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Optimizing player health, recovery, and performance in basketball

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Optimizing player health, recovery, and performance in basketball

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Editorial: Optimizing player health, recovery, and performance in basketball

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Editorial on the Research Topic
Optimizing player health, recovery, and performance in basketball

Basketball is one of the most popular team sports globally, with participation rates ranging from 2 to 5% among adults (aged >18 years), 7–14% among adolescents (aged 13–17 years), and 5–25% among children (aged 5–12 years) in African, American, and Western Pacific regions (Hulteen et al., 2017). This participation rate has grown recently in many countries—for example, 27.1 million people from the United States over 6 years of age participated in basketball in 2021 compared to 22.3 million in 2016 (Statista, 2022). Furthermore, basketball is played across many competitive levels ranging from recreational settings to international tournaments such as the Olympics. In line with this broad appeal and increased participation, the number of journal publications focused on basketball has grown in the past 20 years (Figure 1), placing it second in publication outputs among Olympic team sports (Millet et al., 2021). Consequently, this Research Topic, *Optimizing player health, recovery, and performance in basketball*, was conceptualized as an outlet for this increased scientific interest to further strengthen the available evidence base for basketball end-users.

The development of relevant research questions that meet the needs of end-users and provide real-world impact is essential to evidence-based practice (Fullagar et al., 2019a). In this way, the different focal areas of this Research Topic (i.e., player health, recovery, and performance) align with preferences for research evidence among end-users working in competitive sport (Fullagar et al., 2019b; Schwarz et al., 2021). For instance, most surveyed practitioners employed within a sports organization (at the collegiate, professional, or Olympic level) in the United States ($n = 67$, with 16% working in basketball) indicated they used research evidence for health-related functions [injury prevention (91%), nutrition (85%), and rehabilitation (81%)], recovery (94%), and performance-related functions [fitness (79%) and load monitoring (73%)], with research contributing most to developing individualized preparation/recovery strategies and optimizing individual performance (Fullagar et al., 2019a). Furthermore, most of the

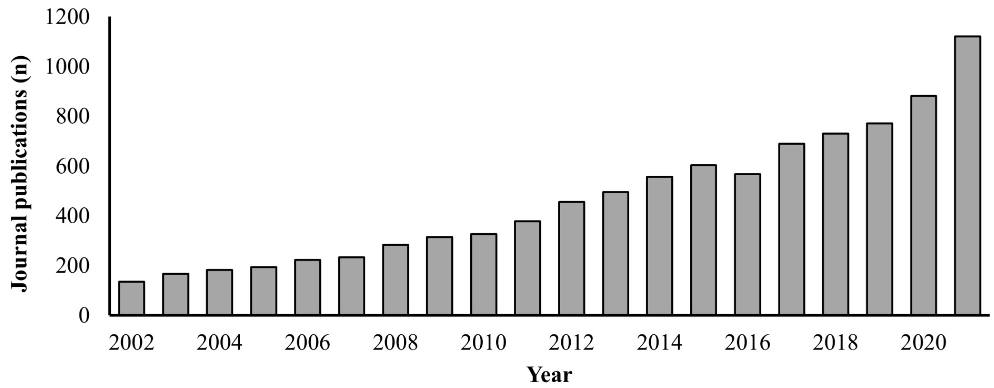

FIGURE 1
Growth in the number of basketball Scopus-indexed journal publications between 2002 and 2021. Search conducted using Scopus on 27 October 2022 for "basketball" within "Article title, Abstract, Keywords" field, with "Journal" selected as source type and "Article in Press" excluded.

basketball literature has been identified to focus on topics related to physiology (Millet et al., 2021), injury (Scanlan and Dalbo, 2019; Millet et al., 2021), testing/assessment (Millet et al., 2021), load monitoring (Scanlan and Dalbo, 2019), and game statistics (Scanlan and Dalbo, 2019), which likely encompasses various health-, recovery-, and performance-related research questions. Consequently, the studies published in this Research Topic provide novel evidence in areas that are relevant to basketball end-users by extending upon popularized areas and expanding areas in need of further attention such as technical/tactical components and skill acquisition (Fullagar et al., 2019a).

Three studies published in this Research Topic focused on external load monitoring among basketball players. Player monitoring is commonly employed by basketball practitioners (Fox et al., 2020), with external load data indicating what players do and being an integral part of the physical training process to impact health, recovery, and performance outcomes among players (Jeffries et al., 2022). Firstly, Russell et al. provide the most comprehensive analysis of external loads imposed upon a National Basketball Association (NBA) team to date, reporting demands during different tasks according to player role, experience, and position across a season. Secondly, Stone et al. provide insight into the utility of different external load variables measured using microsensors according to position among male, National Collegiate Athletic Association Division I players. Thirdly, Pernigoni et al. used video-based time-motion and microsensor technologies to quantify the demands experienced during jumps, sprints, and high-intensity specific movements, as well as with and without ball possession according to position among semi-professional, male basketball players.

Four further descriptive studies focused on quantifying anthropometric, fitness, behavioral, or technical/tactical attributes among basketball players, generating evidence that may inform practical strategies in health- and performance-related areas including player assessment, selection, and nutrition. Firstly, Sato et al. described the associations between facial width-to-height ratio measurements and performance during games (i.e., efficiency rating) among professional, male basketball players. Secondly, Popowczak et al. highlighted the importance of anthropometrical attributes when elucidating associations between physical and cognitive variables during reactive agility and change-of-direction speed tests in professional, female basketball players. Thirdly, Rösch et al. concluded that the Basketball Learning and Performance Assessment Instrument possessed adequate reliability in assessing various performance and technical variables but lacked diagnostic validity in identifying selected (vs. non-selected) youth (under-15 years), male players within a national program. Fourthly, Sánchez-Díaz et al. demonstrated male players had superior physical fitness and led more active lifestyles than female players, with all players possessing inadequate nutritional habits and knowledge among youth (under-14 years) players from a national program.

An additional three studies examined training strategies and statistical indicators in relation to technical performance, team performance, and injury rate in basketball players. Firstly, Caparrós et al. demonstrated that irrespective of the strength training program undertaken, strength variables alongside muscle injuries were associated with team performance outcomes in professional, male basketball players. Secondly, Milley and Ouellette showed that using an external focus of attention imagery technique benefited free-throw shooting performance compared to an internal focus of attention strategy in collegiate basketball players. Thirdly, Yi et al. concluded that various game-related statistics including two-point field goal percentage, offensive rebounds, assists, and turnovers were key for team success in professional, female players.

The collection of studies presented in this Research Topic cover various areas encompassing player samples spanning across sexes, ages, and competitive levels. This openness to research among basketball teams is encouraging and should be nurtured through the continued development of studies that are symbiotic for stakeholders in terms of implementation and outcomes. Accordingly, dedicated work is advocated to ensure the most impactful questions are developed in future studies (Buchheit, 2016) and identify how the generated outcomes can be most effectively disseminated for implementation (Buchheit, 2017)—which is yet to be explored specifically among basketball practitioners. In this way, embedding research students (*via* partnership with institutions) or research staff (e.g., sport scientists) within basketball teams may assist in ensuring not only the most relevant evidence is generated, but also effectively communicated and implemented (Fullagar et al., 2019a). Of note, no studies in this Research Topic examined 3 × 3 basketball, which should be given greater attention moving forward given its rapid rise in global popularity and recognition as an official Olympic sport at the recent Tokyo 2020 games. Furthermore, innovations to technology and strategies that reduce injury/illness risk, enhance return-to-play progression, improve the recovery process during specific seasonal phases, and promote desired performance levels should continue to be developed and tested *via* empirical research to ensure we are continually optimizing player health, recovery, and performance in basketball.

