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A comprehensive analysis of internal and external load monitoring systems in basketball

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Different methods have been developed to monitor training load in basketball, so it is necessary to establish a common criterion to identify the reference variables to control the player's load. This study aimed to determine the most appropriate variables to measure each type of load. An retrospective methodology was used to monitor 16 professional players of the Spanish basketball first division (ACB league) during 19 training sessions. Five measurement systems were used for monitoring: the load programmed by the coach, heart rate, WIMU Pro inertial devices, the SIATE tool, and the RPE-CR10 subjective load scale. A Coefficient of Variance statistical analysis (CV%) was performed to measure the stability of the intrasession variables, a Principal Component Analysis to analyse the similarity between variables, a Cross-Correlation analysis to see the relationship and proportionality between variables, a Linear Mixed Model to analyse the innate individual influence of the subjects to each variable, a STEN normalisation to compare the behaviour of the variables between sessions and a Bland Almand Plot analysis to compare the agreement of the measurement variables. The results suggest that SIATE variables, when weighted by time and participation, along with the coach's planned load, serve as a key and robust indicators of both internal and external load. When resources allow, it is recommended to complement these with objective external load measures (e.g., Player Load, Distance) and subjective internal load indicators (e.g., sRPE).

Keywords Training, Male, External load, Internal load, Coach load

Load monitoring is essential in team sports at any competitive level for players' development[1], to enhance performance[2] and to reduce injury risk[3]. Load monitoring also allows a comprehensive training management, which can include strategies to select the most appropriate training tasks[4,5] or optimal loads to optimize performance[6,7]. This process could also assist in ensuring the player's availability, which is a key point for performance in elite team sports[8]. Therefore, several methods have been developed and employed over the years to monitor the dose of training that is administered to players. Several load monitoring methods have been developed in basketball, grouped in different blocks or families with common characteristics. Firstly, coaches employ their own training load monitoring systems for pre-training session planning[9], referred to in this research as Coach-Planned Load (PCL). Many strength and conditioning coaches lack access to high-cost technological resources. As a result, they often rely on their professional experience to implement load quantification systems based on qualitative observational records[10]. They use scales along with basic objective external load variables (such as time, number of players, rest time, etc.). This approach facilitates the specific selection of training tasks to achieve various technical, tactical, and physical objectives throughout the season. It also allows for load modulation across training sessions within the microcycle, based on performance needs dictated by the competition calendar[11].

Internal Training Load refers to how an athlete's body responds internally (cardiovascularly, metabolically, perceptually) to imposed training and game demands. These values can be obtained either objectively (OITL) or subjectively (SITL). Among the most commonly used tools for monitoring ITL in basketball are heart rate (HR) and session-rated perceived exertion (session-RPE). Heart rate provides coaches and sports scientists with direct, real-time insight into physiological strain. This allows them to ensure that each player trains at an intensity that fosters adaptation without risking excessive fatigue[12]. At the same time, session-RPE captures the athlete's own perception of effort and is valued for its simplicity and practicality[13]. Together, these objective (HR)

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and subjective (session-RPE) methods have gained widespread popularity because they can be easily integrated into daily training routines and consistently deliver reliable indicators of overall load[14].

External Training Load (ETL) refers to the measures of work performed (e.g., distances, speeds, accelerations) irrespective of internal responses. As with ITL, values can also be obtained either objectively (OETL) or subjectively (OITL). ETL monitoring is crucial in basketball to quantify the physical demands players currently experience during training and games. Among the most common methods reported in basketball literature are time-motion analysis (TMA) and the use of microsensor technology[13,15]. Time-motion analysis, involving video recording and subsequent categorization of movements (e.g., sprinting, shuffling, jumping), has been extensively applied to quantify players' movement patterns and intensities during competition. However, it has limitations such as being time-consuming and prone to human error, as well as the challenge of defining consistent intensity thresholds[13]. On the other hand, microsensors, particularly accelerometers, offer practical advantages due to their ability to measure movements objectively and conveniently, capturing intensity and accumulated load across three-dimensional planes. Despite these clear benefits, microsensor technologies in basketball require further validation to firmly establish their accuracy and consistency for widespread implementation[13,14]. Ultimately, the integration and advancement of these monitoring systems could significantly enhance player preparation, help prevent injuries and improve basketball-specific training strategies.

Several studies have been carried out that have partially compared different methods of load monitoring in basketball, the most frequent methods in the literature being the session RPE and HR-based methods, both from ITL[16,17]. When ETL has been analysed, distance (Dist) or speed has usually been used[18,19]. No research has been found that analyses the PCL compared to other load monitoring systems. When different methods have been compared, correlations have usually been made, with most research finding correlations between ITL variables[16,18,19] and between ITL and ETL[1]. It is worth highlighting the study conducted by Reina et al. [20], in which a partial study was made of the one presented here, with the comparison of ITL, OETL and SETL. The result of the research showed a statistically significant correlation between the three types of measurement. However, even though HR correlates in many of the mentioned research studies, most of the investigators mentioned limitations on its use or recommend using it with caution. Lopez-Laval, et al. [18] do not recommend the use of HR. Dalbo et al.[19] indicate that in most cases, no correlation of HR with variables derived from HR itself is found. Scanlan et al.[16] find limitations when monitoring load modulations with HR and Espasa-Labrador et al.[17] in their review list different limitations of HR, especially making a recommendation that it should be used at the individual level, and not at the team level.

