3 vs. 12 ± 2.3
	backhand vs. smash	*	4.0	32.8 ± 7.4 vs. 12 ± 2.3
Height of shot	under vs. over the head	****	24.6	80.0 ± 2.6 vs. 20.0 ± 2.6
Errors				
Type of error	serve vs. ball out of the court	****	5.3	30.6 ± 7 vs. 3.7 ± 2.8
	serve vs. width	**	3.2	30.6 ± 7 vs. 12.4 ± 4.9
	net vs. out	****	7.1	32.0 ± 5.2 vs. 3.7 ± 2.8
	net vs. width	**	4.1	32.0 ± 5.2 vs. 12.4 ± 4.9
	longboard vs. ball out of the court	**	3.5	21.3 ± 6.9 vs. 3.7 ± 2.8
Serve				
Type of shot	forehand vs. backhand	****	2.9	83.7 ± 24.6 vs. 16.3 ± 24.6
Type of error	net vs. sidewall	***	2.2	47.4 ± 14.3 vs. 21.4 ± 10.4
Points won				
Origin	volley vs. bounce	***	10.0	75.0 ± 8.8 vs. 6.4 ± 5.2
	volley vs. service return	****	10.5	75.0 ± 8.8 vs. 3.8 ± 5
	volley vs. board	**	8.8	75.0 ± 8.8 vs. 8.4 ± 6.9
Type of shot	smash vs. backhand	***	2.2	48.3 ± 16.1 vs. 18.7 ± 11.8
Height of shot	overhead vs. under the head	*	1.4	57.2 ± 10.8 vs. 42.8 ± 10.8
Winning (W)/Loosing (L)				
Points won	volley: (W) vs. (L)	*	2.0	69.1 ± 6.2 vs. 80.9 ± 6.7
Errors	ball out of the court: (W) vs. (L)	*	1.6	2.1 ± 2.5 vs. 5.4 ± 2.0
	errors/shots ratio: (W) vs. (L)	**	2.5	11.5 ± 1.3 vs. 15.45 ± 2.3
	volley: (W) vs. (L)	*	1.7	11.0 ± 1.8 vs. 14.6 ± 2.9
	serve return: (W) vs. (L)	**	2.2	9.3 ± 3.3 vs. 18.7 ± 5.7
	backhand: (W) vs. (L)	*	1.3	8.0 ± 2.6 vs. 13.7 ± 6.2
	smash: (W) vs. (L)	**	2.2	10.0 ± 2.8 vs. 18.7 ± 5.4
	overhead shots: (W) vs. (L)	*	1.5	10.0 ± 2.7 vs. 14.6 ± 3.8

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$, **** = $p < 0.0001$.

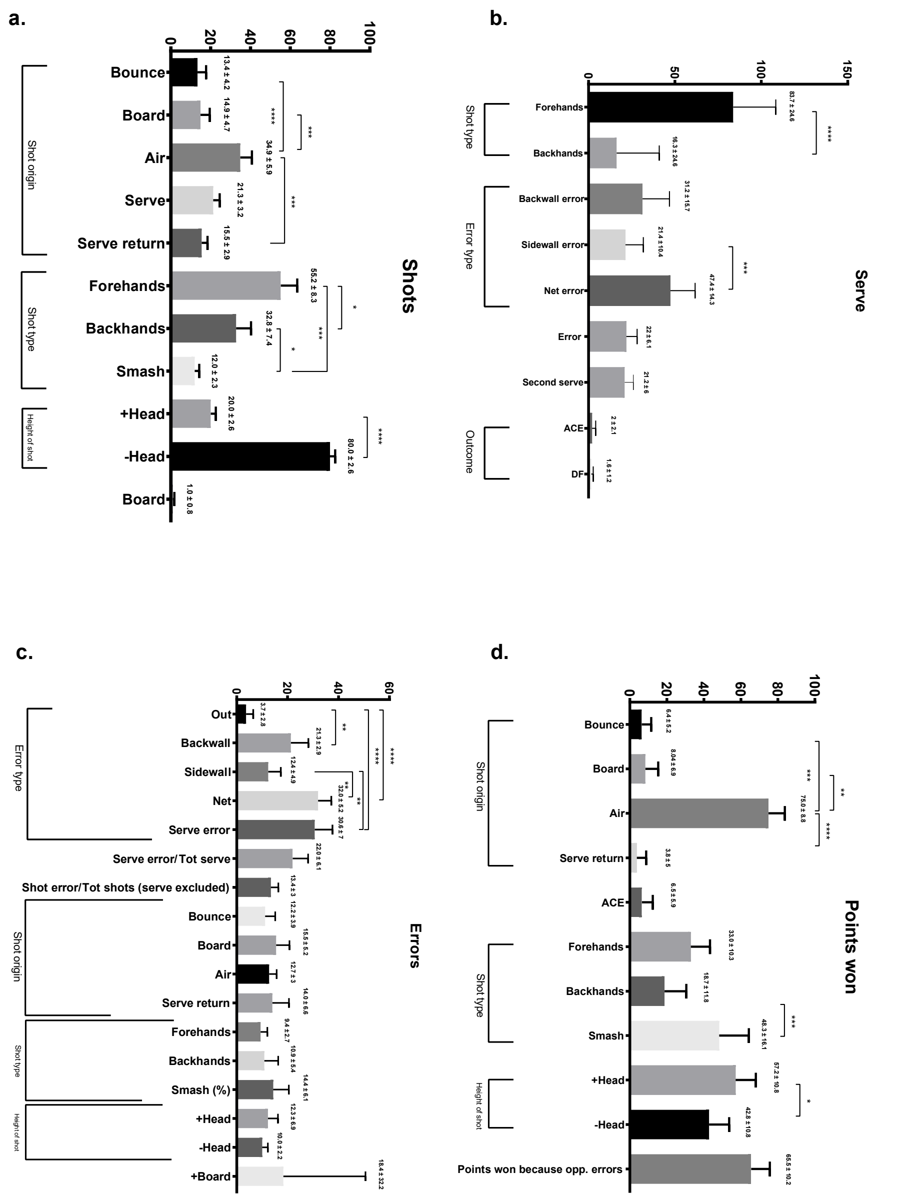

Figure 1. Characteristics of shots (**a**), serve (**b**), errors (**c**) and points won (**d**). Data are expressed as mean percentage ± standard deviation. * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; **** $p \leq 0.0001$.

4. Discussion

The present study described Italian sub-elite level padel competitions (i.e., national second division "Serie B") through technical, tactical and TMA key performance indicators. The results of this descriptive study represent a reference point for practitioners and coaches concerning the sub-elite padel performance model. Moreover, these results allow sports scientists to compare sub-elite to elite performance and highlight specific features of the sub-elite male matches in padel.

From the TMA perspective, sub-elite padel can be considered an intermittent sport as the elite one [17,26]. In fact, actions (i.e., shots) occurred frequently (e.g., 43 shots/minute) during short rallies (e.g., 6.7 s) at low density (e.g., WRR = 1:3.4). The effective playing time for elite players was heterogeneous, ranging from 35 to 46% [5,10]. However, the effective playing time reported in this study for sub-elite players (i.e., 31%) is lower than for elite. Indeed, performance level tends to decrease from the elite to the sub-elite level in terms of duration of the rallies, the number of shots and rate of play (i.e., strokes per minute) [15]. On the contrary, time-motion data in this study is in line with previous studies in elite padel, in terms of strokes per minute (~43) [15] and total match duration (~50 min) [5], but not for the WRR. Even though WRR varies between studies (i.e., 0.4 to 0.9) [13,27], the value reported in this study (i.e., 0.3) is significantly lower. On the one hand, these dissimilarities may be due to the normal fluctuation of the TMA variables within an open skill sport such as padel, while on the other hand, it could be due to a lack of consistency in data analysis. For instance, in this study, WRR was analyzed by averaging the ratio of the active (i.e., rally duration) and the subsequent recovery intervals, while other authors compared the total playing time with the total rest time [13].

From a technical and tactical perspective, shots were characterized by three important features: they were forehand volleys performed underhead. These evidences differ slightly from those reported for the elite level [28]. In fact, elite players perform more smashes and backhand strokes than sub-elite level [6,10,17,18], and they are even more efficient at volley shots [15]. Specifically, an offensive strategy is based on volleys shots to gain the net (i.e., to advance in a strategic position near the net) and smashes to score. On the other hand, the defensive strategy is based on sending the opponents to the backcourt and using the balls bouncing on the walls in the baseline [17]. In terms of efficacy, volleys and smashes were more likely to end with a point than the ground or wall shots, but they also led to errors. In fact, in this study, sub-elite winning pairs performed fewer volleys than the losing side (i.e., 69.1 vs. 80.9%) and fewer errors on volleys (i.e., 11 vs. 14.6%). On the contrary, elite winning players are more efficient at volley shots, and perform a significantly higher percentage of smashes and volleys and a lower number of ground and walls shots than the losing players [3,19]. This phenomenon may be explained by the different levels of players' skills. Indeed, sub-elite players are generally less skilled, and could be more inclined to use less challenging shots (i.e., ground) rather than volleys or smashes [9]. In addition, less skill level and lower experience in high-level competitions may also influence the kinematics of the smash shots. Sub-elite players were reported to perform smashes at lower velocities than elite players, especially when affected by the opposition, to maximize the velocity-precision tradeoff [29]. Based on this evidence, one could speculate that greater smash and ball of the court errors in this study originated from shots executed at the high velocity at the expense of precision.

In this study, serves accounted for 21.3% of all shots, similarly to other sub-elite level performances [15]. One serve out of five (i.e., 22.6%) ended by error (vs. 8.8% for the elite level) [30], and almost half were net errors (i.e., 47.4%). In contrast to the elite level [30], a higher percentage of second serves occurred in this sample. In fact, sub-elite players struggled to perform successful first serves (i.e., 78.8%) compared to elite ones (i.e., 92.9). On the one hand, this evidence highlights the poor accuracy in executing the serve task, as well as an opportunity for the sub-elite players to gain an advantage by improving their serve skills and increasing their first serve efficacy. From the total errors that occurred in a match perspective, serve errors accounted for 30.6%. Special focus should be put on the serve and the serve return, since it was suggested that their quality could influence the rally outcome and duration, especially for sub-elite players [15,31]. According to Ramón-Llin et al., a good or bad serve could anticipate the end of the rally and lead to shorter rally durations [15]. Similarly, in professional padel, the beginning of each point is very important and decisive for increasing the chances of winning the point [30]. In particular, the beginning of each point consists of both serve and serve return. Hence, the serve effectiveness is directly related to the opponent's serve return skills [32]. However, serves did not distinguish between winners and losers in this study. Conversely, fewer errors during serve return shots were advantageous for the winning pairs in this study (i.e., 9.3 vs. 18.7%). In general, serve return error percentage in padel is lower than in other sports such as tennis, due to the lower serve power [32]. From the regulation perspective, an underhand shot from a bouncing ball is mandatory for the padel's serve, so it is relatively easy to play. In fact, in this study, aces (2%) and double faults (1.6%) were even lower than in elite tennis tournaments (e.g., Wimbledon) [33]. Therefore, sub-elite players should focus on the serve return technical and tactical skills to prevent the server from winning the rally quickly [30]. In fact, according to Ramón-Llin et al., the server has a significant advantage in padel, especially during short rallies up to 6 to 8 shots [31].

Finally, error analysis for the winning rallies (see Figure 1d) highlights that unforced errors caused 65% of the points scored. The reason for this phenomenon may be due to the poor technical and tactical skill level of the sub-elite players. This scenario is consistent with the differences between winning and losing players presented in this study. From the quantitative perspective, winning players tend to perform less challenging actions (e.g., volleys), take fewer risks and let the opponent make the error, while from the qualitative perspective, winning players are also more effective (i.e., make fewer errors) when performing (e.g., volleys, smashes, serve returns) the shots.

Nevertheless, this study presents some limitations. First, we did not provide evidence on the kinematic match demands such as distance covered, velocities, accelerations and decelerations, change of directions and type of displacement (e.g., standing, walking, running, sprinting) to describe the physical load. We only assumed TMA components such as effective playing time (i.e., volume) and WRR (i.e., density) to provide information on physical load. Secondly, we did not provide insights about scoring strategies and players' location (i.e., baseline or net) according to winning and losing matches. Therefore, further research on the kinematic match demands through GPS or Video tracking technology, as well as on the players' offensive and defensive strategies concerning the match outcome (i.e., winning/losing), is needed in sub-elite competitions to compare technical and tactical patterns with elite ones [34]. Finally, information about the participants (i.e., average age, number of official matches played per year, national league players success ranking) is not reported. Thus, caution is necessary when interpreting these data.

5. Conclusions

This study presented new contributions to performance indicators in sub-elite padel competitions. Data suggested that the sub-elite matches showed a lower density and less effective playing time than elite ones. The results indicated that when the points were scored, the more challenging shots were used (e.g., volleys, smashes). However, more challenging shots also resulted in more unforced errors. In fact, when analyzing outcomes from the winning and losing players perspective, the winning sub-elite players generally performed easier shots (i.e., ground) than volleys or smashes, adopted a more conservative playing style, and let the opponents to commit unforced errors. Data also suggested that serves, especially the serve returns, may be key factors to train. Indeed, training technical and tactical skills to prevent the server from winning the rally quickly may be a pivotal strategy in sub-elite padel. This information may contribute to the existing knowledge in padel for setting benchmarks and adapting training plans specifically for sub-elite competitions. However, since technical and tactical performance is closely linked to the physical one (e.g., strength and conditioning) [17], future studies should focus on analyzing the sub-elite level in terms of physical fitness, strength and conditioning training, and time-motion analysis.

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2. Training load in team sports

2.1. Introduction

Training load has been defined as the "cumulative amount of stress placed on an individual from a single or multiple training sessions over a period of time" (Soligard et al., 2016). It has become a wide applied scientific approach to understand athletes training and competition responses since it was conceptualized for the first time in 1975 (Calvert et al., 1976). Since then, it was applied to implement training strategies with the goal to enhance physical abilities, motor, technical and tactical skills (Bourdon et al., 2017; Viru & Viru, 2000). Although it is said that "practice make perfect", the practice must be modulated in terms of frequency, intensity, type, and time to induce a functional adaptive response (Impellizzeri et al., 2019; Viru & Viru, 2000). In fact, the training stimulus, whether it is physical, cognitive, or technical and tactical, can elicit acute adaptive responses if applied occasionally, as well as determine chronic adaptation if it is repeated systematically. In other words, the organization, the quality, and the quantity of the exercise bout determine the characteristics of the physical work prescribed in the training plan (Impellizzeri et al., 2019).

Moreover, the training stimulus should be constantly monitored and applied at sufficient time intervals and at a proper magnitude to obtain specific performance adaptation. In particular, the training plan (i.e., organization, quality, and quantity of exercise bouts) represents the external load that acts then on the internal homeostasis in the form of biochemical stresses (internal load) (Impellizzeri et al., 2019). When delivered appropriately, exercises induce psychophysiological and biomechanical responses that lead to functional adaptations in different areas such as physical performance (i.e., endurance, speed, strength, power), injury resistance (i.e., increased tendon stiffness, cartilage regeneration), and health (Impellizzeri et al., 2019; Vanrenterghem et al., 2017). On the contrary, excessive training load can lead to overload the biological system's capacity and to increase risk of injury and illness, while insufficient load will not trigger the biological adaptation to the stressor. Therefore, the training process consists in challenging players adequately through appropriate periodization of their activities, alternating sufficient recovery between bouts of activity in order to enhance their physical abilities. According to Impellizzeri et al. (2019), the concepts of external and internal load do not have a single or gold standard measure, but they can be quantified by a multitude of variables. In fact, the validity of a load indicator depends on the context. For example, heart rate can be a valid measure of internal load for endurance training but not for resistance training. Moreover, even for endurance training, heart rate may be a valid indicator of internal load in long distance but not in short duration and intermittent high-intensity efforts (Impellizzeri et al., 2019).

The external load is measured specifically to the nature of the training. For example, the load lifted, the work completed, the time under tension, as well as the velocity generated during lifting can be considered external load in resistance training (Impellizzeri et al., 2019). From the running-based team sports perspective, external load can be explained both by cinematic variables such as distance covered, speed, acceleration (Osgnach et al., 2010) and by technical and tactical variables (e.g., (Ungureanu, Brustio, et al., 2021). In fact, tackling, passing, and positive work rate were associated to cinematic variables (e.g., total distance, metres/minute, %high speed running, and explosive distance) according to playing roles (i.e., backs and forwards) in rugby union (Ungureanu, Brustio, et al., 2021).