Author contributions

AS and DF wrote the original draft of this editorial, while DC reviewed and edited it. All authors have approved the final version of this editorial.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Assessing the External Load Associated With High-Intensity Activities Recorded During Official Basketball Games

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Load monitoring in basketball is fundamental to develop training programs, maximizing performance while reducing injury risk. However, information regarding the load associated with specific activity patterns during competition is limited. This study aimed at assessing the external load associated with high-intensity activities recorded during official basketball games, with respect to different (1) activity patterns, (2) playing positions, and (3) activities performed with or without ball. Eleven male basketball players (six backcourt, five frontcourt, age: 20.5 ± 1.1 years, stature: 191.5 ± 8.7 cm, body mass: 86.5 ± 11.3 kg; experience: 8.5 ± 2.4 years) competing in the Lithuanian third division were recruited for this study. Three in-season games were assessed *via* time-motion analysis and microsensors. Specifically, the high-intensity activities including sprints, high-intensity specific movements (HSM) and jumps were identified and subsequently the external load [PlayerLoad^{TM} (PL) and PlayerLoad^{TM}/min (PL/min)] of each activity was determined. Linear mixed models were used to examine differences in PL, PL/min and mean duration between activity pattern, playing positions and activities performed with or without ball. Results revealed PL was lower in jumps compared to sprints [$p < 0.001$, effect size (ES) = 0.68] and HSMs ($p < 0.001$, ES = 0.58), while PL/min was greater in sprints compared to jumps ($p = 0.023$, ES = 0.22). Jumps displayed shorter duration compared to sprints ($p < 0.001$, ES = 1.10) and HSMs ($p < 0.001$, ES = 0.81), with HSMs lasting longer than sprints ($p = 0.002$, ES = 0.17). Jumps duration was longer in backcourt than frontcourt players ($p < 0.001$, ES = 0.33). When considering activity patterns combined, PL ($p < 0.001$, ES = 0.28) and duration ($p < 0.001$, ES = 0.43) were greater without ball. Regarding HSMs, PL/min was higher with ball ($p = 0.036$, ES = 0.14), while duration was longer without ball ($p < 0.001$, ES = 0.34). The current findings suggest that external load differences in high-intensity activities exist among activity patterns and between activities performed with and without ball, while no differences were found between playing positions. Practitioners should consider these differences when designing training sessions.

Keywords: time-motion analysis, physical demands, PlayerLoad, inertial measurement units, accelerometers, microsensors

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INTRODUCTION

Basketball is a popular court-based team sport of intermittent nature, which involves periods of high-intensity activity (e.g., sprinting, jumping) alternated with periods at low- to moderate-intensity (e.g., walking, jogging, running) (Stojanović et al., 2018). Teams implement training strategies with the aim of enhancing players' performance on the court and achieve collective success (Schelling and Torres-Ronda, 2013). In this regard, load monitoring can provide important information to develop more appropriate training programs, maximizing physical performance while preventing overreaching and reducing injury risk (Conte et al., 2018; Ferioli et al., 2020a, 2021). Specifically, training and game load can be determined in terms of internal (e.g., heart rate, hematological markers, Session-Rating of Perceived Exertion) and external (e.g., frequency and duration of activities, distance covered) responses (Fox et al., 2017). Recent research has increasingly focused on quantifying the external demands imposed on basketball players during games (Conte et al., 2020; Ferioli et al., 2020b,c). The assessment of external load in basketball becomes particularly useful when also accounting for the role of contextual factors such as playing position and ball possession status, given that differences have been shown to exist with respect to these variables (Puente et al., 2017; Stojanović et al., 2018; Vázquez-Guerrero et al., 2018, 2019b; Pino-Ortega et al., 2019; Ferioli et al., 2020b; Fernández-Leo et al., 2020; García et al., 2020; Ransdell et al., 2020). Hence, practitioners could use these data to structure training sessions with a clearer understanding of how different activity patterns contribute to the total external load and what differences exist between playing positions and activities which are performed either with or without ball. In particular, high-intensity activities play an important role during competitive basketball games, as players perform quick and forceful movements during key phases of both offensive and defensive possessions (e.g., driving toward the basket, securing a rebound, blocking, screening playing 1-on-1 defense), which are ultimately crucial for team success (Ferioli et al., 2020b). Indeed, the ability to sustain high-intensity activities during competitions is a key component of basketball, as it has been shown to discriminate between players of different competitive levels (Ferioli et al., 2019, 2020c).

Two of the most commonly adopted tools to assess external load in basketball are video-based time-motion analysis (TMA) and wearable inertial measurement units (IMUs) (Fox et al., 2017; Russell et al., 2020). These tools can provide many useful pieces of information including the work:rest ratio and frequency, duration, speed, and distance for specific game activities (Scanlan et al., 2015; Fox et al., 2017; Russell et al., 2020). The extensive use of TMA is justified by its inexpensive nature (Barris and Button, 2008), the capability to provide descriptive information about player activities (Bailey et al., 2017) and the fact that it allows for key elements of performance to be quantified in a valid and consistent manner (Nevill et al., 2008). However, despite the great amount of information that can be obtained, some limitations should be acknowledged. Firstly, the observers' reliability must be systematically assessed to obtain meaningful data. Secondly, data analysis and interpretation is time-consuming, making this method impractical to obtain timely relevant information to adapt the planned training stimulus on a regular basis (Fox et al., 2017). Nonetheless, despite its limitations, TMA is still a valid and reliable method that is widely used in basketball (Conte et al., 2015; Ferioli et al., 2020b,c).

IMUs are a popular alternative to TMA for measuring external load in basketball (Fox et al., 2017) and can provide information about the inertial movements that players execute on the court. Many commercially available IMUs typically integrate a gyroscope, magnetometer and triaxial accelerometer into a single unit (Fox et al., 2017). These devices are able to collect inertial data and combine the instantaneous rate of change of acceleration in all three planes of movement to obtain a single measure of accumulated load, reflective of the external load imposed on the athlete, such as the PlayerLoad™ (PL) and its value per minute played (PL/min) indexes (Catapult Innovation, Melbourne, Australia) (Fox et al., 2017). Furthermore, these devices are usually small and lightweight and can be easily integrated in custom-made straps or vests, which makes them comfortable for the players (Fox et al., 2017). In addition, IMUs provide objective data available immediately after a training session or game, thus resulting as an easier and faster tool to collect and process data than TMA (Portes et al., 2020). Due to these advantages, IMUs are one of the main technologies adopted by basketball practitioners and sport scientists (Schelling and Torres, 2016; Pino-Ortega et al., 2019; Vázquez-Guerrero et al., 2019a,b; García et al., 2020; Portes et al., 2020; Ransdell et al., 2020). However, IMUs are much more expensive than TMA, which limits their applicability in several contexts, such as non-elite practice (Fox et al., 2017). Additionally, there may be an underestimation when quantifying the external load associated with static activities (e.g., screens, picks, boxing out, low-post situations), as these actions could result in low inertial acceleration loads although encompassing an high muscle activity (Schelling and Torres, 2016). Finally, the use of IMUs during match-play is forbidden in some competitive leagues, limiting the possibility of data collection and comparison (Schelling and Torres, 2016).