Figure 1 depicts a cyclical framework in which the Strength & Conditioning Coach (S&C Coach) and the Manager collaborate to set, implement, and evaluate training loads for the athlete. The S&C Coach's Planned Load anchors the entire cycle: it accounts for fitness levels, match calendars, fatigue, and other physical needs, providing the baseline for how strenuous each session will be. This planned load then interacts with the Manager's tactical considerations (opponent analysis, task design, court dimensions) to shape what ultimately becomes the Actual External Load. Subsequent Internal Load Monitoring (e.g., heart rate or subjective RPE) and Physical Performance Assessments guide rest and recovery decisions, feeding back into the athlete's Fitness Status and informing the next phase of load prescription. By continuously iterating through these steps, where data on internal load (how the body responds) meets actual external load (how training is executed), coaches

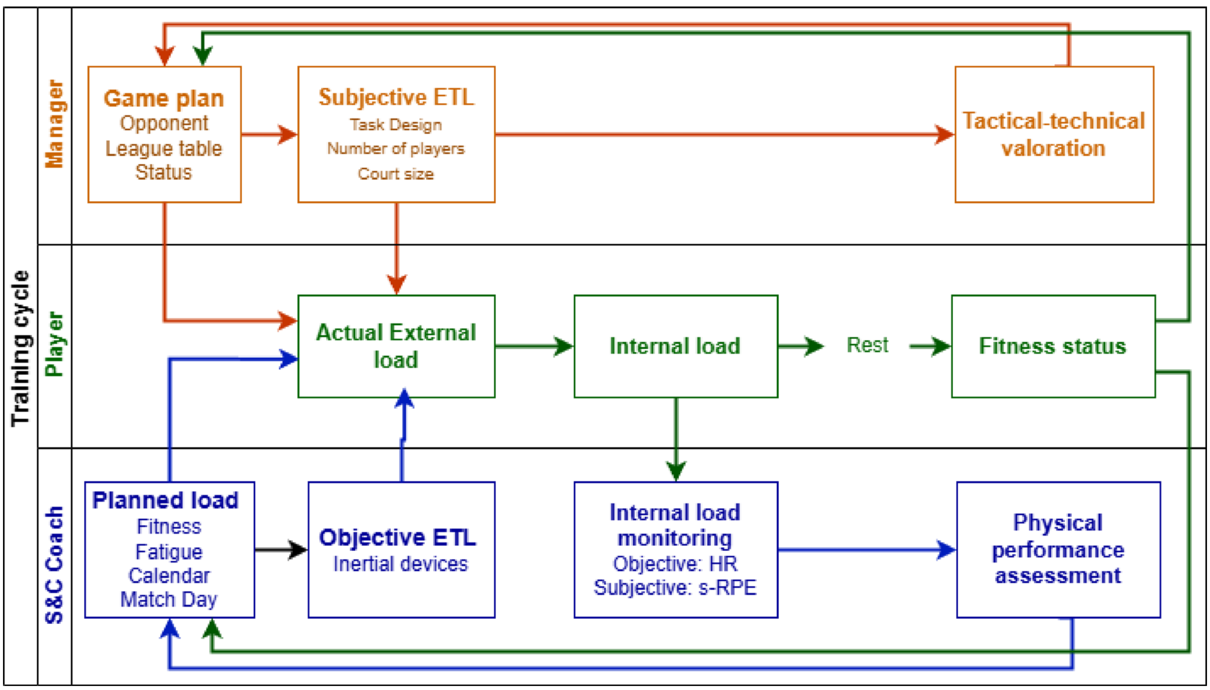

Fig. 1. The different stages of the training cycle.

can refine load prescription. This process is key to both enhancing performance and preventing injuries in high-level sports setting[21].

After reviewing the literature, numerous systems for monitoring load have been detected, each with strengths and limitations, which means that there is no clear consensus in the literature on the methods to be used to monitor training load in basketball. Furthermore, that review highlights a significant scarcity of studies incorporating practical tools routinely used by professional teams. Most research focuses on validated instruments, which, in many cases, are rarely adopted in applied settings. Therefore, to bridge the gap between scientific research and professional practice, it is essential to include and examine tools currently implemented in real-world high-performance environments. Therefore, the present study aimed to analyse different types of load monitoring methods (i.e., PCL, OITL, SITL, OETL and SETL) in a real basketball context. The objective is to unify criteria and identify the most relevant tools from a statistical and scientific standpoint. In doing so, the study seeks to establish a common framework for the use of variables in practical settings, addressing the wide variety of methods currently found in the literature. The specific objectives were (i) to analyse the intrasession stability of the different variables, (ii) to identify similarities between different variables that may be providing redundant data, (iii) to identify the existing correlations between variables, (iv) to analyse how the individuality of the players affects the different variables, (v) to check the behaviour of the variables throughout the different sessions and (vi) to study the agreements between different measurement systems.

Materials and methods

Design

The current study is an ex post facto research[22] that attempts to discover causal or determinant factors of an event of interest retrospectively. In particular, the aim was to obtain load data with different tools during the training process to retrospectively analyse how each tool assessed the load and the interaction between the different tools. Furthermore, according to the validity of the study, this research was ecological, analysing real situations where the players perform. As the data were monitored in the real training sessions of the team, without intervention of the research team in the design of tasks or intervention during the session, the ecological principle of the research was respected.

Participants

The study was conducted in a professional men's basketball team, playing in the Spanish top professional division (ACB league) during the 2022–2023 season. The sample consisted of 16 players, of which five were point guards, four were forwards, and seven were centers. Table 1 shows the data on body composition and years of experience of the players in general and by specific positions.

The coaching staff consisted of a head coach, four assistant coaches and a physical trainer. The head coach, with a long history at the club, had thirteen years of coaching experience. He had been with the monitored club for ten consecutive years, achieving a total of four league promotions, leading the team that same year to the Spanish first division (ACB league). The planning of the sessions was always carried out with the approval of the physical trainer, who had the same authority as the rest of the coaches during the design and development of the training sessions. This situation is exceptional and virtually nonexistent in the context of high-performance sport. In almost all professional teams, there is a clear hierarchy in which the head coach has the final say on every decision. This is the first instance in which a strength and conditioning coach has been observed to influence the head coach's final decisions. This likely stems from the head coach's own background and experience in strength and conditioning, which allows him to understand and appreciate the importance of load management in maintaining players' health and availability throughout the season. The physical trainer had been with the club for 11 years, four years in foreign leagues and seven years in Spanish leagues. He had been with the club for one full season, although he had been with the club for four years before his development in foreign leagues.

The participants in this research were selected by non-probabilistic convenience sampling[23], as only subjects who expressly agreed to be included were selected, based on the convenience of accessibility and proximity of the subjects for the researcher. This type of sampling is common in studies carried out with subjects belonging to the sporting elite, since the vast majority of clubs are reluctant to participate in research work for fear of seeing their sporting performance diminished. In addition, the target population of this study is very small in high-performance basketball (36 professional men's teams in Spain between the first and second divisions), so the accessible population is even more limited.