Although the external load is linked to the internal one, the latter is an individual phenomenon modulated by several factors such as training status, nutrition, health, psychological status, genetics, and environmental stressors (i.e., extreme hot or cold conditions) (Bouchard et al., 2011; Impellizzeri et al., 2004; Mann et al., 2014; Smith, 2003). Specifically, the internal load caused by the training was investigated primarily from the physiological perspective (e.g., oxygen consumption, cardiac and tissutal efficiency), although a separating physiological and biomechanical load-adaptation pathways framework was suggested to improve the adaptation process and the players' management (Vanrenterghem et al., 2017). In fact, separating biomechanical and physiological effects from a theoretical point of view may allow trainers to correctly periodize the training across the season. For example, in running-based team sports, trainers would like to decrease, at a certain moment during the competitive season, the ground reaction force and therefore the biomechanical stress, while still maintaining a high physiological load. Consequently, they might choose to cycle or to run on sand at high intensity levels, or even to run on harder surfaces excluding changes of direction, extreme accelerations, or decelerations. On the contrary, biomechanical conditioning (i.e., changes of direction, extreme accelerations, and decelerations) is possible while maintaining a relatively low level of physiological stress. In this regard, it was reported that a reduced pitch size small-side game tends to increase the biomechanical stress while reducing the physiological one (Gaudino et al., 2014; Hill-Haas et al., 2011; Hodgson et al., 2014).

From the internal load monitoring perspective, it was proposed that the athletes' training could be quantified in arbitrary units as training impulses (TRIMPs), and that these TRIMPs would be a measure of training dose. However, the validity (i.e., the construct validity) of using TRIMPs to quantify the training dose was never tightly established although it was demonstrated that TRIMPs are correlated to the athletes' changes in performance (Calvert et al., 1976; Morton et al., 1990). Historically, TRIMPs were calculated in different way. Starting from the Banister's early work, where the swimmer's TRIMPs were calculated as the product of the distance swam and an intensity factor, plus the volume (i.e., the number of repetitions) performed in the swimmer's resistance training (Calvert et al., 1976), several modifications were published afterwards. In general, TRIMPs were calculated based on the heart rate effort or on ratings of perceived exertion. In particular, Edwards proposed the definition of 5 arbitrary heart rate zones (i.e., from 1 to 5) in order to calculate TRIMPs as the sum of the products of the time spent in each zone weighted by the 1 to 5 coefficients (Edwards, 1994). Similarly, Lucia et. al considered specific exercise intensity domains according to the VO_{2max} consumption (i.e., phase I below ~70% VO_{2max}, phase II between ~70 and ~90% VO_{2max}, and phase III above ~90% VO_{2max}) as the coefficient to be multiplied by the time spent in that intensity domain. (Lucía et al., 2003). Moreover, Manzi et al. (2010) introduced further detail on the TRIMPs calculation by adding an individual weighting factor that reflects the profile of a typical blood lactate response curve to increasing exercise intensity (Manzi et al., 2010). Finally, a popular method that calculated training load considering the individual perception (i.e., RPE- Rate of Perceived Exertion) of the training intensity was proposed by Foster et al. (2001) and it was validated by comparison with Edward's TRIMPs (Foster et al., 2001). Specifically, athletes were asked to answer to ''How was your workout?" by reporting their perception based on a 11-points (i.e., 0 to 10) verbal anchored perceived perception scale (Foster et al., 2001).

Projecting, delivering, monitoring, and adjusting training loads aim to increase athletes' performance while simultaneously preventing injuries, especially from a musculoskeletal perspective. But while increasing performance can be constantly verified (by the means of athletic tests or during competitions and trainings), injuries are continuously avoided through prevention strategies, because once they happen, it is too late to turn back. Neuromuscular training, sporting rule modification and policy changes, equipment recommendations, and training load application are the principal prevention strategies for musculoskeletal injuries (Emery & Pasanen, 2019). In particular, it was proposed that athletes chronically exposed to high training loads may have a lower risk of injury than athletes training at lower workloads (Gabbett, 2016). On the contrary, excessive and rapid increases in training load may increase the risk of musculoskeletal injuries and the acute-to-chronic training workload ratio (i.e., ACWR) may predict training-related injuries (Benson et al., 2018). In fact, in 2016, the International Olympic Committee (IOC) published a consensus statement that suggests the use of the ACWR approach for injury prevention (Soligard et al., 2016), since level A evidence was reported to underpin the sRPE (i.e., Session Rate of Perceived Exertion) ACWR as an effective tool to prevent non-contact injuries in elite athletes (Myers et al., 2020). However, the validity of this metric was questioned in recent times because it creates remarkable statistical artefacts in the effect estimates (Impellizzeri et al., 2020, 2021; C. Wang et al., 2020). Moreover, it was suggested that ACWR should be dismissed while new metrics should be created based on reliable conceptual reference models (e.g., including mechanical workload) rather than statistical significance only (Impellizzeri et al., 2021).

In conclusion, the relationship between training load (psychophysiological dose-response) and injuries remains uncertain since injuries may occur independent of training loads (Kalkhoven et al., 2021). In fact, mechanical loads may represent a substantial contribution to injury occurrence by the means of tissue fatigue and failure, and the focus should be oriented both on physiological and biomechanical load-adaptation pathways (Kalkhoven et al., 2021; Vanrenterghem et al., 2017). In this perspective, training load can still inform coaches about how athletes are coping with the prescribed loads and help them to implement and to adjust periodization (Kalkhoven et al., 2021). Moreover, a complex and pluralistic approach to the training load analysis may allow sport data analysts to turn data (e.g., psychophysical load, mechanical load, technical and tactical performance) from different sources (e.g., psychophysical scales and questionnaires, wearable devices, technical and tactical video analysis) into relevant information for all the stakeholders (e.g., coaches, athletes, managers, therapists). In addition, a more extensive availability of wearable and non-wearable technologies (e.g., GNSS-Global Navigation Satellite System, accelerometers, video tracking, notational analysis) may represent a cutting-edge methodology to better understand the interaction between workload and performance, as well as between workload and injury risk (Ghali et al., 2020; MacDonald et al., 2017).

2.2 Technology

Regarding team sports, players' activity profiles (i.e., external load) are quantified in order to enhance performance within trainings and competitions by the means of the Electronic Performance and Tracking Systems (EPTS), such as GPS (Global Positioning System) / GNSS (Global Navigation Satellite System), LPS (Local Position System), and Video Tracking (Pons et al., 2019; Rico-González, Pino-Ortega, et al., 2020a). Tactical positioning (e.g., geometrical centers) and kinematics (e.g., displacement and changes of direction), as well as derivatives of distance with respect to time (e.g., speed, acceleration, deceleration) are the principal variables estimated by the EPTS. On the one hand, these information allow coaches and sport data analysts to understand teams' organization as well as tactical and technical patterns, while on the other hand allow to monitor the psychophysical workload and to manage it accordingly. From the usability and reliability perspective, each of these technologies comes with its pros and cons. GPS devices are useful for detecting the spatial positioning of players in outdoor locations, while LPS and video tracking are commonly used in indoor locations. However, indoor systems are also used in outdoor environments (e.g., LPS and video tracking systems) (Rico-González, Pino-Ortega, et al., 2020a), especially in official match stadiums.

In intermittent high-intensity sports such as rugby, hockey, and soccer, which involves collisions, impacts, high-speed running interspersed with low-intensity efforts and rest periods, absolute total (m) and relative distance (m·min−1), high-speed running (HSR) and very-high-speed running (VHSR) distance (m or m·min−1), repeated high intensity efforts (RHIE), accelerations and decelerations are the most common GPS metrics taken into analysis (Bridgeman & Gill, 2021; Cummins et al., 2013). In addition, wearable triaxial accelerometer systems are integrated into GPS devices to record impact and collision frequency and magnitude (Cummins et al., 2013). Several other variables such as Exertion index, Exertion index per minute, Time at steady state, Efficiency, High metabolic load distance, Energy expenditure, Dynamic stress load, etc., (for more details see Hennessy & Jeffreys, 2018) are used in soccer, although more applied research is required in establishing the reliability and validity of these metrics (Hennessy & Jeffreys, 2018). Differently, explosive efforts (i.e., the count of accelerations > 3.5 $m \cdot s^{-2}$ recorded in the mediolateral and anteroposterior axes), jumps (i.e., the count of accelerations occurring in the craniocaudal axis), as well as the player load overall (i.e., the sum of instantaneous accelerations in all 3 axes) are common metrics more solidly used to evaluate external training load in volleyball and basketball (Charlton et al., 2017; Gageler et al., 2015; Scanlan et al., 2014).

2.2.1 Wearable

2.2.1.1 Inertial devices

The inertial measurement units (IMU) such as accelerometers, gyroscopes, and magnetometers, are instruments that detect linear acceleration, rotational rate, and a heading reference of an object over a period of time. In particular, accelerometers use a piezoelectric system to measure the incidence and magnitude of accelerations in 3 different vectors (vertical, horizontal, and lateral) at up to 100 Hz sample rate (Theodoropoulos et al., 2020). Nowadays IMUs are small, comfortable, and affordable (i.e., roughly 100€ each) devices that are used in team sports to quantify the athletes' external load in terms of collisions, tackles, shots, and strokes (i.e., stoke detection and classification in tennis, badminton and squash, classification of activities in basketball and soccer) (Bridgeman & Gill, 2021; Cummins et al., 2013; McGrath et al., 2021). Evidence regarding the validity and reliability of those devices in recording sport-specific activities (e.g., accelerations, decelerations, changes of direction), especially for accelerometers and gyroscopes components, was reported to be acceptable under laboratory conditions (ICCs ranged from 0.77 to 1.0) (Nicolella et al., 2018; Roell et al., 2018) only when human-induced accelerations are separated by the external bias, including earth's gravity, through proper sensor fusion techniques (Roell et al., 2018). In fact, raw accelerometer data are not accurate enough when measuring impacts during jumping movements or average acceleration during HSR (Alexander et al., 2016; Tran et al., 2010). Therefore, it is crucial to integrate information from multiple sensors (e.g., accelerometer, magnetometer, and gyroscopes) and to assess the validity and reliability of sensor fusion algorithms (e.g., incorporating a gravity compensation formula) according to different movement patterns and intensity zones in order to accurately describe an athlete's locomotion (Roell et al., 2018). In fact, it is recommended to put wearable devices to periodic reliability and validity assessments as well as to develop validation and reporting standards to increase the chance to use devices from different manufactures interchangeably (Nicolella et al., 2018). For instance, simple low-pass filtering to extract gravity-induced high-frequency components does not provide acceptable results, while sensor fusion algorithms result in improvements of accuracy and precision of the data (Roell et al., 2018).

Notwithstanding training load is also assessed by the means of non-inertial devices (i.e., Global and Local Positioning Systems – GPS & LPS, Video Tracking), inertial approach such as accelerometry may provide additional information on impacts (Wundersitz et al., 2015), small changes of direction (Luteberget, Holme, et al., 2018; Meylan et al., 2017) and vertical work (Meylan et al., 2017), especially in indoor activities. However, both GPS-integrated and stand-alone accelerometer devices should incorporate a gravity compensation formula in order to gather reliable information about these events (Alexander et al., 2016). For instance, acceleration data collected with devices that do not include a magnetometer or a gyroscope, such as ActiGraph GT3X+ (ActiGraphTM Inc., Pensacola, FL, USA), was not able to distinguish between jumping and non-jumping activities in a group of male elite volleyball players (Jarning et al., 2015). On the contrary, commercially available and relatively inexpensive inertial devices including gyroscope can collect jump load in volleyball matches, although they underestimate maximal and submaximal jump height (MacDonald et al., 2017). This solution could be a more efficient alternative to time-consuming retrospective video analysis in jump-based sports like volleyball (Charlton et al., 2017).

Finally, when inertial technology is integrated into non-inertial (i.e., GPS) devices, they can automatically detect static and intensive technical and tactical events such as scrums and rucks in rugby games (Chambers, Gabbett, & Cole, 2019; Chambers, Gabbett, Gupta, et al., 2019), and provide additional information about players' load in events that are not able to be recorded by GPS metrics.

2.2.1.2 Non-inertial devices

GPS/GNSS and LPS are the main non-inertial wearable technologies used in outdoor team sports time-motion analysis in order to estimate players' external load (i.e., kinematic metrics such as distance, speed, acceleration, as well as movement categorizations such as standing, walking, jogging, running, and sprinting) (Rico-González, Los Arcos, et al., 2020; Rico-González, Pino-Ortega, et al., 2020a). GPS uses the first ever American satellite navigation network while Global Navigation Satellite System (GNSS) comprises both American (GPS) and Russian satellite navigation networks, totaling a 48 satellites network (Jackson et al., 2018). On Earth, players' position (typically only latitude and longitude rather than altitude) is constantly recorded by the receiver device located on the players' back, at a given sampling frequency (commonly from 1 to 10 Hz), by the means of trilateration calculus technique (Jackson et al., 2018; Larsson, 2003). The accuracy of this information requires at least four satellites and it is influenced by the atmosphere and by bouncing off various local obstructions before reaching the receiver (Larsson, 2003). However, GPS devices have demonstrated a good accuracy level when measuring total distance covered in team sports (Coutts & Duffield, 2010; Jennings et al., 2010) although it becomes less reliable when accelerating, decelerating, running at high speed, or updating the software (Buchheit, al Haddad, et al., 2014). In addition, common players' movement in team sport trainings and competitions, such as rapid changes in direction and speed (i.e., when accelerating and decelerating), have been reported to decrease GPS accuracy (Akenhead et al., 2014). Since these movements are highly relevant for the players' workload and energy expenditure monitoring, they might be considered with caution when recorded with GPS devices. On the contrary, reliability tends to increase when recording total distance, peak and average speed, and low-speed running variables with GNSS-enabled devices while no improvements occur when measuring high-speed running and acceleration/deceleration variables (Jackson et al., 2018). However, recent findings suggest that GNSS should be preferred to conventional GPS devices and data from the two devices should be not interchanged (Jackson et al., 2018). Moreover, devices with a sampling frequency less than 10 Hz and comparing data from different brand devices should be avoided in order to increase reliability (Hennessy & Jeffreys, 2018). In addition, manual time-motion analysis by the means of the notational analysis was also successfully validated in relation to GPS tracking (i.e., time and distance while standing, running, sprinting were recorded manually by a researcher), although it is difficult to implement this process on a club daily basis since data collection is quite laborious and monotonous, and results are produced post event (Doğramaci et al., 2011). Finally, wearing the same GPS tracking unit as well as using validated metrics should be considered when estimating players' workload according to the signal-to-noise ratio (i.e., magnitude of changes over time with respect of the inter and intra-unit variability) (Buchheit, al Haddad, et al., 2014; Scott et al., 2016; Vickery et al., 2014).

LPS (Local Position System), also referred to as LPM (Local Position Measurement), is a radio-frequency technology like GPS, with the difference that satellites are substituted by a set of antennas around the pitch. Similar to GPS, LPS require athletes to carry a receiver which constantly communicates with the antennas in order to calculate the players' position (Rico-González, Los Arcos, et al., 2020). This setting allows to mitigate the communication problems due to atmosphere interference and local obstructions such as tall buildings, as well as to track players in indoor activities. However, LPS accuracy depends on the environmental conditions, (i.e., obstructions and materials in the surroundings of the field of play), the geometry between signal anchor nodes and the units on the athletes), and the signal analysis and parameter calculation process (Luteberget, Spencer, et al., 2018). In fact, large differences between LPS and reference systems in kinematic variables (i.e., up to 30% for distance and > 74% for instantaneous speed) occur in relation with the position of the antennas (i.e., anchor nodes) with respect to the field of play (Luteberget, Spencer, et al., 2018). In particular, accuracy could be relatively poor when walls and corners of the room are close to the field of play in indoor sport halls (Luteberget, Spencer, et al., 2018). Moreover, validity and accuracy also depend on the task (i.e., linear movement or changes of direction, turns, high or low speed, acceleration, and deceleration). In fact, LPS's accuracy was reported to be less reliable when measuring high dynamics movements and instantaneous velocities, as well as for peak acceleration and deceleration (Pino-Ortega et al., 2022). When comparing LPS results with a criterion measure (e.g., timing gates, trundle wheel, retroreflective-marker-based systems) within sport specific courses (i.e., soccer, hockey, basketball), it results to be accurate enough for time-motion analysis (i.e., roughly 3.5% difference from a reference measure)(Leser et al., 2014), although limitations occur when measuring changes of direction or sudden variations in speed and acceleration (Linke et al., 2018; Pino-Ortega et al., 2022).

In comparison to GPS, LPS might over- (i.e., Peak Speed, Distance >14.4 km/h, Total Distance) and under-estimate (i.e., Accelerations) metrics in an outdoor real-life scenario (i.e., on the field, for training or competition purposes) and for different pitch sizes (Buchheit, Allen, et al., 2014). Latest investigation also showed that the LPS had more noise than the GPS technologies, especially when estimating higher velocities movements (Hoppe et al., 2018). Hence, caution is required when comparing training and match activities measured by different systems (Buchheit, Allen, et al., 2014; Pons et al., 2021).