While providing descriptive information about external demands in players, TMA cannot quantify the load associated with single activities (Bailey et al., 2017). On the other hand, IMUs cannot systematically detect different activity patterns, such as sprinting versus high-intensity-specific movements (HSM). The use of an integrated approach could provide experts with a quantitative description of the external load associated with single basketball-specific activities. To the best of our knowledge, no previous investigations in basketball have integrated measures of external load collected through TMA with those from IMUs to establish the accumulated load associated with single activities. In the only study conducted in a similar fashion, TMA and IMUs datasets were aligned to calculate the PL associated with single activities in elite netball players, with off-ball guarding and passing corresponding to the highest and lowest PL, respectively (Bailey et al., 2017). A similar approach in basketball may provide relevant insight for sport scientists and coaches regarding load management when planning training sessions. Therefore, the aim of this study was to quantify the external load measured *via* IMUs of high-intensity activities recorded using TMA during official basketball games with respect to different: (1) activity patterns, (2) playing positions, and (3) activities performed with or without ball.

MATERIALS AND METHODS

Participants

Data were collected from 11 adult, male basketball players (age: 20.5 ± 1.1 years, stature: 191.5 ± 8.7 cm, body mass: 86.5 ± 11.3 kg; experience: 8.5 ± 2.4 years) belonging to the same team competing in the Lithuanian third division [Regionu Krepšinio Lyga (RKL)] and the Lithuanian Student League [Lietuvos Studentu Krepšinio Lyga (LSKL)]. Players were grouped according to playing positions including backcourt ($n = 6$, age: 20.9 ± 1.2 years, stature: 185.8 ± 5.5 cm, body mass: 81.0 ± 4.0 kg; experience: 9.2 ± 2.9 years) and frontcourt ($n = 5$, age: 20.1 ± 1.0 years, stature: 198.4 ± 6.5 cm, body mass: 93.0 ± 14.1 kg; experience: 7.6 ± 1.3 years). The inclusion criteria included being part of the team during the entire study period, being free of injuries, completing the standard training program of the team during the entire data collection period and taking part in at least two of the three investigated games. Throughout the study period, players attended 3–4 training sessions per week and competed twice a week (i.e., one game for each league). After verbal and written explanation of the experimental design and potential risks and benefits of the study, written informed consent was gathered from all players. The study design and procedures were approved by the University of Milan Ethics Committee (code: 124/20) and followed the ethical principles for medical research involving human subjects set by the World Medical Association Declaration of Helsinki.

Design

This observational study was conducted during the in-season period assessing three consecutive home games of the 2019/20 RKL season played between the 7th and 21st of February 2020. According to the FIBA rules, games consisted of four 10-min quarters, with 24-s shot clock, 2-min inter-quarter breaks and a 15-min half-time break (FIBA, 2018). The three games resulted in three losses, with the final scores being 70–85, 78–98, and 80–89, respectively. Each investigated game was recorded and successively analyzed using video-based TMA technique to assess high-intensity activities patterns and their duration. Moreover, the external load measured *via* IMUs (PL and PL/min) was quantified for each player. Successively, TMA and accelerometer datasets were aligned to establish the duration, PL and PL/min of each high-intensity activity instance. Specifically, 32 individual TMAs were conducted across the study, with one player participating in two out of the three investigated games, resulting in a total of 465 sprints, 896 HSMs, and 496 jumps. Each high-intensity activity was assessed according to playing position (backcourt and frontcourt), activity pattern (sprint, HSM and jump), and activities performed with or without ball.

TABLE 1 | Intratester reliability of time-motion analysis variables.

	ICC (90% CI)	CV (90% CI)
Frequency (n/min)		
Sprint	0.98 (0.93–0.99)	11.94 (8.71–19.65)
HSM	0.98 (0.95–0.99)	7.29 (5.32–11.99)
Jump	1.00 (1.00–1.00)	0.00 (0.00–0.00)
Duration (s)		
Sprint	0.99 (0.97–1.00)	5.49 (4.00–9.03)
HSM	0.88 (0.67–0.96)	11.16 (8.14–18.36)
Jump	1.00 (0.99–1.00)	1.83 (1.33–3.01)

CI, confidence interval; ICC, intraclass correlation coefficient; CV, coefficient of variation; HSM, high-intensity specific movements.

PROCEDURE

Time-Motion Analysis

Each of the three games was recorded using a smartphone-embedded camera sampling at 30 Hz (Redmi 5 Plus, Xiaomi, Beijing, China), appropriately positioned to allow a full view of the court. A freely downloadable Android software (Timestamp Camera Free, Bian Di, Google Play Store) that allows to include an on-screen timeline indicating the exact actual time of day (hours, minutes, seconds, and milliseconds) in which activities are happening while recording was used. The recorded files were then exported to a personal computer and a manual TMA was performed using a freely available frame-by-frame software (PotPlayer, Kakao Corporation, South Korea). As previously described (McInnes et al., 1995; Conte et al., 2015; Ferioli et al., 2020c), high-intensity activities were classified into the following three patterns: (1) sprint, identified as forward or backwards activity at a high intensity, characterized by effort and purpose at or close to maximum; (2) high-intensity-specific movements (HSM), which are activities differing from ordinary walking or running performed at high intensity with urgency such as shuffling, rolling, reversing, screening, and cross-over running activities (Conte et al., 2015) and (3) jump, indicated as the time from the initiation of the jumping action to the completion of landing. For each activity, the specified characteristics included the starting and ending time of day (hh:mm:ss.ms), activity pattern (sprint, HSM, or jump), duration (s) and whether activities were performed with or without ball. All activities were examined during live time (i.e., when players are on court and game clock is running). The analysis was carried out by a single experienced video analyst. Intra-tester reliability was determined by having the observer analyze the relative frequency (n/min) and duration (s) of activities during the first quarter of the first game for all players on two separate occasions. The resulting values for the intraclass correlation coefficient and the coefficient of variation (CV) were deemed acceptable (**Table 1**).

Inertial Movement Analysis

Inertial data for each player were collected using IMUs (Clearsky T6, Catapult Innovation, Melbourne, Australia) firmly positioned in custom-made vests between the players' scapulae. Players were assigned the same device every game to minimize any variations in data between IMUs. PL was calculated *via* Catapult proprietary software (Catapult Openfield, v1.17, Catapults Innovations, Melbourne, Australia) as the sum of the accelerations across all axes during movement using the tri-axial accelerometer component of the IMU (Nicolella et al., 2018). The index takes into account the instantaneous rate of change of acceleration and divides it by a scaling factor of 100 (Nicolella et al., 2018). The reliability of PL (within-device CV = 0.91–1.05%, between-device CV = 1.02–1.90%) has been previously assessed (Boyd et al., 2011) and this metric has been widely used in basketball (Schelling and Torres, 2016; Fox et al., 2017, 2018; Pino-Ortega et al., 2019; Vázquez-Guerrero et al., 2019a,b; Conte et al., 2020; García et al., 2020; Lukonaitienė et al., 2020; Portes et al., 2020; Ransdell et al., 2020; Russell et al., 2020).

Integration of TMA and Accelerometer Data

The IMU and TMA datasets were aligned using the starting and ending time of each activity coded with the "Timestamp Camera Free" app. Immediately after each game, PL data were downloaded and stored *via* Catapult proprietary software. This procedure allowed the quantification of the PL, PL/min and duration for each coded high-intensity activity. This analysis resulted in a fully comprehensive dataset containing all activities.

Statistical Analysis

Data are presented as mean ± SD for each dependent variable (i.e., PL, PL/min, duration) and analyzed using linear mixed models, which correctly deals with missing values and repeated measures. Separate models were used (one for each dependent variable) to assess the differences between the three investigated activity patterns (i.e., sprint, HSM, and jump). In these models, activity pattern was considered the fixed effect, while player, game and quarter were used as random effects. In case of statistically significant differences, Tukey *post hoc* analyses were run. Additionally, linear mixed models were also used to assess the differences between playing positions (backcourt and frontcourt) for each dependent variable during each activity. In these models, playing position was used as fixed effect and player, game and quarter as random effects. Finally, linear mixed models were also used to assess the differences between activities performed with and without ball (fixed effect) for each investigated dependent variable with playing position, player, game and quarter as random effect. Significance was set at $p < 0.05$. Linear mixed models and *post-hoc* analyses were conducted using the "lmerTest" and "emmeans" packages, respectively, in RStudio (R.3.5.2, R Foundation for Statistical Computing). The magnitude of differences for pairwise comparisons was assessed using effect size (ES) with 95% confidence intervals. ESs were calculated using JASP team 2019 (v0.10.2) and interpreted as <0.2 = *trivial*, 0.20–0.59 = *small*, 0.60–1.19 = *moderate*, 1.2–1.99 = *large*, and ≥2.0 = *very large* (Hopkins et al., 2009).