All team members were informed of the benefits and risks of participating in the research. Participants decided to participate voluntarily, and an informed consent form was signed by all coaches, coaching staff and players of both teams. The research followed the Declaration of Helsinki[24] and the Ethical Standards in Sport and Exercise Science Research[25]. Additionally, the study was approved by the Bioethics & Biosafety Committee of the

	Age (y)	Height (m)	Body mass (kg)	Fat mass (%)	Experience (y)
Team	26.4 ± 5.2	2.0 ± 0.1	95.6 ± 12.2	10.0 ± 4.3	6.7 ± 5.0
Guards	26.4 ± 7.7	1.9 ± 0.1	82.9 ± 4.7	8.8 ± 2.7	7.0 ± 6.5
Forwards	27.6 ± 3.0	2.0 ± 0.1	101.2 ± 8.6	11.0 ± 5.4	7.7 ± 4.3
Centers	23.7 ± 5.1	2.1 ± 0.1	103.6 ± 12.6	9.4 ± 4.5	4.0 ± 3.6

Table 1. Descriptive analysis of the participants.

University of Extremadura (code: 233/2019). The investigation respected the framework of Organic Law 3/2018 of 5 December on Personal Data Protection and guarantee of digital rights.

Eligibility criteria

The following criteria were used for the selection of participants: (i) having been monitored by the research group for at least 75% of the sessions, and (ii) not being injured or recovering from injury during the duration of the study.

Sample

The sample was obtained from the monitoring of 19 training sessions conducted over three microcycles. These sessions took place during the 2022–2023 pre-season of a professional basketball team competing in Spain's first division, the ACB League. The data were obtained using five different tools to monitor training load. This resulted in 221 cases with 32 variables each, generating a data matrix of 7,072 entries. Each case corresponded to each player in each training session.

Instruments and variables

Different instruments were used for the present investigation, each with a different purpose. These instruments were the Coach-Prescribed Workload tool, Heart Rate bands, the WIMU Pro inertial devices, the SIATE tool and the RPE-CR10 scale.

Firstly, a scale from 1 to 5 was used to collect the PCL variable. The coaching staff, during the design of the training session (and always before the implementation of the session), rated from 1 to 5 according to their tool to predict the training load based on the assessment of the load of each of the tasks. This tool yielded a value between 0–45 au (very low session load), 50–65 au (low load), 70–85 au (medium-low load), 90–105 au (medium load), 110–125 au (medium-high load), 130–145 au (high load), 150–165 au (very high load) and 170 au (extreme load). From these values, the five levels were extracted: level one - very low load, level two - low or medium-low load, level three - medium or medium-high load, level four - high or very high load, level five - extreme. The very high and extreme levels would correspond to 40' of play in an official match.

Secondly, Garmin HR bands (Garmin International Inc., Kansas, USA) were used to obtain OITL data (Avg HR, Max HR and Edwards' Training Load (SHRZ)).

Thirdly, the RPE-CR10 scale of Borg[26], weighted from 0 to 10, was used to monitor SITL data, using the RPE at the end of the session (measured after five minutes of rest and in isolation for each player) and the sRPE was calculated taking into account the duration of the training session in minutes[27].

To obtain OETL data, WIMU Pro (Hudl, Nebraska, United States) inertial devices were used with the indoor ultra-wideband (UWB) measurement system consisting of eight UWB antennas. For this purpose, the players were equipped with a harness with a pocket located at the level of the thoracic vertebrae T2-T4, which is the optimal place for obtaining positioning data validated with these devices[28]. The measurement error was 0.08 ± 0.04 m, measured from the distance between two inertial devices placed one next to the other, covering all the lines of the field to detect problems in the UWB signal in the whole signal area of the devices. With these devices, KOETL variables (Dist, Explosive Dist, High Speed Running, High Speed Running & Sprint, Maximum Speed, Maximum Acceleration, and Accelerations & Decelerations) and NOETL variables (High Intensity Actions, Impacts + 8G and Player Load) were collected.

Finally, the SIATE tool was used to collect SETL data[29], which through six qualitative variables with a range of scores from 1 to 5 in a rubric, a maximum task load value of 30 a.u. is obtained. From this value, called SIATE Task (ST) in the article, the SIATE Task Time Participation variable (STTP) is obtained, where the task load is assessed according to the task load, taking into account the duration of the task and the number of simultaneous participants involved in the task concerning the total number of players who are developing the session. In the case of this article, as there was only one value per session, and not per task, the value of the SIATE variables corresponded to the sum of the load derived from each task that made up each training session.

Table 2 shows a summary of all the variables used, with their unit of measurement and the instrument used to collect them.

Procedure

The club was contacted to make the research proposal. After the favourable acceptance of the club, coaching staff and players, the data collection was organised. The day before the start of the measurement, the quality of the data from the pavilion was analysed to install the UWB system with the lowest possible constant data error. A total of 19 sessions were collected in three microcycles. The first microcycle consisted of seven sessions, the second of six sessions, and the third of six sessions. The duration of the session and the number of tasks were variable, depending on the tactical and physical objectives planned by the coaching staff. However, all monitored sessions were tactical-technical, with similar load and structure. Technical sessions were not measured due to their influence on data analysis. In all microcycles, there was one day with a double session. A total of 110 tasks were monitored, with the following distribution of tasks per session (5.79 ± 1.75). The mean duration of the sessions was 83.60 ± 21.08 min.

To minimise the influence of potential confounding variables during data collection, a daily wellness questionnaire was administered each morning by the strength and conditioning coach. This questionnaire collected information on players' sleep quality and nutritional status, enabling individual adjustments to training loads when necessary. Nutritional monitoring was also supervised throughout the training period. Additionally, due to the high temperatures recorded during the measurement phase in Spain, players' hydration status was assessed through pre- and post-training bodyweight measurements conducted by the strength and conditioning coach.