2.2.2 Non-wearable - Video tracking (VT)

Along with GPS and LPS, monitoring of team sport players can also be achieved through the so-called optical tracking systems (OTS) or video tracking systems, a semi-automatic multi-camera optic-based system that includes multiple cameras and computer vision–based technologies (Figueroa et al., 2006; Rico-González, Pino-Ortega, et al., 2020a). The cameras are fixed throughout the match and each of them covers a part of the court, in order that together they cover the complete play area. The cameras are calibrated with respect to the court dimensions while image processing algorithms present spatial-positioning variables of players data through a Cartesian system (X, Y coordinates) at a sampling rate between 10 and 30 Hz (Rico-González, Pino-Ortega, et al., 2020b). Comparing to GPS and LPS, video-tracking is a non-invasive instrument to track players' positioning since it does not require players to wear transponders during the monitoring. On the other hand, installation difficulties (i.e., the installation of multiple high-definition cameras around the field can be restricted by its infrastructure) on training pitches on behalf of official match stadiums restricted the assessment of the training process (Linke et al., 2018). Moreover, VT requires proper lighting conditions as well as an experienced analyst to control occlusion between players, to recover the tracking process, and to code the technical and tactical activities (e.g., passes, duels, shots, offsides, fouls, corners, etc.) that occur during the game (Castellano et al., 2014; Hoppe et al., 2018).

Time-motion analysis (i.e., the movement of an athlete over a period of training or match play) by the means of VT spread around the 2000s and it was the most used positioning system until 2014, after which GPS became more frequently used, aided by the fact that FIFA (i.e., Federation Internationale de Football Association) started to permit the use of GPS and LPS in competitive matches (Rico-González, Pino-Ortega, et al., 2020b). Analysis of spatiotemporal measurement accuracy of VT systems under field conditions (in soccer) found position errors (mean absolute errors) ranging from 7 to 56 cm against a criterion reference (Linke et al., 2018, 2020).

On the other hand, deviations from the criterion measure tend to significantly increase when estimating high-intensity performance indicators (i.e., peak acceleration and deceleration), due to raw data smoothing decisions, as well as to the environmental contingencies (e.g., consistency of weather and lighting conditions) (Linke et al., 2018, 2020). However, VT represents a valid instrument to be used both in indoor (i.e., basketball, futsal, hockey, or in aquatic sports such as water polo) and in outdoor sports (i.e., field hockey, soccer, rugby, football) (Linke et al., 2020; Maalej et al., 2011; Plestina et al., 2020; Rico-González, Pino-Ortega, et al., 2020b; Sampaio et al., 2015). In fact, VT was used in soccer to determine players' physical profiles in relation to player position within the research field of time-motion analysis (Castellano et al., 2014). Starting from a reductionist approach where only physical variables (e.g., total distance, high- and very high-intensity running) were explored, time-motion analysis moved to a more complex and dynamic analysis including contextual factors such as match status, match location, opponent level, percentage ball possession, and team formation (Castellano et al., 2014).

In addition to time-motion analysis, VT allows to store and use video recording for notational analysis purposes (i.e., recording events in an accurate and objective record of what actually took place) (Carling, Williams, & Reilly, 2005) as well as to automatically recognize players and their interaction such as passing and interceptions in the field of human motion tracking (Chen et al., 2012; Yoon et al., 2019). Moreover, almost-real-time ball tracking allows different types of shots (i.e., serve, bump, set) played in a single volleyball game sequence to be correctly identified (Chakraborty

& Meher, 2012). Finally, experiments extracting high-level semantic knowledge (i.e., the technical and tactical meaning of the players' movements and actions within a game action) from motion tracking in sports (e.g., detecting an event starting from when a player is ready to shoot from the free-throw line to when the ball goes in the box and land is a free-throw event in a basketball game video) show that different shooting items or player actions in basketball games video footages can be accurately identified (Du et al., 2021). Although this research is in its infancy, its application can add valuable information to coaches and players on "when" and "where" an action (e.g., a shot) is appropriate to be done (Li et al., 2022).

2.3 Practical applications

2.3.1 Paper #5

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Human Kinetics
ORIGINAL INVESTIGATION

Effects of Presession Well-Being Perception on Internal Training Load in Female Volleyball Players

Alexandru Nicolae Ungureanu, Paolo Riccardo Brustio, Gennaro Boccia, Alberto Rainoldi, and Corrado Lupo

Purpose: To evaluate if the internal training load (ITL; Edwards heart rate [HR]-based and session-rating of perceived exertion [RPE] methods) is affected by the presession well-being perception, age, and position in elite (ie, Serie A2) female volleyball training. ***Methods:*** Twelve female elite volleyball players (age: 22 [4] y, height: 1.80 [0.06] m, body mass: 74.1 [4.3] kg) were monitored using an HR monitor during 32 team training sessions (duration: 1:36:12 [0:22:24], in h:min:s). Linear mixed-effects models were applied to evaluate if well-being perception (ie, perceived sleep quality/disorders, stress level, fatigue, and delayed-onset muscle soreness) may affect ITL depending on age and tactical position. ***Results:*** Presession perceived fatigue influenced ITL according to the session-RPE ($P = .032$) but not according to the Edwards method. Age was inversely correlated to the Edwards method ($P < .001$) and directly correlated to the session-RPE ($P = .027$). Finally, central blockers experienced a higher training load than hitters ($P < .001$) and liberos ($P < .001$) for the Edwards method, as well as higher than hitters ($P < .001$), liberos ($P = .003$), and setters ($P = .008$) for session-RPE. ***Conclusions:*** Findings indicated that female volleyball players' perceived ITL is influenced by presession well-being status, age, and position. Therefore, coaches can benefit from this information to specifically predict players' ITL in relation to their individual characteristics.

Keywords: women's volleyball, perceived exertion, team sports, heart-rate monitoring, Hooper index

To elicit peak performance in sports, training programs should be carefully developed to produce the desired physiological adaptations. In particular, physical internal training load (ITL) is one of the parameters that is controlled to elicit the desired workout response. As a consequence, ITL can be considered as the psychophysiological response to the external training load and can be used as the primary outcome when monitoring athletes.[1]

Rate of perceived exertion (RPE) and the session-RPE (ie, the duration of training session multiplied for RPE) have been proven to be accurate, valid, simple, and inexpensive tools to quantify ITL in team sports.[1–4] In particular, the CR-10 Borg scale modified by Foster has been commonly used to measure RPE in sports,[5] whereas the Edwards heart rate (HR)-based method resulted in being the most adopted reference criterion.[3,6]

Although ITL has been extensively studied in invasion team sports (eg, soccer,[1] American football,[7] and basketball[6]), it has been less considered in net team sports, such as volleyball.[8,9] Due to its intermittent nature, volleyball is characterized by short duration and high-intensity and explosive efforts.[10–12] From a technical and tactical point of view and compared with the males' performance, female volleyball players used to perform less efficient receptions, less powerful attacks, and longer rallies. Moreover, female performance has a higher occurrence of digs, less jump serves, more jump float, and float serves with respect to the men's counterpart.[13] These characteristics would require an ecological quantification of the ITL. In this scenario, session-RPE was used to describe and analyze the distribution of ITL throughout the whole training season, on a daily and a weekly basis, in preparatory, regular, and congested weeks, to provide essential information about the planning and organization of training sessions.[14] Session-RPE was also demonstrated to be a valuable method for monitoring ITL in both genders and different competition levels (ie, amateur and elite) in net team sports, such as beach volleyball.[9] Nevertheless, differences in relationship between session-RPE and Edwards HR-based method emerged in relation to types of training sessions.[3,9] Specifically, very large correlations have been reported for conditioning training in beach volleyball[9] and youth basketball,[3] while different scenarios emerged for the technical and tactical training sessions. In fact, for these last types of training sessions, strong correlation occurred only in basketball,[3] whereas they were only moderate in beach volleyball.[9] However, regardless of specific differences for types of training sessions, genders, and competition levels, session-RPE and the Edwards HR-based method were highly correlated for monitoring ITL in team sport.[1–3,6,9]

Even if the RPE score is mainly linked to physiological variables, such as HR, ventilation, respiratory rate, oxygen uptake, and blood lactate concentrations,[15] psychological factors also appear to be correlated. Indeed, impaired psychological well-being factors (ie, stress, anxiety, and emotional response) can negatively affect readiness to train and perform in competition,[16] or influence acute neuromuscular performance and hormonal concentration in elite female volleyball players.[17] Nevertheless, controversial results emerged for the relationship between session-RPE and well-being scores (ie, Hooper index [HI]) or delayed onset muscle soreness (DOMS).[18] In fact, despite the ITL quantified with the session-RPE method related to perceived presession muscle soreness both in American football[7] and soccer players,[19] for the latter sample of athletes, only partial relationships with the well-being scores (ie, stress, sleep, and fatigue factors) emerged,[19] especially during the weeks when 2 official matches were played. Yet no effect of the HI variations on RPE during a 10-minute submaximal exercise training session was highlighted.[20]

The authors are with the Neuromuscular Function Research Group, School of Exercise & Sport Sciences (SUISM), Dept of Medical Sciences, University of Turin, Turin, Italy. Lupo (corrado.lupo@unito.it) is corresponding author.

In volleyball, age was reported to influence technical execution and tactical efficacy[21] on the one hand and mood state on the other hand.[11] In fact, despite that mood state was reported to be relatively stable regardless of changes in ITL, it appears to be affected by the experience of the athletes with a higher total mood disturbance in the younger players.[11] In professional male players, moderate-to-strong relationships occurred between HI and acute and chronic training load, especially in the second third of the season.[8] In particular, poor sleep, stress, perceived fatigue, and DOMS were reported to be highly correlated to RPE, although no internal or external training load quantification was assessed in terms of HR, accelerometer-based metrics, or tactical positions. However, to our knowledge, no study has investigated the relationship between well-being and training load on female volleyball players. In addition, differences in the playing demands, physical load, and player's characteristics between positions[12,22] need to be taken into account when analyzing ITL in volleyball. Thus, the aim of this study was to evaluate if the perceived training load (ie, Edwards values and session-RPE) can be affected by the presession well-being perception in elite (ie, Serie A2) volleyball players, in relation to different ages and position roles.

Methods

Subjects

A convenience sample of 12 female elite volleyball players (mean [SD]; age: 22 [4] y, height: 1.80 [0.06] m, body mass: 74.1 [4.3] kg), members of a team competing in the 2019–2020 Italian Serie A2 (ie, the second National Senior Division) volleyball championship, participated in this study. The inclusion criteria for participating in this study were as follows: (1) at least 8 years of volleyball training experience; (2) at least 2 previous years of volleyball training experience consisting in a minimum of 4 to a maximum of 7 weekly training sessions for 90 to 180 minutes; and (3) players should have participated in more than 80% of the weekly training sessions. The players were classified in relation to the following tactical roles as hitters (n = 3), liberos (n = 2), central blockers (n = 3), opposites (n = 2), and setters (n = 2). Before the data collection, the institutional review board of the University of Turin approved this study, and an informed consent regarding the potential risks and benefits associated with participation has been signed by each participant in the study.

Design

An ecological longitudinal approach (ie, the training was exclusively planned by the technical staff of the team and it was never influenced by the researchers) was adopted to collect data during in-season sessions. Each training week included 5 to 6 field-training and 2 weight-training sessions. The typical organization of the training week is represented in Figure 1. The players were monitored over 16 weeks, including 32 training sessions from October 2019 to February 2020. To avoid the technical error of measurement, the adopted RPE and well-being scales were familiarized by players for 2 weeks (before the data collection) under the researchers' supervision. All the answers of RPE and well-being scales were recorded individually and collected by the same researcher.

Methodology

Well-Being. Hooper's index is widely used in volleyball[8,14] to self-report the well-being status. Approximately 20 minutes before each training session, each player was asked to rate her perceived sleep quality, stress level, fatigue, and DOMS.[18] The sum of these 4 subjective ratings, using a scale ranging from a minimum of 1 (very very low-or-good) to a maximum of 7 (very very high-or-bad), allows detecting individual well-being status before performing the training session.

Internal Training Load. The HR response was recorded every 1 second using Polar H10 (Polar Electro Oy, Kempele, Finland). HR monitors with transmitter belts placed on players' chest bands and connected to a wireless mobile tablet (I-pad Air 1; Apple, Infinite Loop, Cupertino, CA) by means of a Bluetooth connection. According to Lupo et al[2] the Edwards HR-based method[23] has been considered as a reference criterion to verify the validity of the session-RPE to quantify ITL during the sessions. Specifically, in the Edwards HR method, individual ITLs were obtained by expressing the players' HR responses as percentages of their estimated maximal HR (ie, $HR_{max} = 220 - \text{age}$), multiplying the accumulated time (ie, in minutes) in 5 HR zones of individual HR_{max} for the corresponding coefficient (ie, 50%–60% = 1; 60%–70% = 2; 70%–80% = 3; 80%–90% = 4; 90%–100% = 5) and then summing the 5 scores.

The CR-10 Borg scale modified by Foster et al[5] was used to monitor the RPE of the players after each training session. In particular, the RPE scores were recorded approximately 20 minutes after each session, in response to the question "how was your workout?" The scale varied between 0 (rest) and 10 (maximal), and it was applied individually in each training session. According to Foster et al,[5] players' session-RPE values were obtained by multiplying each player's RPE value for the corresponding total session duration (expressed in minutes).

Statistical Analysis

Descriptive data (means and 95% confidence interval [CI]) of the players' well-being and ITLs (ie, session-RPE and Edwards

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Morning	**Rest**	**Gym**	**Technical exercises** Low volume Low intensity	**Rest**	**Gym**	**Tactical full squad (6v6)** Low volume Low intensity	**Game**
Afternoon	**Rest**	**Technical exercises** Low volume Low intensity	**Tactical full squad (6v6)*** High volume High intensity	**Tactical full squad (6v6)*** High volume High intensity	**Tactical full squad (6v6)** Low volume Low intensity	**Rest**	

Figure 1 — Typical organization of the training week during the competitive season. *Internal training load, both subjective (rating of perceived exertion) and objective (heart rate), and well-being status monitoring.

methods) were reported in relation to the players' tactical position. Successively, a series of linear mixed-effects model (LMM) was applied to determine the relationship between well-being and ITLs (ie, Edwards ITL and session-RPE). As younger players were reported to be more susceptible to mood disturbance in volleyball,[11] age was added as a fixed effect in the analysis. Specifically, an LMM was performed using RPE score as dependent variable, with Edwards ITL scores, position, and age as fixed effects. Two other LMMs were performed using ITL Edwards and session-RPE scores as dependent variables, respectively, while the fixed effects were presession well-being (i.e., sleep quality/disorders, stress level, perceived fatigue, and DOMS), position, and age. In all LMMs, to account for error in repeated measures, players and sessions were considered as nested (subject in session) random effects. In case of significance for the 5 position groups, post hoc pairwise comparisons were performed using the Tukey correction. Linear models with and without position and age as fixed effects were compared with each other using the Bayesian information criteria, determining the model with the lowest Bayesian information criteria score as "parsimonious."[24] Cohen d effect sizes were calculated to describe the practical meaningfulness of the differences in mean values.[25] The level of significance was set at 5% ($P < .05$). All data were analyzed using the R statistical package (version 3.5.2; R Core Team, Foundation for Statistical Computing, Vienna, Austria)[26] with the packages "lme4"[27] and "emmeans."[28]

Results

A total of 290 individual training sessions (mean session duration = 1:36:12 [0:22:24], in h:min:s) were monitored within 32 team training sessions. The overall descriptive results (mean and 95% CI) about the HI (ie, sleep quality/disorders, stress level, perceived fatigue, DOMS, and the session-RPE) are reported in Table 1.

Edwards score ($\beta = 0.006$; 95% CI, 0.001 to 0.009; SE = 0.002; t ratio = 2.75; $P = .006$; $d = 0.16$) significantly predicted the RPE score.

Perceived fatigue index ($\beta = 32.97$; 95% CI, 2.75 to 63.33; SE = 15.30; t ratio = 2.15; $P = .032$; $d = 0.13$) and age ($\beta = 5.77$; 95% CI, 0.66 to 10.89; SE = 2.59; t ratio = 2.22; $P = .027$; $d = 0.13$) significantly predicted session-RPE. Moreover, significant differences between positions were observed ($F = 4.13$; $P = .027$). Central blockers showed higher session-RPE compared with the liberos (estimate mean difference = 102.62; 95% CI, 5.18 to 200.20; $P = .033$; $d = 0.17$) and hitters (estimate mean difference = 86.91; 95% CI, 15.07 to 158.80; $P = .008$; $d = 0.19$). Yet, no difference was observed between the other roles (all Ps > .05).

Only age significantly predicted Edwards score ($\beta = -4.04$; 95% CI, −5.69 to 2.38; SE = 0.83; t ratio = −4.81; $P < .001$; $d = -0.28$) and session-RPE ($\beta = 5.77$; 95% CI, 0.66 to 10.89; SE = 2.59; t ratio = 2.22; $P = .027$; $d = 0.13$). Moreover, significant differences between positions were observed ($F = 10.5036$; $P < .001$). Central blockers showed higher Edwards scores compared with the liberos (estimate mean difference = 38.85; 95% CI, 7.41 to 70.29; $P = .007$; $d = 0.2$) and hitters (estimate mean difference = 41.84; 95% CI, 18.64 to 65.04; $P < .001$; $d = 0.29$). Moreover, liberos showed a lower score compared with the setter (estimate mean difference = 41.80; 95% CI, −75.29 to −8.30; $P = .006$; $d = -0.2$). On the contrary, no difference was observed between the other roles (all Ps > .05). An overview of LMM outputs for Edwards and session-RPE is reported in Table 2, whereas the values regarding the 2 observed methods in relation to each position's roles are shown in Figure 2.