RESULTS

Table 2 shows activity frequency and the mean and standard deviation for all variables for each activity pattern. The linear mixed model analysis highlighted significant differences in PL ($p < 0.001$), PL/min ($p = 0.025$) and duration ($p < 0.001$) among activity patterns. First, *post-hoc* analysis showed higher PL values for sprints compared with jumps ($p < 0.001$, ES = 0.68, *moderate*) and for HSMs compared with jumps ($p < 0.001$, ES = 0.58, *small*). No significant differences in PL were found between sprints and HSMs ($p = 0.960$, ES = 0.02, *trivial*). Second, higher PL/min values were evident for sprints compared with jumps ($p = 0.023$, ES = 0.22, *small*). No significant differences in PL/min were found in sprints compared with HSMs ($p = 0.100$, ES = 0.16, *trivial*) and in HSMs compared with jumps ($p = 0.592$, ES = 0.07, *trivial*). Finally, higher duration values were reported in HSMs compared with sprints ($p = 0.002$, ES = 0.17, *trivial*) and jumps ($p < 0.001$, ES = 0.81, *moderate*), and in sprints compared with jumps ($p < 0.001$, ES = 1.10, *moderate*).

TABLE 2 | Activity frequency and mean ± standard deviation for all variables in each activity type.

	Sprint (*N* = 465)	HSM (*N* = 896)	Jump (*N* = 496)
PL (AU)	0.44 ± 0.43*	0.44 ± 0.44#	0.22 ± 0.16
PL/min (AU/min)	21.69 ± 14.05†	19.61 ± 13.02	18.70 ± 13.43
Duration (s)	1.18 ± 0.60‡ ¥	1.32 ± 0.93₡	0.72 ± 0.11

PL, PlayerLoad™; PL/min, PlayerLoad™ per minute; AU, arbitrary units.
**Significant difference with jump [p < 0.001; mean difference = 0.22 (95% CI: 0.18–0.26); ES = 0.68, moderate (95% CI 0.55–0.81)]; #significant difference with jump [p < 0.001; mean difference = 0.21 (95% CI: 0.17–0.25); ES = 0.58, small (95% CI: 0.47–0.69)]; †significant difference with jump [p = 0.023; mean difference = 2.99 (95% CI: 1.25–4.73); ES = 0.22, small (95% CI: 0.09–0.34)]; ‡Significant difference with HSM [p = 0.002; mean difference = -0.14 (95% CI:-0.23– -0.05); ES = -0.17, trivial (95% CI: -0.28– -0.06)]; ¥ significant difference with jump: [p < 0.001; mean difference = 0.46 (95% CI: 0.41–0.52); ES = 1.10, moderate (95% CI: 0.96–1.23)]; ₡significant difference with jump [p < 0.001; mean difference = 0.60 (95% CI: 0.52–0.69); ES = 0.81, moderate (95% CI: 0.69–0.92)].*

Differences in PL, PL/min and duration for all activity patterns between playing positions are displayed in **Table 3**. Significantly higher values were found for jumps duration in backcourt compared with frontcourt players ($p < 0.001$, ES = 0.33, *small*). No other significant differences were found between playing positions for all the other variables.

Differences in PL, PL/min and duration between activities with and without ball are displayed in **Table 4**. When considering all activity patterns combined, significantly higher values were found for PL ($p < 0.001$, ES = 0.28, *small*) and duration ($p < 0.001$, ES = 0.43, *small*) when players did not have the ball. With respect to HSMs, PL/min was significantly higher with ball ($p = 0.036$, ES = 0.14, *trivial*), while duration was longer without ball ($p < 0.001$, ES = 0.34, *small*). No other significant differences were found for all the other variables.

DISCUSSION

The present study is the first to quantify the external load measured *via* IMUs during single high-intensity activities recorded using TMA in basketball games. This is also the first study to compare the external load quantified using IMUs during single high-intensity activities according to

TABLE 3 | Differences in PL, PL/min and duration for all activity patterns between backcourt and frontcourt positions.

						95% CI for MD			95% CI for ES		
Dependent variables	**Backcourt**	**Frontcourt**	**% difference**	***P* value**	**MD**	**Lower**	**Upper**	**ES**	**Lower**	**Upper**	**Interpretation**
Sprint (BC=313; FC=152)											
PL	0.45 ± 0.46	0.43 ± 0.38	4.65	0.920	0.02	−0.06	0.11	0.05	−0.14	0.25	*Trivial*
PL/min	22.15 ± 15.07	20.74 ± 11.66	6.80	0.909	1.40	−1.33	4.13	0.10	−0.09	0.30	*Trivial*
Duration	1.16 ± 0.58	1.22 ± 0.62	4.92	0.579	−0.06	−0.18	0.06	−0.10	−0.30	0.09	*Trivial*
HSM (BC=534; FC=362)											
PL	0.45 ± 0.48	0.41 ± 0.39	9.76	0.783	0.04	−0.02	0.10	0.09	−0.04	0.23	*Trivial*
PL/min	19.49 ± 13.50	19.78 ± 12.31	1.47	0.550	−0.28	−2.02	1.46	−0.02	−0.16	0.11	*Trivial*
Duration	1.37 ± 0.99	1.25 ± 0.83	9.60	0.196	0.13	0.00	0.25	0.14	0.00	0.27	*Trivial*
Jump (BC=286; FC=210)											
PL	0.23 ± 0.17	0.22 ± 0.15	4.55	0.872	0.01	−0.02	0.04	0.03	−0.14	0.21	*Trivial*
PL/min	18.41 ± 13.84	19.09 ± 12.86	3.56	0.569	−0.68	−3.08	1.72	−0.05	−0.23	0.13	*Trivial*
Duration	0.73 ± 0.10	0.70 ± 0.12	4.29	**<0.001**	0.04	0.02	0.05	0.33	0.15	0.51	*Small*

Data presented as mean ± standard deviation.
BC, activity frequency for backcourt; FC, activity frequency for frontcourt; PL, PlayerLoad^{TM}; PL/min, PlayerLoad^{TM} per minute; HSM, high–intensity specific movements; MD, mean difference; CI, confidence interval; ES, effect size. Bolded P value represents significant difference (P <0.05).

TABLE 4 | Differences in PL, PL/min and duration for activities with and without ball.