Variable type	Measuring instruments	Variable	Abbreviation	Definition	Measurement Units
Coach-Prescribed Workload	Coach's own system of session load planning	Coach-Planned Load	PCL	Estimated load of the session scheduled by the coaching staff before the training session	au
Objective Interal Load	Heart Rate Band	Average Heart Rate	Avg HR	Average beats per minute	bpm
		Maximum Heart Rate	Max HR	Maximum value reached in beats per minute during the session	bpm
		Sum of the Heart Rate Zones	SHRZ	Weighted time in each heart rate zone, previously divided in five zones	au
Subjective Internal Load	Rate of Perceived Exertion Scale	Rate of Perceived Exertion	RPE-CR10	RPE Borg scale, using values from 0–10.	au
		Rate of Perceived Exertion per session	sRPE	RPE-CR10 scale weighted by session time in minutes.	au
Kinematic Objective External Load	Inertial Devices	Distance	Dist	Total distance covered	m
		Explosive Distance	Expl Dist	Distance covered with an acceleration greater than 1.12 m/s^2	m
		High Speed Running	HSR	Number of times the player has exceeded the HSR speed	n
		High Speed Running & Sprint	HSR & Sprint	Number of times the player has exceeded the HSR or Sprint speed	n
		Maximum Speed	Max. Speed	Maximum speed achieved	Km/h
		Maximum Acceleration	Max. Acc.	Maximum acceleration achieved	m/s^2
		Accelerations and Decelerations	Acc & Dec	Total number of accelerations and decelerations	n
Neuromuscular Objective External Training Load	Inertial Devices	High Intensity Actions	HIA	Number of high intensity actions	n
		Player Load	PL	Vector sum of accelerations recorded by the device in its three axes	au
		Impacts	Imp	Vector sum of the forces G supported by a player in all three planes	G
Subjective External Load	SIATE	SIATE Task	ST	Quantitative variable obtained by adding the value assigned within six previous variables (1 to 5 points).	au
		SIATE Task Time Participation	STTP	It allows to know the load adjusted to the level of participation of the athletes. It is the Time Task Load per Effective Participation of the athletes.	au

Table 2. Summary of instruments and variables used in research.

Statistical analysis

After data extraction from the different tools, a database was created for statistical analysis. The analysis was carried out with the Jamovi 2.5.6 tool (The Jamovi Project, 2022). The criteria assumption tests were performed, grouping the variables into parametric and non-parametric. The significance level was set at $p \leq .05$.

Firstly, a coefficient of variation analysis was performed for each of the 18 intra-session variables between subjects. In this way, the aim is to see if there is a high coefficient of variation (CV%) in each training session independently among the players. A high coefficient of variation would indicate that for the same stimulus (same training session), players respond differently. The following ranges were used to interpret the coefficient of variation: excellent when CV% was < 10%, good when CV% was between 10 and 20%, acceptable when CV% was between 20 and 30%, and poor when CV% was > 30%[30].

After excluding variables with a high coefficient of variation, as they did not faithfully represent the scheduled load of the session, a Principal Component Analysis (PCA) was performed for factor reduction of the loading variables. The model was established with Varimax rotation adjustment, interpretation of the rotated matrix with coefficient values greater than 0.6, with an eigenvalue of 1.5 to establish the dimensions[31], and an automatic selection of dimensions or factors. In this way, redundant variables of the same loading type were screened out.

Thirdly, after selecting the variables measuring session load and eliminating redundant variables, a correlation analysis was carried out. Being non-parametric variables, Spearman's correlation coefficients were used. Variables that did not correlate with variables of the same type, or that measured the same thing, were excluded from further analysis.

Once the variables of different types of load that correctly measured the training load and that were correlated with each other were selected, a Linear Mixed Model (LMM) adjusted for the random factor (player ID) was carried out for each of the variables to find out the level of individual affectation of the subjects to each variable. In this way, it was possible to see statistically whether the result of the load depended mostly on the load applied during the session or on the existing differences between the players. For the linear mixed model, the PCL and the microcycle were taken into account as a factor, the training session as a covariate, the player as a grouping variable for calculating individuality and each load variable as a dependent variable. To analyse the model fits, the values of the AIC/BIC and the marginal and conditional R^2 were considered. Likewise, for each analysis, the ICC values and their significance are presented to determine if the random response of the subjects was significant. Those variables with a very high ICC were excluded for the last analysis, due to the fact that practically all of their variation depends on the player and not on training, not being a representative variable of the training processes.

After the individuality analysis, which allowed us to determine the variable least influenced by the innate differences in the players, which, together with the results of the previous analyses, allowed us to determine the most suitable variable for measuring each type of load. In this way, a Bland-Altman Plot was carried out for each pair of variables to analyse the agreements or interchangeability of one type of measurement with the similarity of another type of load[32,33]. In this way, the variable with the best results in the pairwise comparisons would be the one that best represents the rest of the load variables. For this purpose, the distribution of the differences

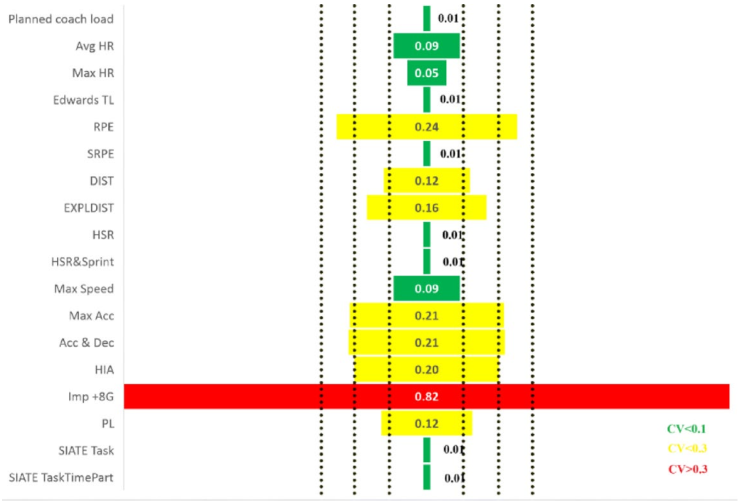

Fig. 2. CV% results.