Discussion

As ITL is considered a complex psychophysiological response to both the external training load and the well-being state, the aim of this study was to assess the association between the presession well-being and the athletes' ITL (ie, Edwards values and session-RPE) in elite female volleyball players. The main finding of this study was that the presession perceived fatigue influenced ITL only according to session-RPE but not according to the Edwards method.

Owing to the peculiarities of volleyball, results in this study should be considered specifically for senior female volleyball. Consequently, because in this study, only perceived fatigue influenced session-RPE ITL, it may specifically contribute toward players' response to the training stimulus more than sleep quality, stress, and DOMS. However, this is partially in contrast to previous studies that reported muscle soreness on the one hand, and perceived stress, sleep quality, and fatigue on the other hand, which are associated with ITL in American football[7] and soccer,[19] respectively.

Nevertheless, in this study, well-being perception was related to the perceived (ie, session-RPE) but not to the HR-based ITL (ie, Edwards). In association with the trivial relationship ($d = 0.16$) found between session-RPE and Edwards scores, it may be suggested that HR-based ITL could not be fully considered as a "gold standard" in net sports, such as volleyball. In fact, aerobic metabolism is relevant in volleyball to restore the energy consumed during repeated explosive anaerobic efforts, such as attacks, blocks, and defense actions.[12,29] In this scenario, HR-based ITL, apart from perceived exertion, could be characterized by limitations when properly evaluating in short but maximal anaerobic efforts.

Similar to the mood states reported in male volleyball,[11] players' perceptions are influenced by age. In fact, in our study, this variable resulted negatively and positively correlated to Edwards and session-RPE ITL, respectively. In particular, older

Table 1 Descriptive Statistics (Mean; 95% CI) of Well-Being and ITL (ie, Edwards and Session-RPE) Parameters According to Position

	Well-being					ITL	
Position	Sleep quality	Stress	Fatigue	DOMS	Hooper's index	Edwards	Session-RPE
Hitters	3.1; 3 to 3.3	3.3; 3.1 to 3.5	3.6; 3.5 to 3.8	3.8; 3.6 to 4	13.8; 13.3 to 14.3	172; 161 to 184	402; 360 to 445
Liberos	3.2; 2.8 to 3.6	3.5; 3.2 to 3.9	4; 3.7 to 4.3	4.8; 4.4 to 5.2	15.6; 14.6 to 16.5	180; 165 to 196	313; 267 to 359
Central blockers	3.4; 3.2 to 3.7	3.7; 3.4 to 3.9	4.3; 4.1 to 4.6	4.6; 4.3 to 4.8	15.9; 15.2 to 16.7	207; 193 to 221	534; 468 to 601
Opposites	3.1; 2.8 to 3.4	3.9; 3.6 to 4.2	3.9; 3.6 to 4.2	4.4; 4.1 to 4.7	15.3; 14.4 to 16.3	206; 190 to 221	463; 395 to 531
Setters	3.8; 3.6 to 4.0	3.6; 3.4 to 3.8	3.8; 3.6 to 4	3.8; 3.5 to 4.1	15.0; 14.4 to 15.5	233; 206 to 261	351; 315 to 388

Abbreviations: CI, confidence interval; DOMS, delayed-onset muscle soreness; ITL, internal training load; RPE, rating of perceived exertion.

Table 2 Outcomes of Linear Mixed-Effects Models (β) Applied for Well-Being Parameters, Age, and Position (Compared With the Central Blockers) in Relation to the 2 Internal-Training-Load Methods (ie, Edwards and Session-RPE)

	Edwards			Session-RPE		
Parameter	β	**SE**	***P***	β	**SE**	***P***
Well-being						
Sleep quality, AU	2.30	3.71	.534	0.11	11.53	.991
Stress, AU	1.57	3.67	.667	14.56	11.39	.202
Fatigue, AU	−5.01	4.89	.306	32.96	15.30	.032*
DOMS, AU	−0.49	3.28	.880	10.58	10.23	.302
Age	−4.04	0.83	<.001***	5.77	2.59	.027*
Position						
Hitters	−41.83	8.27	<.001***	−86.91	25.68	<.001***
Liberos	−38.84	11.23	<.001***	−102.67	34.86	.003**
Opposites	−14.99	9.05	.099	−35.22	28.04	.21
Setters	2.94	10.89	.786	−89.32	33.75	.008**

Abbreviations: AU, arbitrary units; DOMS, delayed-onset muscle soreness; RPE, rating of perceived exertion; SE, standard error.
$^*P \leq .05$, $^{**}P \leq .01$, $^{***}P \leq .001$.

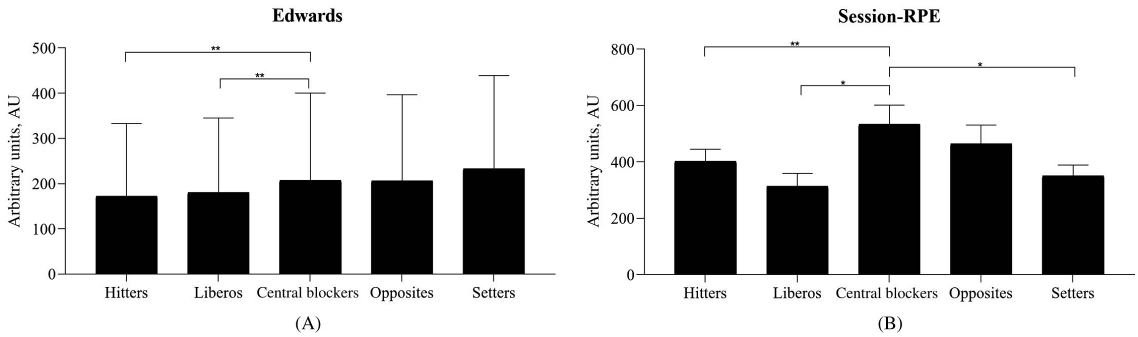

Figure 2 — Differences regarding the 2 observed methods (Edwards and session-RPE) in relation to each position role ($^*P \leq .01$; $^{**}P \leq .001$). RPE indicates rating of perceived exertion.

players have perceived training to be harder than the younger players, despite the HR-based ITL seems to report the opposite scenario. In fact, for the observed training sessions, in which real competition was simulated, it could be speculated that the lower mean HR intensity reported by the older players is associated with a lower ability in coping with the intensity level required by the coaches, thus confirming the finding of a previous study for which high-intensity and short-duration exertion may not be directly related to the enhancement of the Edwards ITLs.[30] Consequently, in this training scenario, coaches should take age into account when monitoring both objective and subjective ITLs.

According to the specialized fitness and morphological qualities associated with the different playing positions,[22] effects for ITL (ie, Edwards values and session-RPE) related to different positions were also expected. The results of this study reported that central blockers experienced both a higher Edwards ITL than hitters and liberos, and a higher session-RPE level than hitters, liberos, and setters. These differences may be due to the higher involvement of the central blockers during the defensive phase. In fact, according to Araújo et al,[31] male central blockers are involved in almost all blocking systems (ie, man-to-man and zone blocking) with relevant implication for the process of training. Considering blocking as a fundamental skill, with more blocks and fewer blocking errors related to success in elite-level competition,[13] the massive involvement of the central blockers during the training sessions could explain their higher ITL experienced in this study.

However, this study can also been characterized by some limitations. According to the coaches perspective, only the collective (ie, full team and 6v6) training sessions were monitored because they were considered as the most valid representation of the performance during the in-season period. Nevertheless, the other training sessions were didactic, exclusively focused on technical and/or tactical skills, and characterized by low training loads. Thus, they should not have caused any significant effect on the ITL of the analyzed sessions. In addition, despite that strength and conditioning sessions were regularly performed during the season, ITL was not assessed in this study. Therefore, future studies on ITL should define the validity of the experimental approach by providing mixed-effects models able to consider external load (eg, number of jumps), other types of training (ie, technical and strength and conditioning), and training load effects occurring the day after the well-being status recording.

Practical Applications

Coaches should be aware of the importance of well-being status on the perceived exertion in effectively monitoring training in female volleyball players. In fact, presession perceived fatigue should be constantly monitored, despite no relation existing with the Edwards ITL method. Assessing it before the training session could be important to determine if players will be able to effectively perform the training session and benefit from planned training stimuli.

Although it is complicated to propose different intensities for each position during the full squad training (ie, tactical training), coaches should be aware that central blockers experience higher loads than the other players. Therefore, coaches could adopt different substitution strategies during games and training sessions to manage intensity for the central blockers. In addition, physical coaches could also manage loads during strength and conditioning training to better prepare central blockers to cope with the game demands. Practically, they could project repeated-effort training sessions incorporating block jumps, spike jumps, fake spike jumps, and multidirectional court movements. High-intensity exercises, followed by brief rest periods or low-intensity activity, could develop glycolytic metabolic and creatine phosphate pathways for women volleyball players.[32]

Conclusions

This study showed that the presession well-being perception can affect the ITL in senior female volleyball. However, this relationship was verified only between the presession perceived fatigue and the perceived ITL (ie, session-RPE). In addition, older players have been shown to perceive training harder than the younger players, with their HR responses lower than younger counterparts, even suggesting a lower ability in coping with the intensity requested by coaches. Finally, differences in both objective (ie, Edwards HR method) and subjective (ie, session-RPE) ITL were reported for players related to specific tactical roles, highlighting that central blockers experienced higher ITL than hitters, liberos, and setters.

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2.3.2 Paper #6

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Human Kinetics
ORIGINAL INVESTIGATION

Internal Training Load Affects Day-After-Pretraining Perceived Fatigue in Female Volleyball Players

Alexandru Nicolae Ungureanu, Corrado Lupo, Gennaro Boccia, and Paolo Riccardo Brustio

Purpose: The primary aim of this study was to evaluate whether the internal (session rating of perceived exertion [sRPE] and Edwards heart-rate-based method) and external training load (jumps) affect the presession well-being perception on the day after (ie, +22 h), according to age and tactical position, in elite (ie, Serie A2) female volleyball training. ***Methods:*** Ten female elite volleyball players (age = 23 [4] y, height = 1.82 [0.04] m, body mass = 73.2 [4.9] kg) had their heart rate monitored during 13 team (115 individual) training sessions (duration: 101 [8] min). Mixed-effect models were applied to evaluate whether sRPE, Edwards method, and jumps were correlated ($P \le .05$) to Hooper index factors (ie, perceived sleep quality/disorders, stress level, fatigue, and delayed-onset muscle soreness) in relation to age and tactical position (ie, hitters, central blockers, opposites, and setters). ***Results:*** The results showed a direct relationship between sRPE ($P < .001$) and presession well-being perception 22 hours apart, whereas the relationship was the inverse for Edwards method internal training load. Age, as well as the performed jumps, did not affect the well-being perception of the day after. Finally, central blockers experienced a higher delayed-onset muscle soreness than hitters ($P = .003$). ***Conclusions:*** Findings indicated that female volleyball players' internal training load influences the pretraining well-being status on the day after (+ 22 h). Therefore, coaches can benefit from this information to accurately implement periodization in a short-term perspective and to properly adopt recovery strategies in relation to the players' well-being status.

Keywords: women's volleyball, perceived exertion, Edwards method, heart rate, Hooper index

Manipulating and monitoring training parameters is fundamental to elicit peak sports performance and to avoid overtraining.[1] Associations between internal and external measures of training load (TL) and intensity are important in understanding the dose–response nature of team-sport training and competition.[2] For this purpose, training programs should be developed taking into account several variables like external (ie, sprints, distance, impacts, and jumps) and internal (ie, rate of perceived exertion [RPE], heart rate [HR], hormonal, and metabolic responses) TL and well-being indexes (ie, sleep quality, stress, perceived fatigue, and muscular soreness),[1] as well as their interactions.

Volleyball external TL (ETL) consists mainly of jumps, hits, and multidirectional movements.[3,4] In particular, different types of jumps are involved in scoring points (eg, spike, block, and serve) and represent an important key component for success. Nevertheless, jump load can vary in relation to different tactical positions, type of macrocycle and microcycle phase, and along the season.[3,4] On average, central blocker players can achieve about 80 jumps during a training session, followed by opposites, hitters, and setters.[3] In addition, regardless of quantity, jumping characteristics (ie, type of jump) can also vary in relation to position roles. In fact, central blockers on one side, and hitters and opposites on the other, perform maximal jumps more frequently in defense (ie, blocking close to the net) and in attack (ie, spikes), respectively, while setters are involved in almost every rally to set the ball while jumping, but their jump load is considered as a submaximal effort.[5] Considering differences in ETL (ie, total jumps performed during a training session) between tactical positions, total jumps may affect internal TL (ITL), recovery, and well-being.

The ITL in team sports is extensively quantified by the means of RPE and session-RPE (sRPE; ie, the duration of training session multiplied for RPE) as they are considered accurate, valid, simple, and inexpensive tools.[6–8] In particular, the category-ratio 10 Borg scale modified by Foster has commonly been used to measure RPE in sports,[9] whereas the Edwards HR-based[10] method was the most adopted reference criterion.[7,11] sRPE was also demonstrated to be a valuable method for monitoring ITL in both genders and different competition levels (ie, amateur and elite) in net team sports,[12] despite the fact that its validity varied in relation to types of training sessions.[7,12] Volleyball, as well as other team sports (eg, rugby, soccer, tennis, American football), would require a real context-based training quantification of the ITL because of its intermittent nature, characterized by short duration, and high intensity and explosive efforts.[4,13,14] For this purpose, sRPE was used to describe and analyze the distribution of ITL throughout the whole training season, on a daily and a weekly basis to provide essential information about the planning and organization of training sessions.[15]

Along with the objective ETL and ITL parameters, subjective well-being status was also described to provide information about the players' performance in team sports. However, the relationship between self-assessed well-being and workload is controversial. Moderate to strong evidence of improved well-being with an acute increase in TL, as well as evidence of impaired well-being with ongoing training were reported.[16] In particular, presession well-being status was reported to affect Australian football players' ETL,[17] as well as soccer players'[18] and female volleyball players' ITL.[19] Specifically, players' well-being status was described as altered by the type of competitive weeks. In fact, in congested compared with regular training weeks, a similar or higher alteration of players' well-being occurred, despite the TL reduction.[15] Thus,

The authors are with the NeuroMuscular Function Research Group, Dept of Medical Sciences, and Boccia, also the Dept. of Clinical and Biological Sciences, School of Exercise & Sport Sciences (SUISM), University of Turin, Turin, Italy. Lupo (corrado.lupo@unito.it) is corresponding author.

the accumulation of the games significantly decreased sleep quality, and significantly increased stress and perceived fatigue several days a week.[15] During the season, poor sleep, stress, perceived fatigue, and delayed onset muscular soreness (DOMS) were reported to be highly correlated to ITL.[20] In addition, acute load may cause more well-being variations than chronic load or training monotony (within-week loading fluctuations).[20]

However, to the best of our knowledge, no study provided information about the influence of the ETL and ITL on the well-being status in the days after the training. The use of this approach would help to set realistic expectations about fatigue and recovery in the days after training sessions, especially in elite volleyball players who usually train once or twice per day.[19,21] This knowledge may be an indicator of current players' health status and provide a simple screening approach to identify whether players could benefit from specific intervention, which aims to improve exercise intensity (for technical drills included) and minimize psychological stress and risk of injuries at the same time.[22]

Furthermore, as senior team rosters include players of different ages, TL programs and recovery potential might be slightly different among the players. As fatigue resistance and mood disturbance undergo a gradual decline from childhood to adulthood, especially during high-intensity intermittent exercise,[14,23,24] age could have an effect on the recovery process.

To our knowledge, no study investigated the effects of acute TL on well-being in female volleyball players. In addition, differences in the playing demands, physical load, and players' characteristics across tactical positions[4,25] need to be taken into account when analyzing ITL in volleyball. Thus, the aim of this study was to evaluate whether the internal (ie, Edwards values and sRPE) and external (ie, jumps) TL can affect the day after presession well-being perception in elite (ie, Serie A2) female volleyball players, in relation to different ages and position roles.

Methods

Subjects

Ten female elite volleyball players (mean [SD]; age = 23 [4] y, height = 1.82 [0.04] m, body mass = 73.2 [4.9] kg), were recruited from a Serie A2 Italian club (second national senior division). For the purpose of the study, hitters (n = 3), central blockers (n = 3), opposites (n = 2), and setters (n = 2) were included in this study. No libero has been recruited. The inclusion criteria consisted of players having (1) at least 8 years of volleyball training experience, (2) at least 2 previous years of volleyball training experience consisting of a minimum of four to a maximum of seven 90- to 180-minute weekly training sessions, and (3) participated in the 2 consecutive (ie, 24 h apart) training sessions during the training weeks analyzed in this study. Before data collection, the institutional review board of the University of Turin approved this study, and each participant signed an informed consent regarding the potential risks and benefits associated with participation.