					95% CI for MD			95% CI for ES		
Dependent variables	**No ball**	**Ball**	***P* value**	**MD**	**Lower**	**Upper**	**ES**	**Lower**	**Upper**	**Interpretation**
All activities (NB = 1,230, B = 628)										
PL (AU)	0.42 ± 0.43	0.31 ± 0.31	**<0.001**	0.11	0.07	0.15	0.28	0.18	0.38	*Small*
PL/min (AU/min)	19.96 ± 13.45	19.75 ± 13.41	0.730	0.21	−1.08	1.50	0.02	−0.08	0.11	*Trivial*
Duration (s)	1.23 ± 0.84	0.91 ± 0.49	**<0.001**	0.32	0.25	0.39	0.43	0.33	0.53	*Small*
Sprint (NB = 321, B = 144)										
PL (AU)	0.46 ± 0.45	0.42 ± 0.38	0.445	0.04	−0.04	0.13	0.10	−0.10	0.29	*Trivial*
PL/min (AU/min)	21.45 ± 13.57	22.22 ± 15.10	0.195	−0.78	−3.55	2.00	−0.06	−0.25	0.14	*Trivial*
Duration (s)	1.21 ± 0.64	1.11 ± 0.47	0.050	0.10	−0.01	0.22	0.17	−0.02	0.37	*Trivial*
HSM (NB = 715, B = 181)										
PL (AU)	0.45 ± 0.44	0.38 ± 0.39	0.237	0.07	−0.01	0.14	0.15	−0.01	0.32	*Trivial*
PL/min (AU/min)	19.24 ± 12.94	21.04 ± 13.28	**0.036**	−1.80	−3.92	0.33	−0.14	−0.30	0.03	*Trivial*
Duration (s)	1.39 ± 0.96	1.07 ± 0.73	**<0.001**	0.32	0.17	0.47	0.34	0.18	0.51	*Small*
Jump (NB = 194, B = 302)										
PL (AU)	0.24 ± 0.19	0.21 ± 0.15	0.129	0.02	0.00	0.05	0.15	−0.03	0.33	*Trivial*
PL/min (AU/min)	20.11 ± 14.87	17.79 ± 12.35	0.075	2.32	−0.10	4.74	0.17	−0.01	0.35	*Trivial*
Duration (s)	0.71 ± 0.12	0.73 ± 0.10	0.072	−0.02	−0.04	0.00	−0.15	−0.33	0.03	*Trivial*

Data presented as mean ± standard deviation.
NB, activity frequency without ball; B, activity frequency with ball; PL, PlayerLoad; PL/min, PlayerLoad per minute; HSM, high-intensity specific movements; MD, mean difference; CI, confidence interval; ES, effect size. Bolded P value represents significant difference (P <0.05).

playing positions and activities performed with or without ball. The main results revealed PL values were statistically lower in jumps compared to sprints (ES, *moderate*) and HSMs (ES, *small*), while PL/min was statistically lower in jumps compared to sprints (ES, *small*). With respect to playing positions, jumps duration was statistically longer in backcourt compared with frontcourt players (ES, *small*). Finally, PL and duration values appeared to be higher in all activity patterns combined when players did not have the ball with a *small* effect size.

Although multiple investigations have measured the PL and PL/min during official games and games-based drills in basketball (Schelling and Torres, 2016; Fox et al., 2018; Vázquez-Guerrero et al., 2018, 2019a,b; Pino-Ortega et al., 2019; Conte et al., 2020; Fernández-Leo et al., 2020; García et al., 2020; O'Grady et al., 2020; Portes et al., 2020; Ransdell et al., 2020), no study has assessed the external load imposed during single basketball-specific activities measured *via* TMA. To the best of our knowledge, a similar approach was previously used only in netball, with two official games analyzed *via*

TMA and IMUs, revealing that on average the highest PL was registered during off-ball guarding actions (Bailey et al., 2017). Considering the importance of load monitoring for the optimization of the training process (Conte et al., 2018), quantifying the load imposed by high-intensity basketball activities can help practitioners in prescribing an adequate training load. Accordingly, the ability to perform at higher intensities has been reported to be crucial to compete at a higher level, with elite basketball players displaying a better ability to sustain high-intensity efforts (Ferioli et al., 2018) and elite basketball games involving more and longer high-intensity activities (Ferioli et al., 2020c) than lower level competitions. The findings of the present study show that PL, which is one of the main measures adopted to assess training volume in basketball (Russell et al., 2020), was higher in sprints and HSMs compared to jumps. Differently, when considering PL/min, which refers to the training intensity, the only significant difference (ES, *small*) was found in sprints compared to jumps, while no statistically significant differences were evident for HSM compared to the other activity patterns. This discrepancy in the results between sprint and HSM when considering training volume and intensity could be explained by the longer ($p = 0.002$) duration of HSMs compared to sprints, that would produce a similar volume and a lower intensity. However, caution is advised when interpreting such results, as differences in duration between sprints and HSMs were *trivial*. These findings should be considered when planning training sessions on a regular basis, as using different proportions of each activity pattern is likely to produce different total load during sessions with the same duration.

It has been shown that playing position can affect players' physical demands during official games (Puente et al., 2017; Stojanović et al., 2018; Vázquez-Guerrero et al., 2018, 2019b; Pino-Ortega et al., 2019; Ferioli et al., 2020b; Fernández-Leo et al., 2020; García et al., 2020). Specifically, while previous research has identified positional differences in the frequency and duration of high-intensity activities during basketball games (Stojanović et al., 2018), there is no indication of the external load registered during single high-intensity activities according to playing position. The findings indicated that, although backcourt players performed a higher number of high-intensity activities compared to frontcourt players (backcourt: sprint, $n = 313$; HSM, $n = 534$; jumps, $n = 286$; $N = 1,133$; frontcourt: sprint, $n = 152$; HSM, $n = 362$; jumps, $n = 210$; $N = 724$), *trivial-to-small* differences were evident in PL, PL/min and duration between backcourt and frontcourt players during each high-intensity activity. Therefore, basketball coaches and practitioners should consider designing drills with a different number of high-intensity activities between backcourt and frontcourt players although with a similar volume, intensity and duration. Regarding average high-intensity activity duration, the only significant difference was a higher (ES, *small*) value for jumps in backcourt compared with frontcourt players. This may be due to the different physical characteristics observed between playing positions (Ferioli et al., 2018), as backcourt players are usually smaller and lighter and therefore able to jump for a longer time compared to frontcourt players, who are taller and heavier (Schelling and Torres, 2016; García et al., 2020).

Previous investigations described the frequency and duration of activities performed with ball during official basketball games (Scanlan et al., 2011, 2012, 2015; Ferioli et al., 2020b). Specifically, three previous studies (Scanlan et al., 2011, 2012, 2015) evaluated the duration of dribbling activities in basketball players. In addition, Ferioli et al. (2020b) assessed positional differences during activities performed with ball, showing that guards, forwards and centers spent 11.9 ± 5.9, 3.5 ± 1.3, and 2.9 ± 1.1% of live playing time in possession of the ball, of which 19.0 ± 13.2, 35.2 ± 16.0, and 36.7 ± 11.4% engaged in high-intensity activities, respectively. However, this study did not explore differences between activities performed with and without ball (Ferioli et al., 2020b). The present study is the first to explore differences in PL, PL/min and duration between high-intensity activities performed with and without ball, showing that overall activities without ball displayed higher PL and duration with *small* effect sizes compared to overall activities with ball. This result suggests that high-intensity activities performed without ball during basketball games elicited higher external load volume due to the longer duration. Differently, high-intensity activities with and without ball produced a *trivial* difference in the external load intensity (PL/min). However, when considering high-intensity activities separately, a statistically higher PL/min and shorter duration were shown in HSMs performed with ball compared to HSMs without ball, even though caution is advised since *trivial-to-small* effect sizes were reported. A likely explanation of these results is that such activities are usually performed when attacking the basket and/or looking to create a scoring opportunity (e.g., dribble crossovers, post-up spin moves), thus producing a higher acceleration load. Therefore, quickness of executions seems to be crucial when performing these activities and may translate to better performance and team success.