Group	Variable	Group 1	Group 2	Group 3	Group 4	Uniquiness
Coach	PCL	0.668				0.280
	Avg HR				0.844	0.188
OITL	Max HR				0.739	0.229
	SHRZ					0.624
SITL	RPE	0.732				0.427
	sRPE	0.880				0.152
	Dist	0.803				0.153
	Expl Dist	0.698				0.427
	HSR		0.932			0.077
KOETL	HSR & Sprint		0.939			0.069
	Max Speed					0.598
	Max Acc			0.865		0.242
	Acc & Dec	0.626				0.188
NOETL	HIA	0.669				0.159
	PL	0.825				0.152
SETL	ST	0.822				0.195
	STTP	0.681				0.262

Table 3. PCA performed to reduce the number of variables corresponding to the same type of load. Note: PCL = "Coach-Planned Load", Avg HR = "Average Heart Rate", SHRZ = "Sum of HR Training Load", Dist = "Distance", Expl Dist = "Explosive Distance", Acc & Dec = "Acceleration and Deceleration", ST = "SIATE Task", STTP = "SIATE Task Time Participation".

within the optimal ranges according to the confidence intervals, the slope of the proportional bias line and the dispersion of the differences concerning the proportional bias line were analysed.

Finally, with the variables selected after the LMM, profiles were established based on the z-scores and STEN values, in order to have values that would allow comparing variables with different units of measurement, but which were intended to analyse the same concept: training load. With the STEN values, a radial graph was made to show the evolution of the variables analysed throughout all the sessions visually.

Results

Figure 2 shows the results of the CV% analysis applied to the 18 variables initially included in the research. The intra-subject variation between subjects is analysed for each of the loading variables.

Of the 18 variables, ten variables have a CV% rated as excellent, three variables with a good CV%, four variables acceptable and one variable with a poor CV%.

Table 3 shows the results of the PCA applied to the 17 variables resulting from the CV% analysis.

It can be seen that four variables are redundant according to the analysis carried out, so they are extracted from the rest of the analysis. These variables are the Max HR, which is explained by the Avg HR; the RPE,

Variable Type		PCL	Avg HR	SHRZ	sRPE	Dist	HSR & SPRINT	Max Acc	HIA	PL	ST	STTP		
PCL	**PCL**	—	0.172	−0.054	0.617	0.435	0.616	0.213	0.685	0.494	0.536	0.857	1	Almost Perfect
OITL		**Avg HR**	—	−0.007	0.341	0.448	0.436	0.056	0.376	0.422	0.359	0.181	0.9	
			SHRZ	—	−0.015	0.005	−0.024	−0.071	−0.042	0.035	−0.011	−0.028	0.8	Strong
SITL				**sRPE**	—	0.65	0.409	0.265	0.658	0.665	0.659	0.637	0.7	
KOETL					**Dist**	—	0.523	0.081	0.696	0.957	0.774	0.444	0.6	Moderate
						HSR & SPRINT	—	0.114	0.652	0.52	0.422	0.573	0.5	
							Max Acc	—	0.368	0.098	0.081	0.235	0.4	Marginal
NOETL								**HIA**	—	0.71	0.596	0.717	0.3	
									PL	—	0.768	0.495	0.2	Poor
SETL										**ST**	—	0.572	0.1	

Table 4. Cross-correlation analysis. Note: SHRZ = "Sum of HR zones", HIA = "High Intensity Actions", PL = "Player Load", ST = "SIATE Task", STTP = "SIATE Task Time Participation", PCL = "Coach-Planned Load". Variables in red $p > .05$.

Variables	AIC	BIC	Marginal R^2	Conditional R^2	ICC	*p*-value
Avg HR	1473.849	1487.825	0.228	0.867	0.827	< 0.001
sRPE	2684.749	2591.606	0.721	0.850	0.462	< 0.001
Dist.	3175.383	3042.617	0.887	0.947	0.532	< 0.001
HSR & Sprint	1156.327	1197.003	0.386	0.631	0.399	< 0.001
HIA	2443.080	2372.991	0.656	0.746	0.260	< 0.001
PL	1461.324	1475.877	0.862	0.930	0.494	< 0.001

Table 5. Results of the LMM for the analysis of individuality of variables. Note: Avg HR = "Average Heart Rate", Dist = Distance.

which is explained by the sRPE; and the Expl. Dist. which is explained by Dist; the variable HSR, which is best explained by HSR and Sprints, and accelerations and decelerations, which are best explained by the variable HIA. In addition, the variables maximum speed and SHRZ do not reach the cut-off points established in the analysis.

Table 4 shows the results of the correlation table between the 11 variables resulting from the PCA.

The SHRZ and maximum acceleration variables show no correlation with the rest of the variables. The rest of the variables show significant correlations with each other, except for the two previously mentioned. The variables PL and Dist show almost perfect correlation values. The ST and STTP variables show strong correlations with EC variables. The maximum acceleration variable is the one with the poorest correlation values.

Table 5 shows the results of the LMM for the analysis of the individuality of the variables derived from the analyses carried out previously. The variables derived from SIATE are not included in this analysis because the resulting value is the same for all the players in the team in the same session, and therefore, it is not possible to extract results of the individuality of the subjects.

All variables show significant patterns. Avg HR is the variable with the highest individuality index as a function of ICC (83%), followed by Distance (53%) and Player Load (49%). HIA is the only variable with a range of individuality below 30%.

Figure 3 shows the differences between the different sessions for each selected variable for each type of load after normalisation of the variables to z-score and sten.

The Avg HR variable is the one that does not follow a pattern across all sessions, as the other variables do.

Figure 4 shows the Bland-Altman graphs comparing the PCL and STTP variables with the rest of the variables for each type of load.

The two variables included in the Bland-Altman graphs show results that confirm the agrements between them. The dispersion of the points is minimal compared to the base line and all differences are within the confidence intervals.

Discussion

The general objective of this research was to compare different load quantification methods for different types of loads. The main findings of this research are the high relationship between the load planned by the coach and the SIATE load control tool. The internal load measured through heart rate has great limitations due to the affectation of the individuality of each player and the great variation depending on the type of variable chosen to interpret the data. The RPE is a useful tool for obtaining internal load data. Inertial devices yield very useful external load values, especially the distance, Player Load and HIA variables.