Design

A real context-based training longitudinal approach (ie, the training was exclusively planned by the technical staff of the team and never influenced by the researchers) was adopted to collect data during in-season sessions. Based on the plan indicated by the coaching staff, each training week included 5 to 6 on-court training sessions (starting on Monday and ending on Sunday with a weekly game), with at least 1 high-intensity game-specific (ie, full team, 6v6) training session, typically scheduled on Wednesday. The organization of the experimental design is represented in Figure 1. Briefly, players' TL was evaluated during (ie, HR, video recording) and post session (ie, sRPE) on Wednesday, while well-being presession (ie, Hooper index) was evaluated on Thursday (ie, 22 h apart). The players were monitored during 13 game-specific training sessions over 16 weeks from October 2019 to February 2020, collecting 115 individual values. Players who participated in only to 1 of the 2 training sessions because of contingent events (ie, sickness, injuries, separate training) were excluded from the analysis within that specific week.

Before beginning the study, the subjects completed 2 weeks of familiarization sessions with the RPE scale and the Hooper questionnaire under the researchers' supervision. All the RPE and Hooper questionnaire answers were recorded individually and collected by the same researcher.

Methodology

External TL. Integral training video recordings were performed by means of a handycam (Canon Legria HF R46 camera; Canon Inc, Tokyo, Japan) placed on the middle side of the court at least 5m height. Video recordings were saved as.mp4 files and stored in a Google Drive private cloud. After training, 6 observers analyzed and recorded each player's jumps by means of the freely available

Figure 1 — Organization of the experimental design during the competitive season. HR indicates heart rate; ITL, internal training load; RPE, rating of perceived exertion; sRPE; session RPE.

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VLC media player (version 3.0.12, GNU GPL2 licensed software, France). A jump was recorded when both feet were off the ground, regardless of the intensity of the jump and the type of skill performed (eg, serving, passing, blocking).[3] One training session was randomly selected, and the intraclass correlation coefficient was computed to assess the agreement between the 6 observers. There was a good absolute agreement between the 6 observers using the 2-way mixed effects model and "average rater" unit,[26] $\kappa = .9$ ($F_{3,15} = 10.00$; $P < .001$). No differences were found ($P > .05$) between observers, and the mean coefficient of variation was 5.6%.

Internal TL. The HR was recorded every 1 second using a HR sensor (Polar H10; Polar Electro Oy, Kempele, Finland) with transmitter belts placed on players' chest band and connected to a wireless mobile tablet (I-pad Air 1; Apple, Infinite Loop, Cupertino, CA). The Edwards HR-based method[10] has been considered as reference criterion to quantify ITL during the sessions. Specifically, in the Edwards HR method, individual ITLs were obtained by expressing the players' HR responses as percentages of their estimated maximal HR (ie, HR_{max}; 220 – age), by multiplying the accumulated time (ie, in minutes) in 5 HR zones of individual HR_{max} for the corresponding coefficient (ie, 50.1%–60% = 1; 60.1%–70% = 2; 70.1%–80% = 3; 80.1%–90% = 4; higher than 90% = 5), and then by adding the 5 scores.

The category-ratio 10 Borg scale modified by Foster et al[9] was used to monitor the RPE of the players after each training session. In particular, the RPE scores of the session were recorded via paper and pencil version approximately 20 minutes after each session, in response to the question "How was your workout?" The scale varied between 0 (rest) and 10 (maximal), and it was applied individually in each training session. According to Foster et al,[9] players' sRPE values were obtained by multiplying each player's RPE value of the session for the corresponding total session duration (expressed in minutes). Training session duration was considered from the specific warm-up with ball (ie, generic mobility warm-up without the ball was excluded) to the last workout of the session (ie, generic cooldown was excluded).

Well-Being. Hooper index was widely used in volleyball[15,20] to self-report the well-being status. Approximately 20 minutes before each training session, each player was asked to rate her perceived sleep quality, stress level, fatigue, and DOMS,[27] via paper and pencil version. Both singular items (ie, sleep quality, stress, fatigue, DOMS) and their sum (ie, Hooper index), rated using a scale ranging from a minimum of 1 ("very very low-or-good") to a maximum of 7 ("very very high-or-bad"), allows detection of individual well-being status before performing each training session.

Statistical Analysis

Descriptive data (means and 95% confidence interval [CI]) of the players' well-being and TLs (ie, sRPE, Edwards score, and jumps) were reported in relation to the players' tactical position. Successively, a series of linear mixed-effects models were applied to determine the association between ITLs (ie, Edwards ITL, sRPE), ETL (ie, jumps), and well-being (ie, Hooper index). As younger players were reported to be more susceptible to mood disturbance in volleyball,[14] age was added as a fixed effect in the analysis. Specifically, 5 separate linear mixed models (LMM) using sleep quality/disorders, stress, fatigue, DOMS, and Hooper index total score as dependent variables, respectively, were performed. sRPE, Edwards scores, jumps, players' position, and age were included as fixed effects. To account for error for repeated measures, players were considered as random effects in all LMM. In case of significance for the 4 position groups, post hoc pairwise comparisons were performed using the Tukey correction. The level of significance was set at 5% ($P < .05$). Cohen d effect sizes (d) were calculated to describe the practical meaningfulness of the differences in mean values. The absolute d value was evaluated according to the following thresholds: < 0.2 = trivial, 0.2 to 0.6 = small, 0.7 to 1.2 = moderate, 1.3 to 2.0 = large, and > 2.0 = very large.[28] The variance inflation factor was assessed to analyze the magnitude of multicollinearity, and a low correlation (ie, variance inflation factor < 5) was found for each of the dependent variables.[29] Cook's distance method was used to detect outliers.[30] All data were analyzed using statistical package R (version 3.5.2, R Core Team; Foundation for Statistical Computing, Vienna, Austria) with the packages "lme4," "car," "emmeans," "base," and "psych."

Results

One hundred and fifteen individual training sessions (mean session duration = 1:41:01 [0:07:52], h:min:s) were monitored within 13 team training sessions. The descriptive results (mean and 95% CI) about the well-being and TLs (ie, sRPE, Edwards score, and jumps) are reported in Table 1. Distribution of HR classes of intensity and players' jumps are described in Figure 2.

According to LMM, Edwards score was significantly associated with perceived fatigue index ($\beta = -0.0018$; 95% CI, –0.004 to

Table 1 Descriptive Statistics (Mean; 95% CI) of Well-Being and Training-Load (ie, sRPE, Edwards Score, and Jumps) Parameters According to Position

	Well-being					ITL		
Position	Sleep quality	Stress	Fatigue	DOMS	Hooper index	Edwards score	sRPE	ETL, jumps
Hitter	3.2 (2.9 to 3.6)	3.2 (2.9 to 3.4)	3.7 (3.5 to 3.9)	3.9 (3.7 to 4.2)	13.9 (13.2 to 14.5)	173 (152 to 195)	427 (344 to 511)	83 (71 to 94)
Middle blocker	3.4 (2.9 to 3.8)	3.6 (3.2 to 4.0)	4.3 (3.9 to 4.6)	4.5 (4.2 to 4.9)	15.6 (14.4 to 16.8)	222 (195 to 249)	516 (417 to 615)	126 (111 to 142)
Opposite	3.3 (2.9 to 3.6)	3.8 (3.5 to 4.2)	3.8 (3.4 to 4.1)	4.4 (4.0 to 4.8)	15.3 (14.1 to 16.5)	209 (179 to 240)	411 (312 to 509)	97 (83 to 111)
Setter	3.7 (3.5 to 4.0)	3.7 (3.4 to 4.0)	4.0 (3.7 to 4.3)	4.3 (3.9 to 4.8)	15.6 (14.7 to 16.5)	239 (193 to 286)	359 (288 to 429)	138 (112 to 165)

Abbreviations: CI, confidence interval; DOMS, delayed-onset muscle soreness; ETL, external training load; ITL, internal training load; sRPE, session rating of perceived exertion.

−0.0004; standard error [SE] = 0.0009; *t* ratio = −2.06; *P* = .042; Cohen *d* = −0.21) and Hooper index (β = −0.007; 95% CI, −0.014 to −0.001; SE = 0.003; *t* ratio = −2.07; *P* = .041; *d* = −0.25). sRPE was significantly associated with perceived fatigue index (β = 0.001; 95% CI, 0.001 to 0.002; SE = 0.0003; *t* ratio = 4.40; *P* < .001; *d* = 0.54) and Hooper index (β = 0.003; 95% CI, 0.001 to 0.005; SE = 0.001; *t* ratio = 2.67; *P* = .005; *d* = 0.21). According to post hoc pairwise comparisons, significant differences between positions were observed for DOMS (*F* = 4.572; *P* = .005). Central blockers showed higher DOMS compared with the hitters (estimated mean difference 3.85; 95% CI, 3.20 to 4.50; *P* = .041; *d* = −0.40). Conversely, no difference was observed between the other roles (all *P*s > .05). In addition, no associations were observed for age variable, on well-being parameters 22 hours apart (all *P*s > .05). An overview of LMM outputs for well-being variables is reported in Table 2.

Discussion

As TL may be a determining factor in well-being variations and recovery, the aim of this study was to assess the effects of the internal (ie, Edwards values and sRPE) and external (ie, jumps) TL on the day after well-being perception in elite (ie, Serie A2) female volleyball players, in relation to different ages and position roles. The main findings of this study were that only ITL quantified according to the sRPE and to the Edwards method influenced perceived fatigue and general well-being on the day after (22 h apart). On the contrary, no effect was observed for external (ie, jumps) TL.

Unlike previous studies,[15,19,20] the present one focused on the acute effects of the TL on the players' well-being status from an interdaily perspective (ie, +22 h). Perceived fatigue was influenced by the psychophysiological measure (ie, sRPE) as well as by the physiological one (ie, HR-based Edwards method) in an opposite

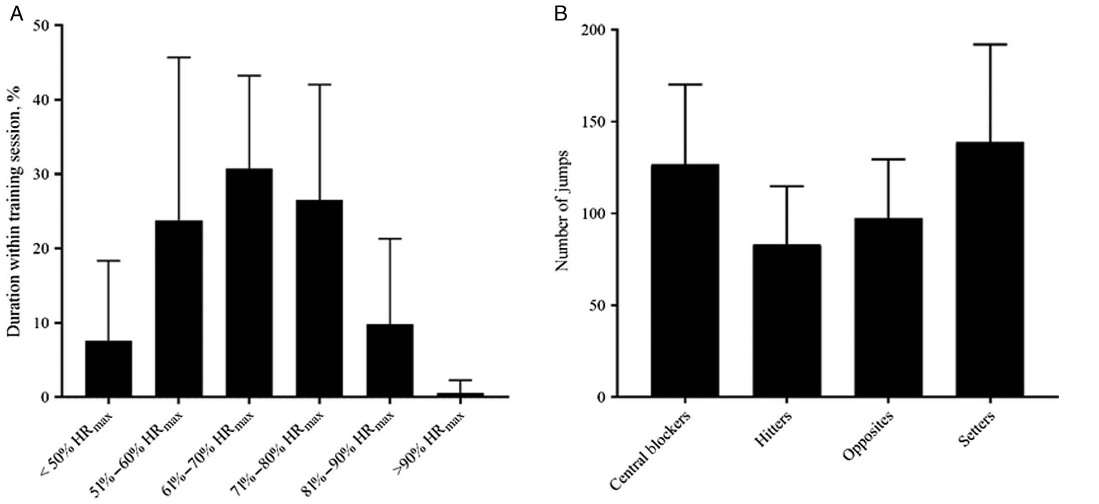

Figure 2 — Means and SDs of the distribution (in percentage) of training duration in relation to the classes of intensity (A) and of the jumps according to position (B). HR_{max} indicates maximum heart rate.

Table 2 Outcomes of Linear Mixed Models (β; SE; *P*) Applied for Well-Being Parameters in Relation to ITL (ie, Edwards and sRPE), ETL (ie, Video Analysis of Jumps) Methods, Positions (Compared With Central Blockers), and Age

Parameter		Well-being: Sleep quality	Stress	Fatigue	DOMS	Hooper index (total)
ITL	Edwards value	−0.001; 0.001; .332	−0.002; 0.001; .082	−0.0018; 0.0009; .042*	−0.001; 0.001; .216	−0.007; 0.003; .041*
	sRPE	0.0004; 0.0003; .206	0.0003; 0.0003; .351	0.001; 0.0002; <.001**	0.0004; 0.0004; .293	0.002; 0.001; .025*
ETL	Jump	0.002; 0.002; .170	0.003; 0.002; .069	0.0009; 0.001; .550	−0.002; 0.002; .374	0.005; 0.006; .414
Position	Hitter	−0.067; 0.338; .850	−0.365; 0.354; .342	−0.475; 0.248; .112	−0.829; 0.222; .0004**	−1.778; 1.003; .113
	Opposite	0.120; 0.389; .769	0.183; 0.406; .667	−0.413; 0.288; .207	−0.592; 0.254; .022*	−0.337; 1.154; .780
	Setter	0.797; 0.428; .116	−0.184; 0.456; .698	−0.023; 0.320; .944	−0.528; 0.287; .070	0.250; 1.294; .853
Age		0.059; 0.036; .163	−0.049; 0.037; .237	−0.002; 0.026; .935	−0.040; 0.022; .081	0.041; 0.107; .968

Abbreviations: DOMS, delayed-onset muscle soreness; ETL, external training load; ITL, internal training load; sRPE, session rating of perceived exertion.
*P < .05. **P < .01.

way. Paradoxically, higher HR-based ITL enhances well-being status, while higher perceived TL (ie, sRPE) disrupts it. Although Edwards method was reported to be correlated to sRPE in the TL monitoring of several sports,[6,9,11,12,18] higher Edwards scores could probably be due to a higher percentage of time spent in the 3 lower HR zones (ie, <50% HR_{max}, 50%–59.9% HR_{max}, and 60%–69.9% HR_{max}) in this study. In fact, more than 60% of the entire training duration was spent below the 70% HR_{max} threshold, which can be considered a light-intensity zone (Figure 2A). Moreover, HR-based ITL alone were not able to exhaustively monitor all aspects of performance and fatigue, thus requiring the combination with other cost-effective tools (eg, daily training logs, psychometric questionnaires, noninvasive performance) to investigate the athlete's status,[31] especially in net sports such as volleyball.[19]

Previous investigations reported that variations in sleep quality, fatigue, and DOMS were more sensitive to acute rather than chronic TL or training monothony.[20] From a weekly perspective, TL was also related to quality of sleep, stress, perceived fatigue, and DOMS, especially during the congested week (ie, 2 or more games).[15] In fact, disruption of well-being was higher during congested compared with regular (ie, one game) weeks despite the TL reduction. In particular, the accumulation of the games significantly decreased the quality of players' sleep and significantly increased players' stress, fatigue, and DOMS several days of the week.[15] On the contrary, from a intradaily perspective, only perceived fatigue was related to the TL according to the players' age.[19] Specifically, older players have perceived training to be harder than the younger players, despite the fact that HR-based ITL seemed to report the opposite.

Although TL, both acute and chronic, were reported to change along with the well-being perception,[15,19,20] objective measures for athletes' monitoring (eg, HR-based ITL) might be limited for the purpose monitoring athletes' well-being due to their lack of responsiveness.[16] In fact, subjective measures reflect acute and chronic TLs with superior sensitivity and consistency to objective measures.[16] In addition, subjective well-being is typically impaired with an acute increase in TL, while an acute decrease in TL improves subjective well-being.[16] In particular, due to the special characteristics of volleyball, where aerobic metabolism is important to restore the energy consumed during explosive anaerobic efforts (eg, jumps, changes of direction, dives, rolls), perceived exertion rather than HR-based ITL could better evaluate short but maximal anaerobic efforts.[19]

Differences were observed between playing positions although both internal and ETL did not affect DOMS. Specifically, central blockers experienced higher DOMS values than hitters. These differences may be due to the massive involvement of the central blockers during the training sessions (Figure 2B). In fact, excluding setters, central blockers performed the highest occurrence of jumps in this study. According to the technical and tactical behavior reported during game performance, it is possible to speculate that central blockers performed the maximal jump load, while setters' jump load was submaximal, despite the fact that they participated in almost every rally to set the ball during the jump.[3,5] Finally, it can be assumed that number of jumps may discriminate DOMS perception in an interdaily scenario (22 h apart).

Well-being perception 22 hours after the training session was not affected by age in this study despite the fact that in previous studies[14,19] mood states were reported to be influenced by age. In fact, older players were more likely than younger players to perceive training to be harder, while the objective measures (ie, HR-based ITL) reported the opposite scenario. Consequently, in a short-term scenario (ie, 1 d apart), coaches should take into account the consequences of the ITL on the well-being perception regardless of the players' age.

However, the present study had some limitations. The most accurate value of HR_{max} can be obtained through direct measurement during maximal exercises, but this was not possible in this study. Thus, estimated maximal HR according to the "220 – age" formula was used, although it was reported to overestimate the age-predicted HR_{max}.[32] However, this systematic overestimation affects all the sampling at the same manner, and it does not represent a significant bias for the statistical analysis. In addition, although it has been shown that different uses of zone ranges of the HR_{max} (ie, 5, 10, or 20 HR zones) produce significantly different summarized TL measures,[33] we were limited in this study by our technology to choose the traditional approach with 5 HR_{max} zones. The inclusion of only one team and the consequent small sample size did not allow us to generalize our results, requiring further studies to consolidate the emerged finding. Only one type of training session (ie, full team, 6v6) was monitored because it was considered the most valid representation of the performance during the in-season period. Nevertheless, the other sessions were characterized by low TLs because they were focused only on technical and/or tactical skills instead of conditioning. In addition, although strength and conditioning sessions were regularly performed during the season, ITL was not assessed in this circumstance. Therefore, future studies on ITL should define the validity of experimental approach by providing mixed-effects models that are able to consider automatic external load measurements (ie, accelerometer to estimate jump frequency), type of training weeks (eg, congested or regular), and other types of training (ie, technical and strength and conditioning).