There are some limitations of the present study that must be acknowledged. First, the recruited basketball players in this study were competing in the same male basketball league, and therefore the findings might not be generalizable to basketball players competing in other male or female competitions, calling for further studies on these specific basketball populations. Second, this study examined activities performed with and without ball without accounting for positional differences, as guards, forwards and centers have been shown to spend different proportions of live time in possession of the ball (Ferioli et al., 2020b). Finally, the current investigation focused on quantifying the external load associated only with high-intensity activities, as they are the most crucial for team success during a competitive game. However, further research also describing low- and moderate-intensity activities could prove useful information about all activity patterns to better describe the external load in basketball games.

Practical Applications

From a practical standpoint, the findings of the present study offer information that can assist practitioners during training planning. Firstly, the higher PL detected during sprints and HSMs compared to jumps indicates that the selection of different types of drills including different proportions of high-intensity activity patterns may influence the total load of the session. Secondly, despite backcourt players performing a higher number of high-intensity activities compared to frontcourts, the external load for each investigated high-intensity activity was similar between positions. Therefore, the use of training drills encompassing activities of similar volume, intensity and duration between positions seems justified. Moreover, a greater use of drills including a higher number of high-intensity activities performed without ball may result in higher total volume. Considering intensity, basketball coaches are suggested to design training drills with high-intensity activities with and without ball with a similar PL/min (∼20 AU/min). Furthermore, focusing on quickness of execution of HSMs performed with ball may be paramount since such activities have shown shorter duration and higher intensity compared to HSMs without ball, and are often employed when looking to create scoring opportunities.

CONCLUSION

The present study reports novel findings regarding the external load sustained when performing high-intensity activities during official basketball games. Different high-intensity activity patterns performed during basketball games are characterized by different levels of external load, with a lower PL in jumps compared to sprints and HSMs, and a lower PL/min in jumps compared to sprints. With respect to playing positions, jumps duration is longer in backcourt compared with frontcourt players. Finally, PL and duration values of all high-intensity movement patterns appear to be higher when players are not in possession of the ball. The findings of the present study should be considered by coaches and sport scientists for a better development of training sessions involving various types of high-intensity activities, as external load may be affected by their development in accordance with various factors (i.e., playing positions and activity performed with or without ball).

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by University of Milan Ethics Committee. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MP: data collection, time-motion analysis, writing of the original manuscript draft, interpretation of results, visualization, contribution to conceptualization, and design. DF: conceptualization and design, supervision, interpretation of results, reviewing, and editing. RB: resourcing, data collection, reviewing, and editing. AL: funding acquisition, submission of the protocol to the ethics committee, supervision, reviewing, and editing. DC: conceptualization and design, resourcing, supervision, contribution to data collection, statistical analysis, interpretation of results, reviewing, and editing. All authors have read and agreed to the published version of the manuscript.

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Putting Attention on the Spot in Coaching: Shifting to an External Focus of Attention With Imagery Techniques to Improve Basketball Free-Throw Shooting Performance

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Attentional focus is an area that has garnered considerable attention in the sport psychology and motor performance literature. This is unsurprising given that attentional focus has been directly linked to performance outcomes and is susceptible to coaching input. While research has amassed supporting benefits of an external focus of attention (EFA) on motor performance using verbal instruction, other studies have challenged the notion that an EFA is more beneficial than an internal focus of attention (IFA) for sport-related performance. Further, it is unclear what type of instructions may serve to direct an athlete to an EFA and, in particular, if coaching can utilize imagery to orient an athlete toward an EFA. In the present exploratory study, we evaluate the effectiveness of instruction to improve free-throw shooting performance with an emphasis on an EFA brought about by implementing techniques borrowed from the imagery literature. This was tested relative to an alternate approach with an IFA induced through an emphasis on technique, devised to more closely resemble input typical of coach-to-athlete instruction. Twenty-five male and female university basketball players completed both conditions in a fully counterbalanced within-subject design. Results confirmed that participants in the EFA imagery condition had greater shooting accuracy than in the IFA technique condition. The study provides initial evidence that EFA coaching can borrow from imagery techniques, though future research should elucidate the underlying mechanisms of the effect.

Keywords: sport performance, motor performance, attentional focus, external focus of attention, internal focus of attention, imagery, coaching, free throw shooting

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INTRODUCTION

Attentional focus is a vital component of sports given the multitude of stimuli to which an athlete must attend (Memmert et al., 2009). Where and when an athlete focuses their attention can have immense impact on their performance (Hill and Shaw, 2013). Importantly, attentional focus can be directed internally (to one's own thoughts, emotions, or physical sensations) or externally (to the environment). Within the motor learning and performance literature, an external focus of attention (EFA) refers to an individual's focus on the effects/outcomes of body movements in a motor action, while an internal focus of attention (IFA) is one's focus on the body movements themselves (Wulf, 2013). In the present study, we evaluate the immediate effects of coaching input that orients the athlete to an EFA; this is done through a novel extension of techniques borrowed from the imagery literature. This approach is tested here relative to technique-focused coaching typical of much coach–athlete interaction during training (Porter et al., 2010) that has, by virtue of its content, more of an IFA.

There is now a considerable body of research examining attentional focus in motor performance; much research has shown that an EFA leads to better motor learning and performance than does an IFA (see reviews: Peh et al., 2011; Wulf, 2013). An EFA has been demonstrated to benefit movement efficiency and effectiveness more than an IFA across several sport-related tasks. Specifically, motor learning and performance benefits have been demonstrated in balance, accuracy, maximum force production, speed, and endurance tasks, involving a wide array of sports such as golf, volleyball, soccer, basketball, swimming, and rowing (Wulf, 2013). This finding has been replicated with isolated tasks as well as with more extensive coordination of muscle groups (Peh et al., 2011). Recent research has also shown beneficial effects of an EFA for both novice and high-performance athletes (e.g., Asadi et al., 2019).

The constrained-action hypothesis provides one explanation for possible performance differences associated with EFA vs. IFA. In this explanation, an IFA may trigger conscious control which could interfere with the more efficient, automatic processing that occurs with an EFA (Wulf et al., 2001). Indeed, an EFA has been shown to reduce attentional load relative to an IFA (Kal et al., 2013). Furthermore, an internal focus may invoke the neural representation of the self, leading to self-evaluative processes that may further interfere with automatic processing (Wulf, 2013). In previous literature, this has been referred to as self-focused attention and has been linked to explicit technical coaching/instructions typical of much coach–athlete interaction (Baumeister and Showers, 1986; Liao and Masters, 2002).

Self-focused attention can also be regarded as counter to central tenets of mindfulness and flow (Csikszentmihalyi, 1990; Gardner and Moore, 2004). Flow has been described as a present moment focus similar to mindfulness, which involves effortless attention, despite immense concentration, and absorption in the task (Bernier et al., 2009; Csikszentmihalyi and Nakamura, 2010). Both mindfulness and flow states emphasize minimal internal cognitive and linguistic processing and self-evaluation (Bernier et al., 2009). Inherent to original depictions, flow state involves a quieting of the mind and a decrease in conscious self-awareness and self-focus (Csikszentmihalyi, 1990). Self-focus has been linked to sudden performance detriments (i.e., choking; Yu, 2015), and contrarily, mindfulness has been associated with the decreased susceptibility of these occurrences (Hussey et al., 2020).

There has been interest in identifying and facilitating conditions that promote mindfulness, flow, and an EFA. Jackson (1995) found that certain factors seemed to influence flow such as focus, confidence, preparation, how the performance felt and progressed, and optimal motivation and arousal. Harris et al. (2018) reported that an EFA increased perception of flow in a simulated driving task. Relatedly, Wulf and Lewthwaite (2016) presented their OPTIMAL theory to account for motor learning, which highlights the importance of an athlete's mindset, which in turn is related to attentional focus, as well as other factors including intrinsic motivation and cognitive and emotional states.