The first specific objective was to analyse the intrasession stability of the different variables. The main findings of the CV (%) show that the impacts vary greatly between players in response to the same stimulus, which seems to indicate that it does not depend directly on the training, but on the player. Impacts, being a variable

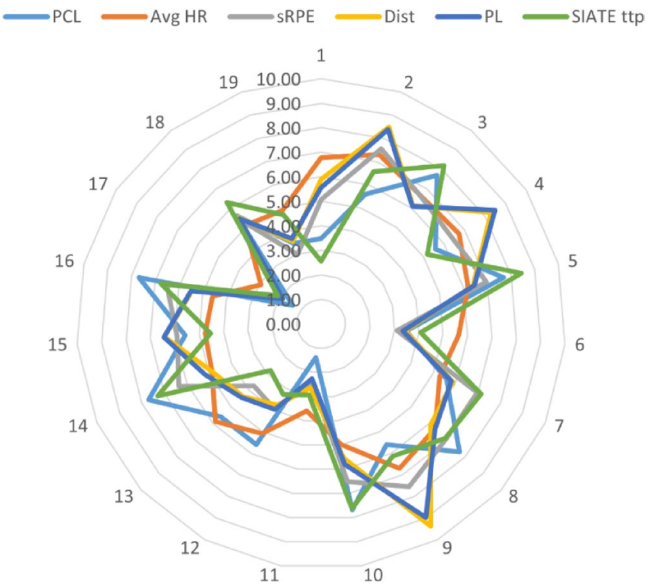

Fig. 3. Radial graph comparing the different variables weighted by session.

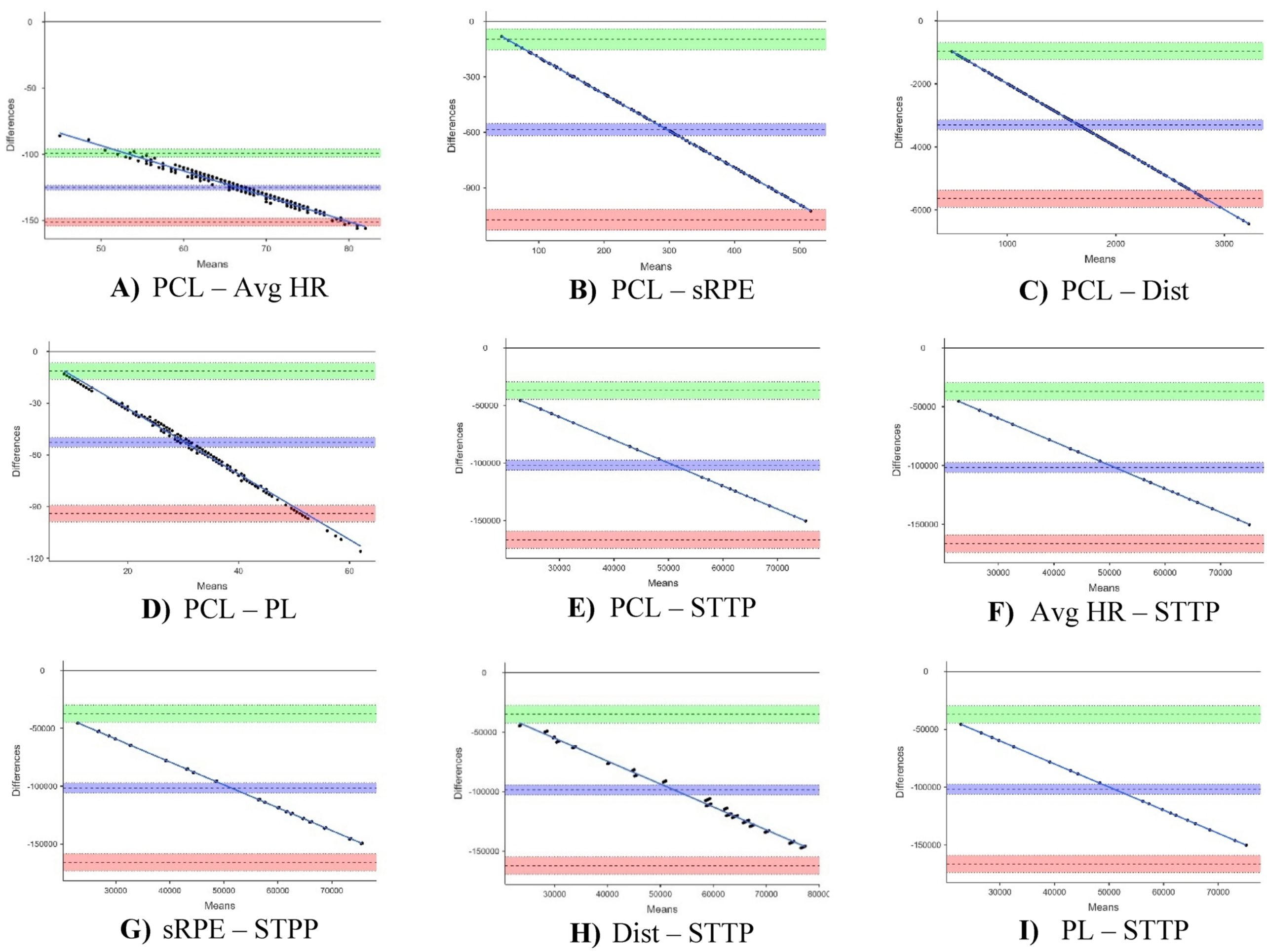

Fig. 4. Bland Almand plots of the CPL and STTP variables.

that measures a force, in this case collisions, depend on the mass of the body and the acceleration with which it moves, being highly conditioned by the player. Firstly, the mass is very different in basketball players[34], which in itself implies differences in impacts at the same acceleration. When two bodies collide, the mass of the two bodies interacts in the force of the collision, which, being so different among the players in the squad, produces even more differences in the impacts[35]. In terms of acceleration, explosive players can reach the same peak velocity (CV% excellent) as less explosive players, but in a shorter time, i.e., with a higher acceleration, also affecting the G-force with which the impact is produced. These conditions influence the individuality of impacts, which is very high in studies carried out in other sports in which numerous collisions occur, such as handball[36]. For this reason, the variable impacts, although it should be taken into account to analyse the training load because collisions produce a high load on the players, is not a load indicator that depends solely on the training session, so it should be used as a load indicator independent of those derived from the planned load in the session. Furthermore, it should be taken into account for intra-subject comparison, and not between subjects, being important to qualify the individual load against the team load. Therefore, the high inter-player variability observed through the intrasession CV% limits the usefulness of impacts as a valid training load indicator, which supports their exclusion from subsequent analyses, despite their potential relevance for individual fatigue monitoring.