Practical Applications

Coaches should be aware of the importance of the perceived exertion in effectively monitoring well-being status in female volleyball players. In fact, postsession perceived exertion should be constantly monitored to estimate well-being in a day-by-day short-term scenario. Assessing perceived TL after the training session could be crucial to determining whether perceived fatigue will arise in players in the next 24 hours.

Moreover, coaches should be aware that central blockers experience higher DOMS than the other players during full squad training (ie, tactical training). Although customizing intensities for each player is complicated during collective training sessions, coaches could choose different strategies (eg, defensive vs offensive tactical training session, substitutions) to manage central blockers' total jumps.

Besides, physical coaches could also manage intensity during strength and conditioning training the day after the technical and tactical training session by considering the related perceived fatigue. According to prior studies, off-field recovery strategies (ie, branched-chain amino acid supplementation,[34] massages, compression techniques, and water immersions[35]) could also be adopted to reduce DOMS and manage perceived fatigue.

Conclusions

The present study demonstrated that ITL can affect well-being perception, especially perceived fatigue, in senior female volleyball players in a day-by-day short-term scenario (ie, 22 h apart). However, this relation was verified only for the ITL (ie, Edwards method and sRPE). No effect was found for the ETL (ie, jumps) on well-being status in this study. In addition, players' well-being was influenced by previous day's ITL regardless of their age. Finally, differences in perceived DOMS were reported for players related to specific tactical roles, highlighting the fact that central blockers experienced higher DOMS than hitters.

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3. Artificial intelligence and Machine Learning

3.1. Introduction

Since digital technology allows sport professionals to gather a big amount of data related to technical and tactical, and physiological performance in team sports, these data must be effectively analyzed to successfully model technical and tactical performance (Bonomi, 2013). Moreover, complex scenarios such as performance in team sports require a non-linear approach to better organize and explain high-dimensional datasets (Ungureanu, Lupo, et al., 2021). The effort of gathering usable knowledge from this data is based on classification task, which is the systematic arrangement of items into groups (e.g., winning or losing performance), according to their similarities and differences (e.g., key performance indicators). This classification will then represent the training example in order to make predictions on the outcomes of new observations. From this perspective, Data Mining (DM) and Machine Learning (ML) algorithms are suitable methods for classifying teams' and athletes' performance according to the game outcome (Horvat & Job, 2020). In particular, DM can be defined as a process to extract information from apparently unstructured and varied data set, while ML concerns to the practical application of formal structures (i.e., algorithms) to do inference, i.e. to reduce uncertainty about a variable (Clarke et al., 2009). Notwithstanding, DM should be complementary to traditional statistical techniques, such as regression, and they should be used together (Chinwe Peace, 2014) for classification and prediction tasks.

Since sport outcome prediction and performance classification by the means of the ML techniques have grown in interest in the last decades [i.e., since 1996 when first study in this domain appears to have been published (Purucker, 1996)] among researchers and sport scientists, especially since 2010 (Bunker & Susnjak, 2022; Horvat & Job, 2020), a detailed discussion about the principal ML tools (artificial neural networks and decision trees) for prediction and classification, as well as their implementation in team sports was carried out hereinafter.

Human expert vs machine learning prediction

Until the application of the ML tools were introduced in game outcome prediction, towards the beginning of the 21st century, experts' opinion was the main source of prediction. However, the ability of human experts to better predict game outcomes compared to the ML tools is controversial. During the early 2000s, human experts were reported to be more successful than ML at predicting the outcomes of international rugby union matches (O'Donoghue & Williams, 2004), although other authors reported the opposite in Basketball, Rugby League, Australian Rules football, Rugby Union, and Soccer (Bunker & Susnjak, 2019; Loeffelholz et al., 2009; McCabe & Trevathan, 2008; Pretorius & Parry, 2016). Nevertheless, combining human knowledge to select the most effective features with the computing power of the ML could be beneficial to increase the prediction performance (Bunker & Susnjak, 2019; Horvat & Job, 2020; Joseph et al., 2006).

3.2. Tools for prediction: Artificial Neural Networks (ANN)

In order to classify performances and predict game outcomes, ML are mainly based on two different learning models: supervised and unsupervised. On the one hand, supervised learning is based on a training data set including both the input and the results, a validation data set, and a test data set which are used to tune and to assess the performance of the classifying model, respectively (Sathya & Abraham, 2013; Akinsola et al., 2017). Supervised learning can involve both classification (e.g., when attempting to predict a class-based outcome as win/loss/draw) and regression (e.g., when attempting to predict a score) depending on the type of the outcome. On the other hand, unsupervised learning models are used to identify hidden patterns in input data when results are not available within that data set (Sarker, 2021). In match and performance analysis for example, supervised learning are usually used when key performance indicators (e.g., shots, pass, tackles, dribbling) and relative outcome of a set of games (win, lose, draw) are available (Ungureanu, Lupo, et al., 2021), while unsupervised learning are used to cluster closed, balanced, and unbalanced games based on the margin of victory in a set of games (Ungureanu et al., 2019).

Although several ML algorithms, such as Linear Regression (LR), Logistic Regression (LogR), Support Vector Machines (SVM), Naive Bayes, and Decision Trees (DT), were used to classify and predict game outcomes in the last years (Haghighat et al., 2013; Horvat & Job, 2020; McCabe & Trevathan, 2008; TAŞPINAR et al., 2021), some of the most frequently used are Artificial Neural Networks (ANN) and Decision trees (R. Bunker & Susnjak, 2022; Horvat & Job, 2020). In particular, when addressing to ANN, the most popular model is the multi-layer perceptron (MPL). Since its ability to learn more complex structures in data (Tax & Joustra, 2015), it became particularly suitable for modelling and predicting both linear and non-linear complex scenarios (Horvat & Job, 2020). However, a long debate in literature has criticize ANN to be a "black-box" system since they do not provide substantial information on how they work even if they are highly accurate to identify relations between inputs and outputs (Benítez et al., 1997). More recently, the black-box approach was revised with a view to the information within the network domain and those in the real world domain (Wu et al., 2016). In particular, it was stated that ANN are black-box models because weights have no specific meaning in the real-world domain even if the structure (i.e., n. of layers, nodes, activation functions) is well known (Wu et al., 2016). Thus, this model can be considered a grey-box model. However, according to Bunker and Susnjak, the majority of studies that have used ML for predicting results in team sports have considered ANNs in their experiments, although they do not necessarily perform better than other ML algorithms (R. Bunker & Susnjak, 2019).

Technically, the multi-layer perceptron (MPL) is a supervised learning algorithm consisting of multiple layers of nodes (also called "perceptrons") organized in layers, with each one connected to the next one (figure 1).

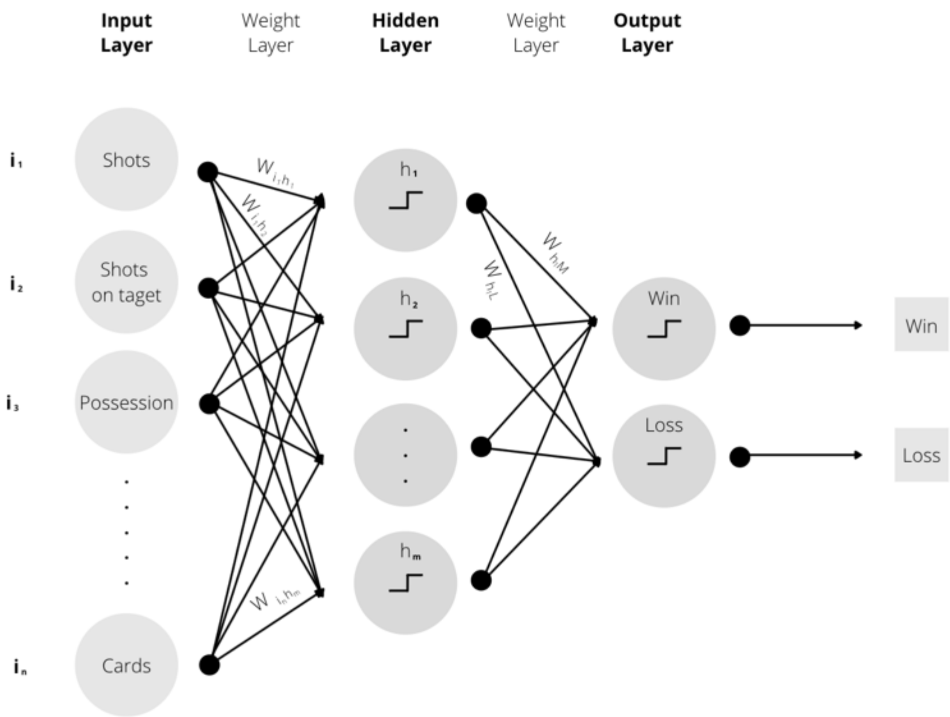

Figure 1. Example of multi-layer perceptron architecture

Except for the nodes in the input layer (i.e., the first one), each node is assigned to compute a non-linear activation function (Soto Valero, 2016). Basically, a MLP is just a mathematical function mapping sets of input to output values. In fact, the output from the MLP network is the result of a set of activation functions that account for each input data (x_i) scaled by a weight (w_i), and summed by a bias (b) (Blaikie et al., 2011). Mathematically it can be represented as

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where y is the output, f is the activation function, w is the weight vector, x_i is the input vector (i = 1, 2, ... n), and b is the bias (Zadeh et al., 2010). There are several activation function for the hidden layer nodes that can be applied, such as the logistic sigmoid (Logistic), the hyperbolic tan function (Tanh), the rectified linear unit function (ReLU), etc. (Sharma et al., 2020). In order to improve the classification performance of the ANN, activation function is one of the most important parameters to set (Sharma et al., 2020). It was reported that the selection of activation function is context dependent, so Logistic and ReLU functions should be preferred for classification problems (Sharma et al., 2020). Respectively, the two abovementioned non-linear functions can be mathematically represented as (Sharma et al., 2020; Zadeh et al., 2010):

$$f(\mathrm{x}) = \frac{1}{(1 + \mathrm{e}^{-\mathrm{x}})}$$

$$f(\mathrm{x}) = \max{(0, \mathrm{x})}$$

Once the architecture and the activation functions within the ANN are selected, ANNs must be trained. The training algorithm allow the network to learn from experience. It consists of two procedural steps through the network. First, the actual response of the system is evaluated in the forward pass and then the internal weights are adjusted by the error-correction rule in the backward pass (Pessoa et al., 1995). The back-propagation learning algorithm adjust the weights (w) to minimize the error between the desired output provided in the learning examples and the output provided by the network through an empirical supervised and self-adapting back-propagation process (Wang, 2021). The learning process was also described as a search of an error surface for a weight vector that leads to the smallest error value while the visualization of this process is complicated because of the high dimensionality of the weight space due to the presence of the hidden layers and multiple connections within the system (Gallagher & Downs, 2003). However, visualization could be useful to qualitatively compare training algorithms and to provide informative representations of the learning behavior (Gallagher & Downs, 2003). In particular, it was demonstrated that the technique of Principal Component Analysis (i.e., PCA) can be used for visualizing the learning process in MLPs through the representation of the learning trajectories in a low-dimensional subspace (Gallagher & Downs, 2003).

Classification improvement

In order to improve classification success different strategies were suggested. First, the outcome of the match was treated as a 2-class variable (i.e., win/lose) and draw results were excluded because of its greater prediction difficulty (Huang & Chang, 2010; Odachowski & Grekow, 2012; Pappalardo & Cintia, 2018; TAŞPINAR et al., 2021). In fact, it was reported that the classifier of a draw has the worst results in comparison to the win or loss (Odachowski & Grekow, 2012). Since the features of a draw contain similarities to those connected to win or loss, it may be misclassified as a win or a loss (Odachowski & Grekow, 2012). Secondly, raw data should be pre-processed to normalize variables to the total occurrences (Hughes & Bartlett, 2010) (e.g. defining the shots on target as a percentage of the total shots) or even generating new parameters that did not exist in the original database (Zdravevski & Kulakov, 2010) in order to achieve better-quality analysis results within the algorithm (Nawi et al., 2013). Moreover, feature selection during the pre-process phase, either through experts' opinion, or using statistical techniques, or even through a heuristic feature selection process (i.e., by removing or adding a feature one at a time to define a final set of relevant features), can increase the efficiency of the ML algorithm (Horvat & Job, 2020). Nevertheless, in most papers the comparison of the classification accuracy before and after the feature selection process is not reported, although it is reasonable to think that results improve after (Horvat & Job, 2020). Thirdly and finally, a model of training and validation approach should be carefully considered. Specifically, when choosing leave-one-out cross-validation (i.e., dataset volume is maximized since it is randomly subsampled entirely used both for training and validation) to train a model on prior matches to predict a future one (or by using historical seasons to predict the current one), it may result in future matches being (erroneously) used to predict past ones (Bunker & Susnjak, 2022). For instance, a split-sample or a rolling cross-validation approach should be preferred in those time-series models (Hyndman & Athanasopoulos, 2018).

3.3. Tools for classifying: Decision trees (DT)

Decision and classification tree (DT) is a machine learning technique that applies an approach of dividing data into smaller clusters to identify patterns that can be used for classification and prediction. Decision trees are constructed by analyzing a set of training examples for which the class labels are known (i.e., supervised learning). They are then applied to classify previously unseen examples. If trained on high quality data, decision trees can make very accurate predictions (Kingsford & Salzberg, 2008). The logical structure consists in a hierarchical combination of decisions from the root to the terminal (i.e., leaf) nodes, and these provide knowledge based on the classification. The construction of a DT from a given dataset is based on algorithms that aim to find the optimal DT by minimizing the generalization error, although some target functions such as minimizing the number of nodes or minimizing the average depth can be defined (Rokach & Maimon, 2005). In fact, defining an optimal DT algorithm could require a heuristic approach that include two conceptual phases: growing and pruning. ID3, C4.5, CART, CHAID, QUEST, are some of the DT algorithms available in the literature. In particular, the Exhaustive CHAID (i.e., Chi-squared Automatic Interaction Detector) method was used in one of our studies (Ungureanu, Lupo, et al., 2021). This algorithm was based on the chi-square test of association, and it constructed a DT by repeatedly splitting subsets of the space into two or more child nodes, beginning with the entire data set, until only two super categories were left. In general, all the algorithms consider the partition of the training set according to a discrete function on the input attributes during the growing phase. These recursive splits subdivide the training set into smaller subsets until a stopping criterion is triggered (e.g., when the maximum tree depth has been reached, the number of cases in the terminal node is less than the minimum number of cases for parent nodes). *Impurity-based Criteria, Information Gain, Gini Index, Likelihood-Ratio Chi–Squared Statistics, AUC–Splitting Criteria* are some of the criteria that induce the growing phase and aim to split the training dataset into as less impure (i.e., characterized by the lowest level of entropy) as possible subsets (Rokach & Maimon, 2005). In our specific case, the stopping criterion was triggered by the *p-value* threshold for the

Pearson chi–squared test. The splitting process was implemented until each child node was made of a group of homogeneous values of the selected attribute according to the *p-value* threshold. Finally, the DT was assessed for accuracy by means of cross-validation techniques (Blockeel & Struyf, 2003). In particular, the dataset was randomly subsampled and it was entirely used both for training and validation, maximizing the dataset volume. Pruning was not performed.

However, growing and stopping are a tradeoff in building decision tree models. Tightly stopping criteria tend to create small and under–fitted decision trees while loosely stopping criteria tend to generate large decision trees that are over-fitted to the training set. To solve this dilemma the pruning methodology was introduced to improve the generalization performance of a decision tree. In particular, a loosely stopping criterion is used to generate an over-fitted DT, which is cut back into a smaller tree by removing sub–branches in excess (i.e., that are not contributing to the generalization accuracy). Although there are various techniques for pruning decision trees, each of them operates by improving a certain criterion (e.g., the tree's accuracy, the error rate, the generalization performance). (Rokach & Maimon, 2005).

Finally, decision trees might be considered a proper classification tool for PA in team sports since they are self–explanatory and easy to understand even by non-professional users. Furthermore, decision trees can handle both nominal and numeric input attributes, and they are capable of handling datasets that may have errors or missing values (Rokach & Maimon, 2005). On the other hand, decision trees may over-fit or overclassify data, especially in small samples. In addition, each algorithm fits for special scenarios. For instance, *C4.5* algorithm does not work very well for a small training set, *CART* splits only by one variable and it may have unstable decision trees (Gupta et al., 2017).

3.4. Implementation in team sports

The use of artificial intelligence for prediction and classification purposes in sports should be implemented through a structured experimental framework to obtain the best possible results with a given data set (RBunker & Thabtah, 2019; Shearer, 2000).