Despite the theoretical and empirical support favoring an EFA over an IFA for sport performance outcomes, there remains some debate as to the strength of this evidence. At the forefront of this debate, Toner and Moran (2015, 2016) maintain that an IFA is needed to make high-level athletes aware of the kinesthetic discrepancies between desired and actual movement; yet, it has been suggested that an EFA does not mean that athletes are completely unaware of their movements, but rather that the primary focus is on the effects of that movement while preparing for movement execution (Wulf, 2015). Still, it must be noted that some recent studies have found only limited impact of EFA on measured performance (e.g., Harris et al., 2018). Further, much of the research in this area has suboptimal ecological validity as it is often laboratory-based, with great variation in length of interventions and how the outcomes are measured (for examples, see Wulf, 2013; Wulf and Lewthwaite, 2016).

Ecological validity in sport research can be maximized by studying attentional focus within natural sporting contexts and environments, while directly evaluating the immediate effects of coaching input on athlete performance. This is especially important considering that a coach may unknowingly induce an IFA over an EFA by overemphasizing technical instructions. Despite evidence of the benefits of an EFA, mindfulness, and flow, increased pressure to win in more competitive sport may lead to more controlling, prescriptive coaching, often high in IFA (Porter et al., 2010). In many ways, this represents a coaching paradox in terms of practice not aligning with research. One potential means of shifting coach–athlete interactions toward more of an EFA can be achieved through techniques borrowed from imagery interventions within the psychological skills training literature.

Imagery is the mental simulation of real experience involving the combination of different sensory modalities (kinesthetic, visual, auditory, olfactory), which allows one to represent perceptual processes in one's mind without the actual sensory stimuli, input or motor movements (Munzert et al., 2009; Fazel et al., 2018). In the context of sport, imagery can complement coaching to the benefit of a multitude of different outcomes, including motor learning and performance, tactical movements, motivation, self-confidence, anxiety, strategies, problem solving, and rehabilitation. Athletes may use imagery prior to, during, or after practices and competitions, as well as during rehabilitation (Guillot and Collet, 2008; Cumming and Williams, 2013).

The Revised Applied Model of Deliberate Imagery Use (RAMI; Cumming and Williams, 2013) outlines many areas that may benefit from imagery while specifying key components of imagery methodology. The RAMI identifies recommended aspects of imagery use, including the "who," "where," "when," "why," and "how." A further personalized approach to imagery acknowledged by the RAMI is the PETTLEP model (Holmes and Collins, 2001). PETTLEP stands for physical, environment, task, timing, learning, emotion, and perspective. Each facet of the model is based on the idea of functional equivalence—or that the motor imagery system is fundamentally related to the motor preparation and execution system of the brain. The imagery environment, internal (first-person) or external (3rd person) visual perspective, and timing should be as close as possible to the one where the actual motor action occurs. Indeed, research has shown that imagery activates similar brain regions as movement execution (Mizuguchi et al., 2012) and has been used to prime the desired approach of a subsequent action (Stoykov and Madhavan, 2015).

Within the domain of psychological skills training, imagery approaches typically do not explicitly consider the role of attentional focus (e.g., see Holmes and Collins, 2001; Cumming and Williams, 2013). As a result, scripts implemented in some research (e.g., Fazel et al., 2018) may unintentionally trigger an IFA due to a focus on body movements. The disconnect between imagery and attentional focus literature may be attributed to imagery being regarded as a longer-term intervention in the domain of psychological skills training, separate from coaching instruction in the domain of attentional focus and athlete performance. Indeed, in a meta-analysis by Cooley et al. (2013), studies that were <5 days duration were not included, as they were perceived to not meet the duration criteria for an imagery intervention.

Yet, there are techniques and aspects of imagery that are amendable to short-term, even on-the-spot, Coach–athlete interactions (Leong et al., 2019). In particular, the RAMI and PETTLEP models suggest methodology that can be implemented specifically to shift an athlete to an EFA through more effective and efficient priming of task-relevant stimuli. Of interest here is how that would impact immediate athlete performance relative to traditional coaching of technique that by nature is oriented more to an IFA. We know of only one such study that has directly compared the implementation of imagery techniques specifically devised to have a high EFA with more typical technical coaching that would have a high IFA, albeit spread out over a prolonged period of time (16 weeks). Guillot et al. (2013) reported that an instructional condition of imagery techniques with a deliberate EFA improved performance on tennis serve performance relative to more traditional technique coaching. It should be noted, however, that this was a small-sample study ($N = 12$), with youth participants only (aged 11 years), and critically the imagery condition was always delivered last in a within-participant design (i.e., there was no counterbalancing). Hence, more research in this understudied area is clearly needed.

THE PRESENT STUDY

We had collegiate-level basketball players complete a free-throw shooting task with instruction designed to promote an EFA through implementation of techniques borrowed from imagery interventions. We opted for a short-term, in-season, single session that took place in the team's regular practice facilities to increase ecological validity; many real-life sport scenarios may benefit from imagery techniques to bring about an EFA but are limited in time (a single practice, before a game, half time, etc.). These same athletes completed a comparison condition (within a fully counterbalanced experimental design), devised to reflect more prescriptive coaching with a high IFA (by emphasizing technique), as often associated with traditional coach–athlete interactions during training. Due to the potential combined benefit of task-relevant multimodal priming (Stoykov and Madhavan, 2015) and optimized attentional focus (Wulf, 2013), it was hypothesized that participants would have better free-throw shooting performance in the EFA imagery condition than in the IFA technique condition. Given the potential overlap between flow and attentional focus as suggested by current theory (e.g., Wulf and Lewthwaite, 2016), flow state measures were also completed after each condition to evaluate any influence on the athletes' perception of flow.

MATERIALS AND METHODS

Participants

Twenty-six Canadian Collegiate Athletic Association basketball players originally participated in the study. During the EFA imagery session for one participant, there was considerable disruptive noise in the gymnasium and the participant reported having difficulty focusing; they were excluded from the data analysis reported here. Remaining participants were 9 male and 16 female university students aged 18–24 years ($M = 19.92$, $SD = 1.48$). Participants reported a mode of 10+ years' basketball experience. All participants had at least moderate imagery ability as determined by a screening measure (MIQ: Movement Imagery Questionnaire-3; Williams and Cumming, 2011). Institutional ethical approval was granted, and all participants provided informed consent. These players were members of a university varsity basketball program; all members of both the men's and women's teams were asked to participate; the sample reported here were those who consented.

Materials

Flow State Scale-2

Flow is described as an optimal state of consciousness involving a challenge-skills balance; action-awareness merging; clear goals; unambiguous feedback; concentration on task; sense of control; loss of self-consciousness; time transformation; and autotelic experience (Csikszentmihalyi, 1990). The short version of the Flow State Scale-2 (FSS-2) was used to measure state flow following each condition as it is intended for use after an event to assess state flow experience (Jackson, 2002). FSS-2 has acceptable validity and reliability ($r = 0.76$–0.90; Jackson et al., 2008).

Free-Throw Performance

In basketball, a fouled player shoots one to three free throws from the free-throw line. Players typically score one point if the basketball goes through the basket. The free-throw line is 4.22 m away from the 0.45-diameter circular basketball rim, which is 3.05 m above the floor. The current study replicated the scoring system by VaezMousavi and Rostami (2009) to measure free-throw accuracy more precisely: 3 points for a basket entering the hoop without touching the rim or backboard, 2 points for a basket that touches the rim or backboard before going in, 1 point for hitting the rim or backboard without scoring a basket, and 0 points for not scoring a basket, touching the rim or the backboard. Each shot was scored live by a researcher.