The second specific objective was to look for similarities between different variables that may be providing redundant data. The PCA result shows a Group 1 in which the variables of PCL, SITL, KOETL, NOETL, and SETL are found. Groups 2 and 3 also include KOETL variables, being the category with the most variables included. Group 4 is made up of only OITL variables. Two variables have not been included in any group as they did not exceed the threshold: SHRZ and Maximum velocity. Scanlan et al.[37] found that in basketball, the dose (ETL) - response (ITL) relationship is not as strong as in other sports. In this case, it is the OITL that is in a different group from the PCA, while the SITL obtains similar results to the ETL. Scanlan et al.[37] associate this lack of dependence with the type of tasks used in basketball training, which are somewhat different from those used in other sports. Thus, the appearance of Groups 2 and 3 in the PCA implies the differences between the more physical tasks, which will stand out for their higher values in Groups 2 and 3, and the more tactical tasks with a greater relationship between players, which will be found in Group 1, which will be more related to the game of basketball. Gómez-Carmona et al.[38] and Espasa-Labrador et al.[39] reveal that there is great heterogeneity in the methods and variables for monitoring ETL, suggesting that in future research, a consensus should be established to use the same variables in the different studies. The PCA allows preliminary discarding of certain ETL variables that could be redundant, applying the variables that best explain Group 1, including also the main variables of Groups 2 and 3, which in principle would explain different aspects of the load that are not explained only by the variables of Group 1. These findings suggest that PCA facilitates the reduction of redundant ETL variables, allowing the selection of those that provide complementary and meaningful information for training load monitoring. In this sense, PCA not only helps to identify groups of related variables, but also provides a practical framework to filter those that add little new information, guiding researchers and practitioners toward the use of the most representative indicators.

The third specific objective was to identify the existing correlations between variables. The results of the correlation analysis show significant relationships for all the variables except SHRZ, which does not correlate with any variable, and maximum acceleration, which only correlates with four of the variables added to the model. The strongest correlations are between variables NOETL and KOETL, followed by the correlations between variables OETL-SETL and SETL with PCL. Moderate correlations are between variables of different typologies (ETL, ITL and PCL), while the poorest correlations result from PCA Group 1 variables with those in Groups 2, 3, and 4. Scanlan et al.[37] and Edwards et al.[1] also found no strong relationships were found with variables derived from HR and those from ETL. Scanlan et al.[37] associate this poor correlation to the presence in basketball of isometric exercises during the game that underestimate the load when measured with HR-derived data. In this case, there is no correlation with the SHRZ variable, which is coherent if we take into account that this formula segments the HR values by percentages, weighting the time in each of the HR zones in an ascending manner. As the HR values are underestimated, it is difficult to find high values in the weightings and, consequently, high SHRZ values appear when the ETL increases. In summary, the correlation analysis highlights consistent relationships between ETL and PCL measures, while confirming the limited value of SHRZ and maximum acceleration for monitoring basketball load.

The results of previous studies showed poor-moderate correlations between OITL and SITL variables, similar to what was found in this research[18,40]. Labrador et al.[41] did find correlations with HR with SHRZ and RPE, but it should be noted that the sample was collected during a developmental programme, where HR is less contaminated by stress than during the top-level league. Svilar et al.[42] and de Dios-Alvarez et al.[43] identify in their studies high relationships between ETL variables, as does the present study. The ETL variables, both OETL and SOTL, are the most highly correlated with each other. The ITL variables have the poorest correlations, although they remain significantly correlated. This seems to indicate that, after the training stimulus, the players have similar ETL values, but not all of them tolerate the ETL in the same way, resulting in different ITL values. This is why the individual load of each player must be taken into account in training sessions, because, although they all go through the same process, each one ends up perceiving very different load values, which must be taken into account for future load planning and to avoid problems with overloads. Overall, while ETL variables show strong internal consistency, the variability of ITL responses underlines the importance of accounting for individual tolerance when planning and monitoring training load.

The fourth specific objective was to analyse how the individuality of the players affects the different variables. The results of the MLM with PCL and microcycles as factors applied to each of the loading variables showed improvements in the marginal R^2 against the conditional in all variables, but with a significant change in the Avg. HR and HSR & Sprint variables. This is reflected in the ICC values, where they are very high for the OITL variable, being affected by 87% of the individuality of the subjects, followed by Dist with 53% of individuality. All models, with PCL as a factor, are significant. These results are not new findings for the literature, but they are interesting because they support the idea that HR, which is still used as an indicator of load in team sports, should be taken with caution when working at the team level and not at the individual level. Moreno et al.[44] show the influence of individuality on HR in basketball players, recommending an individual use of HR in this type of athlete by detecting that each athlete has different requirements and recovery patterns. Sanders et al.[45] also analysed HR individuality, finding clear and significant effects of athlete individuality on these variables. Espasa-Labrador et al.[17] in their review of the literature conclude that HR should be used only on an individualised basis, and not on a team level. These findings can also be seen in the more descriptive results presented in the radial graph introduced in the study, where the values obtained by the team in each of the sessions are compared, showing that all the variables have predictable trends depending on the session and its contents, except for the HR, which has a more random and less predictable behaviour. Therefore, HR should be used as a training session output, but not as a predictor for load planning. Furthermore, when it is used as a result of session loading, it should always be analysed individually for each subject, and always establish intra-subject and not inter-subject comparisons. This, together with the delay that HR presents in its oscillations[13] and the limitations when monitoring load modulations[16], makes it difficult to use HR to contextualise which situations fatigue players, as HR does not increase during explosive movements, but rather it increases once these movements have been performed. In addition to these physiological constraints, HR measures are also subject to device-related limitations. Signal noise, electrode placement, and movement artefacts can compromise accuracy. These technical issues, together with the strong effect of individuality, further restrict the value of HR as a consistent team-level load indicator. These results reinforce that HR should only be employed as an individualized marker of internal load, given its limited reliability for team-level monitoring and load prediction.