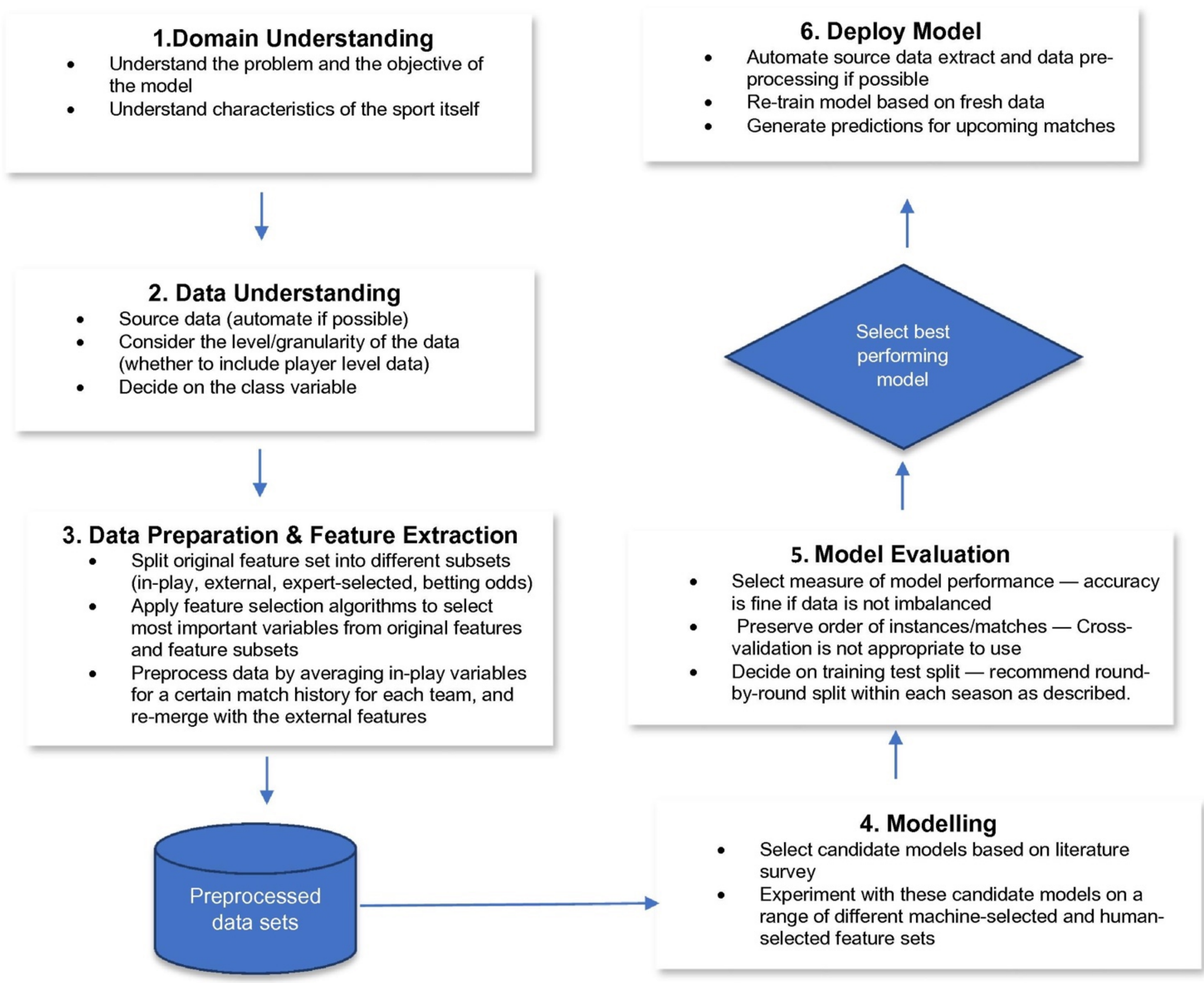

Figure 1 (from *"Bunker, R. P., & Thabtah, F. (2019). A machine learning framework for sport result prediction. Applied computing and informatics, 15(1), 27-33."*). Steps of the **S**port **R**esult **P**rediction **CR**oss-**I**ndustry **S**tandard **P**rocess for **D**ata **M**ining (SRP-CRISP-DM) framework proposed by the authors.

On the one hand, this framework (figure 1) requires specific technical and tactical knowledge about the team sport to properly decide on the class variables to be considered. On the other hand, it includes extensive knowledge about the most appropriate model and the best feature sets to be applied (Bunker & Thabtah, 2019). Based on these considerations, a brief review about the application of ML algorithms for prediction and classification is reported below.

3.4.1 Clustering and Prediction

Clustering and prediction are the two sides of the same coin. According to the goals of the two main ML categories (i.e., supervised and unsupervised learning), the supervised learning aims to develop a predictive model that, based on both input and output known data, predicts future events on previously unseen data. On the contrary, in unsupervised learning, the main goal is to group and interpret data based only on input unlabeled data, that is to say to find data regularities and to cluster events (Horvat & Job, 2020). Moreover, the distinction between the classification and the prediction tasks is not always cleared. In fact, sport predictions are usually treated as a classification problem by which one class is predicted (win/loss/draw) (Prasetio, 2016).

Horvat and Job have recently completed a comprehensive review of more than 100 scientific papers concerning sport predictions or extracting useful facts and regularities (i.e., classification/clustering) related to team sports (Horvat & Job, 2020). Similarly, Bunker and Susnajak, and Rico-González et al., have systematically reviewed ML approaches and techniques for prediction in team sports in recent times (Bunker & Susnjak, 2022; Rico-González et al., 2023). In particular, most of the team sport performances were investigated in basketball, football, soccer, baseball, and cricket, while the most widely used ML models were the artificial neural networks and decision trees (Bunker & Susnjak, 2022). In addition, specific investigations in soccer (i.e., systematic review of 32 studies) have evidenced that decision trees algorithms were applied for predicting game outcomes or final rankings in a league through NA and TMA, as well as for classifying team styles of play according to their technical and tactical inputs such as passing effectiveness (Rico-González et al., 2023). It was also reported that ANNs do not necessarily have primacy over other ML models, especially because of their lack of interpretability. Instead, it was recommended to compare different models, including decision trees which combine accuracy and interpretability for non-professional users (e.g., coaches, managers, and athletes) (Bunker & Susnjak, 2022).

Specifically, the most common ML methods applied in team sports (e.g., American Football, Rugby, Soccer, Basketball, Baseball, Ice Hockey) were ANNs and Decision trees (Bunker & Susnjak, 2022). Although predicting match outcomes within sports is multifactorial, ML models ranged from 46.1% to 93% considering both TMA (e.g., time in possession) and NA (e.g., kicking, passing, interceptions, run scored, goals, fouls, rebounds, assists, steals, turnovers, and blocks) indicators (Bunker & Susnjak, 2022). In addition, the between-sports variability exists due to confounding factors that are difficult to predict (e.g., luck or randomness of events) but also due to objective reasons (Aoki et al., 2017). For instance, large datasets and a multitude of performance indicators available in some sports (e.g., soccer) than others, as well as scoring rates (e.g., competitiveness (e.g., lower level is less uncertain to be predicted), possible outcomes (e.g., soccer has a low prediction accuracy compared to rugby union since in soccer is highly recommend to consider draws that are more probable to occur compared rugby, in which a binary outcome – win/lose – can be accepted), point scoring systems (e.g., score incrementing by one in soccer leads to less predictability compared to basketball, American football, or rugby, in which a single event could increment the score up to 7 points) could support this variability (Bunker & Susnjak, 2022).

Despite ML models were mainly implemented in match outcome prediction and performance classification, they were also applied in team sports for internal training load (i.e., RPE) prediction according to the external one (i.e., kinematic indicators such as distance, speed, duration, acceleration, deceleration, and accelerometry-based metrics such as impacts and high-intensity efforts) (Bartlett et al., 2017; Jaspers et al., 2018; Rago et al., 2020). Although in this studies details on the architecture as well as on the validation methods and metrics of the ANNs were not provided, the authors have concluded that ML techniques may add value in predicting the RPE with respect to the traditional methods (e.g., correlations) (Bartlett et al., 2017; Jaspers et al., 2018). Moreover, it was also reported that ML could be beneficial for selecting key external load indicators within a large dataset of indicators (Jaspers et al., 2018). In fact, the ability of the ML techniques to automatically select a subset of predictive external load indicators, often without correcting for multicollinearity, from a larger dataset allows to build predictive models without reducing the number of indicators a priori and the chance of discarding a relevant indicator (Jaspers et al., 2018).

3.5. Practical applications

3.5.1 Paper #7

International Journal of
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Article

A Machine Learning Approach to Analyze Home Advantage during COVID-19 Pandemic Period with Regards to Margin of Victory and to Different Tournaments in Professional Rugby Union Competitions

Alexandru Nicolae Ungureanu [1,2], Corrado Lupo [1,2,*] and Paolo Riccardo Brustio [2,3]

[1] Department of Medical Science, University of Turin, 10143 Turin, Italy; alexandru.ungureanu@unito.it
[2] NeuroMuscularFunction | Research Group, School of Exercise & Sport Sciences, University of Turin, 10143 Turin, Italy; paoloriccardo.brustio@univr.it
[3] Department of Neuroscience, Biomedicine and Movement, University of Verona, 37131 Verona, Italy
* Correspondence: corrado.lupo@unito.it; Tel.: +39-011-6708083

Abstract: Home advantage (HA) is the tendency for sporting teams to perform better at their home ground than away from home, it is also influenced by the crowd support, and its existence has been well established in a wide range of team sports including rugby union. Among all the HA determinants, the positive contribute of the crowd support on the game outcome can be analyzed in the unique pandemic situation of COVID-19. Therefore, the aim of the present study was to analyze the HA of professional high-level rugby club competition from a complex dynamical system perspective before and during the COVID-19 pandemic. HA was analyzed in northern and southern hemisphere rugby tournaments with (2013–2019) and without (2020/21) crowd support by the means of the exhaustive chi-square automatic interaction detection (CHAID) decision trees (DT). HA was mitigated by the crowd absence especially in closed games, although differences between tournaments emerged. Both for northern and southern hemisphere, the effect of playing without the crowd support had a negative impact on the home team advantage. These findings evidenced that in ghost games, where differences in the final score were less than a converted try (7 points), HA has disappeared.

Keywords: COVID-19; home advantage; rugby union; margin of victory; decision trees

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1. Introduction

Home advantage (HA) in sport depends on several factors and it should be analyzed from a complex dynamical system perspective. Although HA has been well-documented in several competitive sports (baseball, basketball, handball, indoor soccer, roller hockey, rugby, soccer, volleyball, and water polo) [1], the causes are less well understood [2]. According to Nevill and Holder [3], the factors associated with HA for all sports include crowd support, travel fatigue, familiarity with local conditions, territoriality, referee bias, special tactics, and psychological factors, even if territoriality, referee bias, and other psychological factors are all thought to be influenced by the crowd support [2]. In addition, rugby union provides an important context to explore this phenomenon because of the high level of home advantage [1] and the use of a television match official to help to provide a less biased decision by the referees. HA in rugby union was investigated both in northern [1,4–6] and southern hemisphere [7,8]. In particular, HA was reported to be oscillating around 60% in northern hemisphere international competitions between 1883 and 2011 [5] and to have a mean of 7 points in national and international southern hemisphere competition [7,8]. Nevertheless, it varied between teams from season to season [7] and during non-professional era (i.e., before 1995) [5].

Among all the determinants of the HA, the positive contribute of the crowd support on the game outcome can be analyzed in the unique pandemic situation of COVID-19. During the first phase of the COVID-19 pandemic, (i.e., March 2020) several sport competitions started to be suspended and subsequently some of them were resumed, while others were cancelled for the 2019–2020 season [9]. In Europe, the Six Nations Tournament and the main club competitions (i.e., English Premiership, Pro14) were suspended in March 2020 and rescheduled during the following summer, while the club competition in France (i.e., Top 14 2019–2020) was cancelled after the 17th matchday. In the southern hemisphere, the 2020 Super Rugby competition involving teams from Argentina, Australia, Japan, New Zealand and South Africa was cancelled after 46 games, whereas regional tournaments replaced it in New Zealand, Australia, South Africa, and crowds were regularly allowed to attend the tournaments. At a national level, the 2020 National Provincial Championship in New Zealand and the 2020 Currie Cup in South Africa were played but no crowds or limited crowds were allowed, while the National Rugby Championship in Australia was cancelled.

Although the pandemic restrictions was reported to impact HA in rugby [10], the application of a non-linear data mining techniques considering contingencies (e.g., the tournament, the margin of victory, the scoring first) may explore potentially useful information in a large dataset, and produce a simple and understandable message to the stakeholders [11]. In fact, since the game outcome is affected by the location (i.e., home or away), the margin of victory [12], the scoring first [13], and the differences in playing styles across hemispheres [14–16], these aspects should be considered in a data mining investigation.

Data mining is a process of extracting and discovering patterns in datasets. Sports data mining assists coaches and managers in result prediction, player performance assessment, player injury prediction, sports talent identification, and game strategy evaluation [17]. In particular, decision tree (DT) is a machine learning technique that applies an approach of dividing data into smaller clusters to identify patterns that can be used for prediction. The logical structure consists in a hierarchical combination of decisions from the root to the terminal (i.e., leaf) nodes, and these provide knowledge based on the classification. Exhaustive CHAID (i.e., Chi-squared Automatic Interaction Detector) method is used based on the chi-square test of association. An Exhaustive CHAID tree is a decision tree constructed by repeatedly splitting subsets of the space into two or more child nodes, beginning with the entire data set, until only two super categories are left. Exhaustive CHAID can find the best split for each predictor variable by minimize the variation within nodes in order to construct homogenous subgroups in the decision tree diagram [18]. Decision trees are usually assessed for accuracy by means of cross-validation techniques [19]. In particular, dataset is randomly subsampled and is entirely used both for training and validation, maximizing the dataset volume.

In the last decade HA was extensively studied in several sports [1] and classification decision trees were used to assess the effect of performance indicators on game outcome in rugby league [20,21] as well as in rugby union [22,23]. However, to the best of our knowledge, this is the first study to apply a flexible and nonlinear statistical model to investigate HA in professional rugby union. In particular, the aim of the present study was to analyze the HA of professional high-level rugby club competition from a complex dynamical system perspective according to the tournament, the margin of victory, the scoring first, and the crowd support.

2. Materials and Methods

2.1. Design

This study comprised 7934 performances (3967 games) played by professional teams from elite national (i.e., English Premiership = 1824 (23%), French Top14 = 2520 (32%), Currie Cup = 566 (7%), Mitre 10 Cup = 1188 (15%)) and international (i.e., Pro14 = 1836 (23%)) competitions during the last 6 competitive seasons before (2013/14 to 2018/19) and after (2020/21) the COVID-19 pandemic period. The 2019/20 season was excluded from the analysis because of the irregular and intermittent game schedule. Archival data were collected by a researcher from the Ultimate Rugby web domain (https://www.ultimaterugby.com/# (accessed on 16 July 2021)). Data reported in this Web domain were collected by a researcher and stored into a .csv file. The local institutional review board approved this study.

2.2. Methodology

Win and lose but not drawn performances were considered in this study. For each of the 7938 performances fixture (home vs. away), outcome (win vs. lose), margin of victory [$\sqrt{(\text{points scored-points conceded})^2}$], season (Pre-COVID vs. COVID 20–21), tournament (Pro14 vs. Top14 vs. Premiership vs. Currie Cup vs. Mitre 10 Cup), and the first event of the game (scoring, missed scoring, yellow or red card, and substitution) were considered. In particular, scoring included scored try with and without conversion, penalty try, and kick at goal, while missed scoring included missed penalty (i.e., kick at goal failed). Noting the relation of the margin of victory (i.e., final score difference) [12,24] and of the first scoring [20] with the relative success of the game plan adopted by the winning teams, the same were included in this study. The margin of victory was clustered within the decision tree to define 3 clusters (closed, balanced, and unbalanced games).

2.3. Data Analysis

An exhaustive chi-square automatic interaction detection (CHAID) decision tree was grown using win/lose as the binary response variable in IBM SPSS Statistics package (version 27, IBM Corp., New York, NY, USA) using a ten-fold cross validation. Outcome was set as dependent variable while season, fixture, margin of victory, tournament, and first event were set as independent variables. In order to manage both accuracy and complexity of the model (i.e., the maximum tree depth, which contains the highest value of accuracy, is five), grow limits was set to 5 levels and minimum number of cases for parent and child node was set at 100 and 50, respectively. Level of significance for splitting nodes was set at $p \leq 0.05$ and within multiple comparisons, significance values for merging and splitting criteria were adjusted using the Bonferroni method. The intervals for the continuous variable (i.e., margin of victory) was set at 3, corresponding to the closed, balanced, and unbalanced games clusters.

3. Results

Out of the 7934 performances, the model successfully classified 2658 (67.0%) of the 3967 loses and 2663 (67.1%) of the 3967 wins. The model has grown 47 nodes within all the 5 levels and 28 leaves (i.e., terminal nodes). The diagram and the detailed table of the entire model are presented in Figure 1 and in Table S1, respectively. Figure 2 resumes closed games both from the away and home fixture perspective.