The last specific objective was to study the agrements between different measurement systems. The Bland-Altman analysis compares the interchangeability or agreements between the different measurement systems. The results show that Avg. HR and sRPE are the least interchangeable variables, being interchangeable with three of the five possible variables. Dist. is not interchangeable with sRPE, while PL is not interchangeable with Avg. HR. The STTP and the PCL variable are interchangeable with all the variables used, so they are considered key and robust measurement systems. Few investigations have compared PCL, but some have found a significant correlation between PCL and that perceived by players[46]. Regarding SIATE, research conducted with this tool shows strong relationships in how the training session is organized and PCL with the ETL product[4,10]. In addition, the SIATE tool has been validated and is reliable[29], highlighting in its validity the importance of the coach's experience, and naming the tool as key and robust. The use of these tools is suitable for any invasive team sport, but it is important that their use is supervised by a professional in the field, because, due to its subjectivity, it requires experience and knowledge in the field. However, the main advantage of these tools is their ease of use and low cost. From a practical perspective, the Bland-Altman analysis highlights PCL and STTP as robust and reliable systems for load monitoring, combining validity with ease of application in team sports.

The main limitation of this research is that the tools used with the best results require trained and experienced personnel for their use. On the other hand, being a research that requires many technological means (high-cost inertial devices, participation of coaches and physical trainers in obtaining data, continuous measurement of RPE, etc.), the duration of data collection is not very longitudinal. In addition, it should be noted that inertial devices from different manufacturers may use distinct algorithms, which limits the direct comparability of results. Future studies should therefore confirm these findings with different devices to strengthen the generalization of the conclusions. The main strength is that the work has been carried out with a professional team of the highest level, with coaches of a high level and experience and trained in the field. All the research has been carried out ecologically, obtaining the data in real training situations. It also highlights the integration of various validated methods for load monitoring, identifying key and robust tools (PCL and STTP) stable and adaptable to different training situations, that can be applicable to other invasive sports. Furthermore, the results derive the proposal for the inclusion of low-cost and easy-to-implement tools for load monitoring, which will allow teams with fewer resources to benefit from the knowledge provided by load monitoring.

It is recommended that the sample size of the data be increased in future research. In addition, for a correct load planning, simultaneous work of coaches and physical trainers should be carried out, where physical trainers have the same importance as the coach and are not in the background. These investigations should be longitudinal studies that analyze the variation of the load during the season and collect a history of player injuries to try to establish relationships between the occurrence of overload injuries and the training load. Finally, studies similar to this one should be replicated in other invasive sports, where these tools are implemented in contexts similar to basketball and detect if they have the same employability. Future research should refine PCA processes by establishing standardized criteria to filter redundant variables, for example by combining PCA with other multivariate approaches or by validating results with larger and more diverse samples. This would allow researchers to determine with greater accuracy which variables provide unique and meaningful information, and which can be discarded without compromising the monitoring of training load. This would give the possibility, with the help of AI, to develop algorithms that allow the combination of the results of the different tools used to automatically predict the optimal training load for each player. Machine learning and AI-based approaches could complement current monitoring systems by integrating information from different sources (e.g., PCL, SIATE, IMUs, and sRPE) and highlighting relevant patterns for the coach. Rather than replacing existing tools, these methods may support practitioners by simplifying complex datasets, detecting early warning signs of abnormal responses, and helping to prioritize the most informative variables for individualized follow-up.

Conclusions

This research analyzed the different methods of load quantification used in professional basketball to find out which method yields the most information. Key and robust methods for basketball are the Coach-Planned Load and the SIATE value weighted to time and participation, since they meet the following criteria: they are stable intrasession variables, they sufficiently explain the training processes and are similar to other measurement variables, they correlate with the objective load variables with high values, they are not affected by individuality and they are interchangeable with the rest of the load methods. Heart rate is included because it is the most widely used and simplest method of monitoring objective internal load to implement in a device. However, it presents several controversies in its use, because it does not have high correlations with other variables; in fact, it does not even correlate with other heart rate variables. In addition, it is affected by the individuality of the players by 80%. The use of inertial devices is recommended as a complement to SIATE and planned load due to its immediacy, individuality and number of variables to select, although it will depend on the availability, economic capacity and training of club personnel for its implementation. It is more a complement than an indispensable tool, although the performance is obtained by small details that can be yielded by these devices.

Practical applications

It is recommended to implement load monitoring systems in invasive sports at all levels, from youth to elite. PCL and SIATE are simple and sufficient tools to plan and control training load, although results should be individualized when players do not complete the full session or train apart due to injury.

The analysis of impacts showed very high inter-player variability, which limits their value as a collective indicator of training load. Nevertheless, they can provide useful information for monitoring individual fatigue and assessing specific collision demands.

When resources allow, inertial systems can complement these tools by providing detailed individual data. Based on our results, Distance is the main indicator of External Kinematic Load and Player Load the best option for External Neuromuscular Load. Other useful variables include high-intensity actions, HSR & Sprints, and maximum acceleration.

Heart rate shows important limitations in team sports, as it is influenced by individual characteristics, reacts with delay, and does not correlate well with external load, besides adding extra cost.

For Internal Load, the sRPE scale is a practical and reliable option. It is inexpensive, easy to apply, and sufficient if used under a standardized protocol. A familiarization period is recommended, preferably with the RPE-CR10 scale, and data should be collected individually and privately to avoid bias.

Data availability

Data not available due to ethical restrictions and confidentiality of data. For further information regarding the data used, please contact [pablols@unex.es](mailto: pablols@unex.es).

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Author contributions

All authors declare that they have contributed equally to all stages of the research, as well as to the writing and preparation of the article.

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Declarations

Competing interests
The authors declare no competing interests.

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