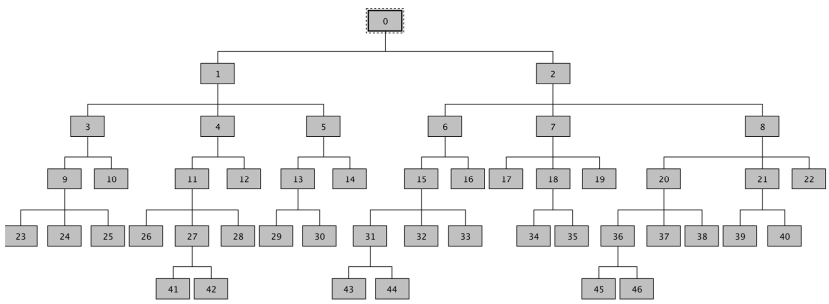

Figure 1. Decision Tree (DT) Diagram.

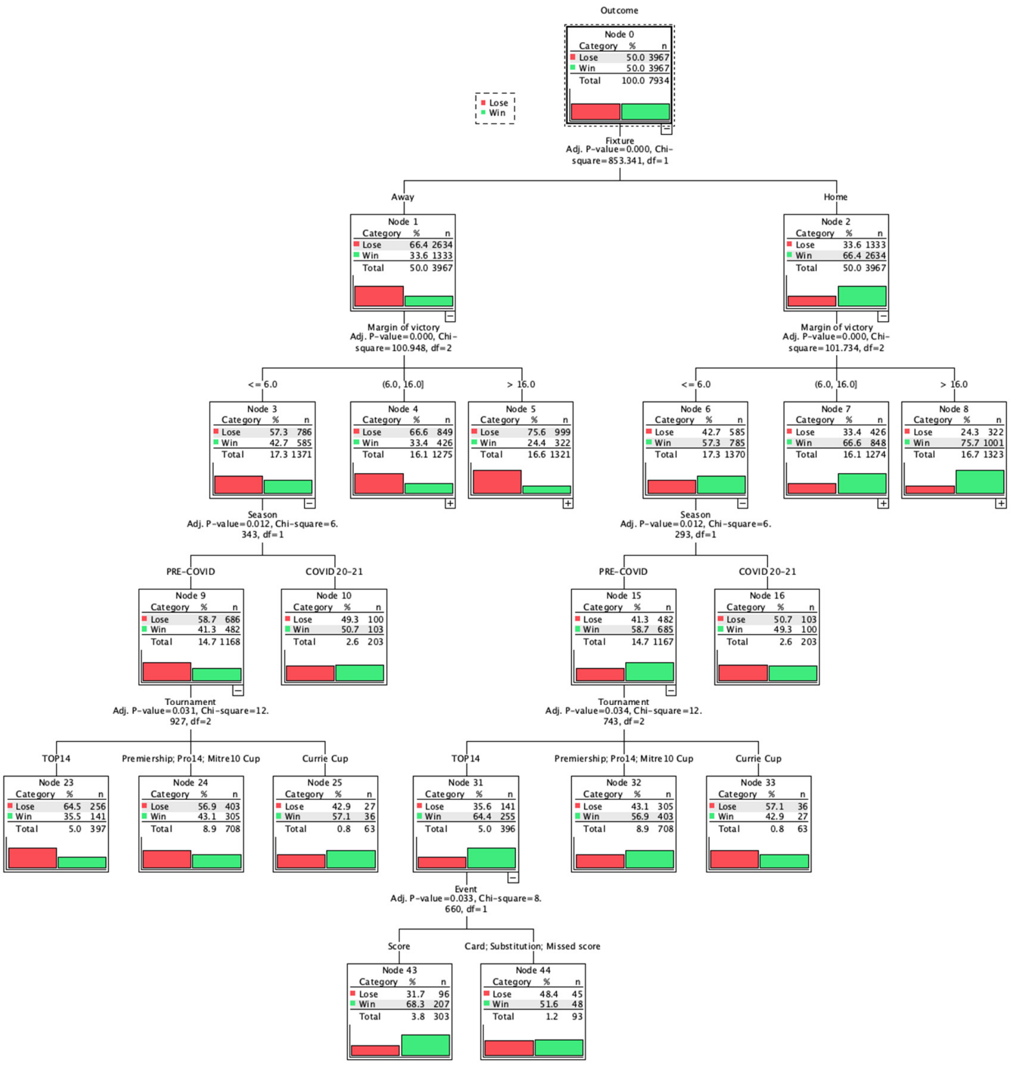

Figure 2. Closed Games Diagram from the Away and Home Fixture Perspective.

From the fixture perspective (node 1–2) teams playing at home were 66.4% likely to win the game. At the second level of depth (nodes from 3 to 8), the values of the margin of victory were divided into 3 clusters, below 6 points for closed, from 6 to 16 for balanced, above 16 for unbalanced games, respectively.

From closed games in home fixture perspective (node 6) the crowd absence affected HA by 9.4% (49.3% vs. 58.7%). At a deeper level, during the Pre-COVID period, the HA was significantly higher for Top14 championship (node 31) compared to other championships (64.4% vs. 56.9% vs. 42.9%). In Top14, HA was higher when scoring was the first event of the game. From balanced games in home fixture perspective (node 7), the highest HA was in Top14 championship (node 17) compared to the others (74.1% vs. 65.9% vs. 53.6%). In Premiership, Pro14, and Mitre 10 Cup (node 18) crowd absence affected HA by 16.2% (68.2% vs. 52%). From unbalanced games in home fixture perspective (node 8), HA was higher (79.8% vs. 45.6% vs. 69.8%) when the first event of the game was scoring (node

20) compared to card or substitution (node 21) and to missed score (node 22), respectively. When scoring first, HA was highest in Top14 (node 36) compared to the others (89.2% vs. 77.8% vs. 70.6%). In Top14 (node 36), crowd absence affected HA by 10.8% (90.2% vs. 80%). When the first event was card or substitution in Currie Cup or Premiership or Mitre 10 Cup (node 40), HA was lower than the others (31.1% vs. 59.4%). Figrues 2, S1 and S2 present the decision tree for home fixture according to closed, balanced and unbalanced games, respectively.

In closed games in away fixture perspective (node 3), results are specular to those in closed games in home fixture perspective (node 6). From balanced games in away fixture perspective (node 4), HA was higher (37.5% vs. 23%) when the first event of the game was scoring (node 11) compared to card or substitution or missed score (node 12), respectively. At a deeper layer, the highest HA (49.6%) was reported in Mitre 10 Cup (node 28) compared to Premiership or Pro14 or Currie Cup (node 27) and Top14 (node 26) when scoring first. Scoring first in Premiership or Pro14 or Currie Cup without crowd support increases HA by 17.1% (54.5% vs. 37.4%). From unbalanced games in away fixture perspective (node 5), HA was higher (30% vs. 12.2%) when the first event of the game was scored (node 13) compared to card or substitution or missed score (node 14), respectively. At a deeper layer, the highest HA (36.4%) was reported in Mitre 10 Cup, Premiership, Pro14, or Currie Cup (node 30) compared to Top14 when scoring first occurred (node 29). Figures 2, S3 and S4, present the decision tree for away fixture according to closed, balanced and unbalanced games, respectively.

4. Discussion

Since HA was reported to be influenced by the crowd support, the aim of the present study was to analyze it considering the crowd absence during the unique COVID-19 pandemic situation. Thus, HA was investigated within professional rugby club competitions according to the tournament, the margin of victory, and the scoring first. The main findings of this study were that the HA disappeared when competing without the supporters, especially in closed games, where differences in the final score were less than a converted try (7 points). Although differences between tournaments emerged, the crowd absence was associated with a detrimental effect on HA in both northern and southern hemisphere competitions.

From a complex system perspective, non-linear approaches for clustering and interpreting high-dimensional datasets, as Self Organizing Maps and Decision trees, were used in rugby union performance analysis [22,25,26] in order to better understand the determinants of success. To date, linear statistical models (e.g., analysis of variance, linear regression, chi-square) are the most common statistical tools used in analyzing HA in rugby union [1,4,7] although the use of non-linear statistics and machine learning techniques were shown to be a powerful and robust tool in detecting the most influent independent variables within large samples [11,27]. In fact, from a multivariate perspective, supervised non-linear statistical modeling technique like Exhaustive CHAID decision tree (i.e., Chi-squared Automatic Interaction Detector) can handle both nominal and numeric input variables, it is capable of handling datasets that may have errors, outliers, and missing values, and is considered to be a nonparametric method [28,29]. Moreover, its representation is easy to follow and it can be comprehensible by non-professional users [28,29]. On the other hand, it can be subject to overfitting and underfitting, particularly when using a small data set and this effect could limit the robustness of the model. Finally, strong correlation between different potential independent variables may improve the model statistics even if they are not causally related to the dependent variable. Therefore, projecting and interpreting DT models should consider these pros and cons [28,29], taking into account that adding multiple contextual variables in a non-linear perspective could enhance insight in performance analysis in rugby [30] and help coaches and coaching staff to better identify opportunities and threats. In this study a rather complex DT was grown, but it can be made simpler by following each variable of interest at a time.

With respect to the variables within the DT, the margin of victory had the highest impact on the classification (i.e., 2nd level of depth) and hence three clusters were built (i.e., $\leq$6, 6–16, >16). Compared to previous studies [12,24] in rugby union, the cutoff values in this study were lower. In fact, closed games were considered when differences in the final score were less than a converted try (i.e., <7 points), compared to 9 [12] and to 15 or 11 [24]. In this situation the HA was significantly lower than in balanced and unbalanced games, stressing the higher outcome uncertainty that was previously reported in rugby union [12,24].

When differences between teams are minimal and the outcome uncertainty is high, like in closed games, alterations in contextual variables can be substantial. In fact, contextual differences caused by COVID-19 pandemic had a significant influence on the game outcome exclusively in closed games. In particular, the crowd absence negatively influenced the HA, reducing it from 58% to less than 50% (i.e., 49.3%). Although the crowd absence had an effect even in balanced and unbalanced games, it resulted less important to the differences between tournaments and to the first event of the game. The scenario induced by the COVID-19 pandemic was detrimental for the HA in any case, even when it was secondary to other variables (i.e., nodes 34, 35, 41, 42, 45, 46), and it altered HA progressively less in closed, balanced and unbalanced games, respectively (i.e., nodes 6, 7, 8).

Differences between tournaments emerged when describing HA in rugby union. In fact, HA was always higher in Top14 compared to other tournaments, providing higher chances of winning without distinction for closed, balanced, and unbalanced games. Moreover, for teams playing away in Top14 in balanced and unbalanced games, scoring first does not represent a significant advantage compared to other tournaments (nodes 26, 29), like in Mitre 10 Cup where scoring first in balanced games nullifies HA (node 28). On the contrary, teams playing home in unbalanced games in Top14, as well as in Pro14, maintained HA even when they received a penalty card or they made a substitution at the very start of the game (i.e., 59.4%), unlike it happened for other tournaments (i.e., 31% in Premiership, Mitre 10 Cup, and Currie Cup). In the Pre-COVIDperiod, HA in Top14 was less affected by negative contextual variables (i.e., penalty cards or early substitutions), especially in unbalanced games (i.e., node 39). Based on several key performance indicators, it was suggested that playing style in Top14 is characterized by very few opportunities to spread the ball wide and to play a fast-paced game [31]. In addition, French Top14 is one of the oldest and more successful championship in the northern hemisphere in terms of attendance [32], as well as one of the highest paid rugby domestic league [33] attracting many elite foreign players. These characteristics could have made Top14 more resilient in terms of HA, less sensitive to negative contextual variables and more sensitive to positive ones (i.e., scoring first).

In general, HA was also modulated by the first event of the game. In rugby league scoring first was reported to increase chances of success [13] and this phenomenon would be in line also with rugby union. Although it was not investigated in rugby union before, in this study scoring first enhanced HA especially in balanced and unbalanced games, for both teams playing away and at home (i.e., nodes 11, 13, 20). Conversely, negative events like receiving a penalty card or making an early substitution reversed the HA for teams playing home (i.e., node 21) and penalized even more teams playing away (i.e., nodes 12, 14). Even if success in rugby union is multifactorial phenomenon depending on technical and tactical and time-motion events [12,34], the first event of the game should be take into account for estimating the outcome of the game.

5. Conclusions

COVID-19 pandemic situation stressed the importance of the crowd support in rugby union elite competitions. HA was influenced by the absence of the crowd support, although it should be considered as a multifactorial phenomenon depending on several variables. Considering the margin of victory, closed games are more sensitive to contextual variables in altering HA with respect to balanced and unbalanced games. Differences in HA depend on the tournament also, notably in the Top14 where playing home adds significant advantage to winning games compared with all the other tournaments. In their turn, all the above-mentioned changes in HA are sensitive to the first technical and tactical event of the game. Similar to rugby league, scoring first increases HA while receiving a penalty card decreases it in rugby union also, especially in balanced and unbalanced games.

This study is in line with others that investigated performance analysis by means of the decision tree classification method, albeit no cut-off is set for the classification validity [21,35]. Moreover, because of the advantages of the non-linear statistics (i.e., such as decision trees) in terms of ability to cope with errors, outliers, and missing values within databases, and ease of understanding by non-professional users, they should be preferred when describing multidimensional complex scenarios in performance analysis. Finally, further investigation on the characteristics of the tournaments (e.g., physical status, relative age effect, presence of top players) should be undertaken to better explain HA.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijerph182312711/s1, Figure S1: Home balanced games, Figure S2: Home unbalanced games, Figure S3: Away balanced games, Figure S4: Away unbalanced games, Table S1. EXHAUSTIVE CHAID decision tree table.

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4. Conclusion

To improve performance in team sports effective, accurate, and reliable feedback should be available to the coaching staff and to the athletes. In this perspective, PA including both Notational Analysis and Time-motion analysis is a fundamental tool within the coaching and physical training cycles that provides objective information through a systematic investigation by the means of the technical and tactical-, and physiological KPIs (i.e., Key Performance Indicators) (Nicholls et al., 2019). In addition, technological advances in computer software and digital video techniques (e.g., high-definition video cameras, high-capacity storage, high-computational capacity), the miniaturized portable tracking devices (e.g., GPS receivers, accelerometers), as well as the increased computing power, will led to a massive recording of data about the demands of play and the physical load. Hence, this scenario provides opportunities for accumulating a substantial body of knowledge in sport science but also challenges in selecting, validating, and standardizing performance indicators and analytical protocol (Rojas-Valverde et al., 2019).

Each of the two branches (i.e., Notational and Time-Motion analysis) is powered by different technologies. Video-based systems as well as wearable inertial and non-inertial devices support training load monitoring, and each of them come with its pros and cons. In fact, the decision to choose the technology for the PA process should always consider the cost-benefit ratio (i.e., costs, usability, reliability, validity) (Buchheit & Simpson, 2017). For instance, GPS devices can be easily used outdoor and they have demonstrated a good accuracy level when measuring some variables, such as total distance and peak speed. On the contrary, they cannot be used indoor and they become less reliable when accelerating, decelerating, running at high speed, or updating the software (Buchheit, al Haddad, et al., 2014; Coutts & Duffield, 2010; Jennings et al., 2010). Video-tracking systems allow players not to wear transponders and it can be used indoor while it requires a proper infrastructure to mount the cameras around the court and an expert technician to supervise the recording process. However, it was confirmed that at least the total distance and peak speed can be measured reliably in team sports by the means of any of the best Electronic Performance Tracking Systems (EPTS) currently available, i.e. global or local positioning systems (GPS and LPS), or video tracking systems (Linke et al., 2020).

From the data analysis perspective, the challenge is to generate reliable models of performance based on high-dimensional datasets resulting from the technological advances. Moreover, the modeling process must consider non-linear approaches to explain complex scenarios such as performance in team sports. For this purpose, machine learning allows a non-linear multivariate exploration of data to predict outcomes, rankings, physiological and technical and tactical performance, to identify the best contributors and determinants to explain training load magnitudes, to classify the team playing styles (Rico-González et al., 2023). Specifically, ML application in team sports has currently investigated far more extensively the match outcome prediction and team playing styles classification rather than injuries and training load prediction (Jaspers et al., 2018; Rico-González et al., 2023). From a practical perspective, a massive data collection regarding training load is quite difficult to achieve in order to set up a training load or injuries ML predictive model with a sufficient level of accuracy. For instance, professional soccer players train roughly 100 times per season and sometimes they are even transferred, which means no possibility to gather longitudinal data over multiple seasons (Jaspers et al., 2018).

However, the research to date might represent useful recommendations for stakeholders in team sports (e.g., athletes, coaches, managers, psychologists, therapists) while future opportunities should focus on collaborations between researchers from sport PA on one side, and ML on the other (R. Bunker & Susnjak, 2022). In fact, it was reported that most of the studies regarding the application of ML techniques for predicting match outcome in team sports were lacking in ample engineering features, although these are fundamental drivers of improvements in predictive accuracy (R. Bunker & Susnjak, 2022; Domingos, 2012). Description of the features by the domain-specific experts helps ML predictive accuracy to improve, its terminology to be clearer and more consistent, and its outputs to be human-understandable (R. Bunker & Susnjak, 2022; Domingos, 2012).

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