EFA Imagery Condition

Instruction within this condition was created with reference to the PETTLEP Model (Holmes and Collins, 2001; Wakefield and Smith, 2012) and the RAMI (Cumming and Williams, 2013). Participants received instruction in the gymnasium wearing their practice clothes, holding a basketball in their hands; participants were instructed to image in real time. These instructions were consistent with the Physical, Environment, and Timing elements of the PETTLEP model while increasing ecological validity. Consistent with the PETTLEP and the RAMI, participants were instructed to try to feel physical movements as they occur and see, hear, and feel as they would in the real world. These instructions were designed to enhance the realism of the task and improve functional equivalence. Participants were instructed to “image through your own eyes” according to information regarding the perspective element of PETTLEP (Wakefield and Smith, 2012). After hearing the instructions, participants listened to a recorded imagery script (recorded to add consistency across participants), using a Tascam Dr-40 player with professional quality (PSB) noise-canceling headphones. A female voice was used to record the script.

The script itself consisted of two halves, each with two sections (for a total of four blocks), and was designed similarly to the retrogressive imagery script in Fazel et al. (2018) in that it transitioned from extensive contextual information in the first half to minimal contextual information by the last, to enhance the selective attention on task-relevant stimuli. This also corresponded with the learning element of PETTLEP, as each section was altered to enhance focus on the outcome of shooting free throws. Scripts included direct instructions such as “…you take a deep breath and begin your free throw routine. As you do your routine, your attention remains focused on the net. As you release your shot, you visualize it going in the basket. You watch the ball soar through the air and drop perfectly through the netting. The sound indicates it was a swish…” Full transcripts of the imagery are available from the authors.

Imagery Manipulation Check

Participants were asked to indicate how well they saw, heard, felt, and experienced their imagery on a zero (not at all) to four (very well) Likert Scale.

IFA Technique Condition

Similar to the self-focused attention design used by Liao and Masters (2002), in this condition participants were instructed to “be aware of what you are doing” and “pay close attention to the mechanics of your shooting process” in order to induce an IFA before shooting free throws. They were told to approach the free throws as they would during an intense basketball game to give context and adding ecological validity to the task. They were provided with a list of technical instructions used by Zachry et al. (2005), intended to reflect technical tips or feedback that would be typical in direct coaching, and were told to review aspects of their free-throw technique before each shot. There were nine related technical aspects provided on a sheet that involved reference to stance, grip, or mechanics of shooting a free throw. They were not directly told to focus on all the techniques provided in the list; instead, the techniques were there to encourage them to remember technical aspects of free-throw shooting as relevant to their own performance (i.e., intended to bring more focus to their own body mechanics).

IFA Manipulation Check

The IFA manipulation check served two purposes: To be a statistical manipulation measure and to further induce an IFA for remaining trials. Participants were asked to indicate how often they focused on their technique when shooting free throws on a zero (never) to four (all the time) Likert Scale. Then, they were instructed to “recall their technique” and were given a space to write.

Procedure

All participants were asked to fill out a demographic information form and the Movement Imagery Questionnaire at time of consent to ensure participants had at least moderate imagery ability for participation in the study. Then, they were randomly scheduled into one of two gender-stratified conditions and counterbalanced in a within-subject design. The conditions were the EFA imagery condition and the IFA technique condition. Participants completed the subsequent condition after a minimum of 1 week and a maximum of 2 weeks. All sessions were conducted individually and in the same university gymnasium where the players played their home league.

Each condition involved a single training session of free-throw shooting, consisting of 10 baseline shots followed by four performance blocks, each consisting of 10 shots. To minimize the number of necessary statistical tests and to correspond to the two halves of each intervention, shooting performance was summed across the first two blocks for a score for the first half of the training session and summed across blocks 3 and 4 to yield a score of shooting accuracy for the second half of each session.

In the EFA imagery condition, participants were given instructions on how to image, following completion of 10 baseline shots and an explanation of the scoring method. Participants then listened to the first of four segments of the recorded imagery script, following which they completed the first of four blocks of 10 performance shots. After every 5th performance shot, participants were reminded to “focus your attention on the ball going into the basketball net.” On each consecutive segment, the script provided progressively less contextual information to focus the participant’s attention on the outcome of shooting. This procedure was repeated for each half of the imagery script, with each half containing two segments/blocks of performance shots (i.e., 10 shots per block; 20 shots per half). After the last block was completed, the imagery manipulation check and the short version of the Flow State Scale-2 were given.

In the IFA technique condition, participants were similarly instructed on the scoring method and completed 10 warm-up shots. They then completed a total of four blocks of 10 shots, with

TABLE 1 | Descriptive statistics and correlations.

Measure	1	2	3	4
1. Flow (IFA)	–			
2. Flow (EFA)	0.523**	–		
3. IFA trials	0.477*	0.215	–	
4. EFA trials	0.470*	0.352	0.773**	–
M	4.146	4.129	2.206	2.282
SD	0.329	0.370	0.243	0.251

*N = 25 for all constructs. The numbers associated with the variables on the first column correspond with the numbers on the top row. *Indicates significance at the p < 0.05 level. **Indicates significance at the p < 0.01 level. Flow (IFA), Dispositional Flow State Scale-2 administered after final shots in the IFA technique condition. Flow (EFA), Flow State Scale-2 administered after final shots in the EFA imagery condition. IFA Trials, free-throw shooting scores averaged across all performance shots in the IFA technique condition. EFA Trials, free-throw shooting scores averaged across all performance shots in the EFA imagery condition.*

reminders following every five shots, as in the imagery condition. Participants were given the IFA technique instructions including directives meant to induce an IFA during free-throw shooting such as "be aware of what you are doing" and "pay close attention to the mechanics of your shooting process." They were also told to review a list of technical aspects of free-throw shooting before each block. After every five free throws were completed, the participant was reminded to focus on their technique. To serve as a manipulation check and further promote an internal focus of attention, participants were asked to recall as much as possible about their shooting processes after each half of the intervention. They were also asked to complete a Likert Scale indicating the degree to which they focused on technique. This process was concluded by asking participants to fill out the short version of the Flow State Scale-2 at the end of the session.

RESULTS

Participant scores on the Movement Imagery Questionnaire ($M = 5.78$, SD $= 0.68$), Imagery Manipulation Check ($M = 3.10$, SD $= 0.47$), and IFA Manipulation Check (M $= 3.23$, SD $= 0.47$) were deemed to be acceptable for inclusion in analysis and confirmed the fidelity of the interventions. Means and standard deviations for key constructs are presented in **Table 1**, along with bivariate correlations to allow for an examination of relations among measures. Shooting performance across conditions is shown in **Figure 1**.

To address the central question of the present investigation, a 2 (EFA imagery vs. IFA technique condition) × 3 (baseline shot performance, performance over the first half of intervention, performance over the second half of intervention), repeated-measures analysis of variance (ANOVA) were conducted. The assumption of sphericity was not violated. Of worthy is that the main effect of condition was significant with a medium effect size, [$F_{(1, 24)} = 2.96$], $MSE = 0.05$, $p = 0.048$ (one-tailed for hypothesis testing), $\eta^2 = 0.111$.

As indicated in **Figure 1**, the main effect of trial was also significant with a large effect size, [$F_{(2, 23)} = 4.76$], $MSE = 0.06$, $p = 0.019$, $\eta^2 = 0.293$. The interaction between condition and trial was also significant with a large effect size, [$F_{(2, 23)} = 3.14$], $MSE = 0.04$, $p = 0.031$, ${\eta_p}^2 = 0.214$.

To further explore the significant interaction, *post-hoc* LSD tests were conducted. Importantly, it was necessary to confirm equivalent performance prior to the start of each condition: this comparison revealed no statistically significant difference between the conditions for performance on the baseline shots ($p = 0.587$). Further comparisons revealed no statistically significant differences between conditions on shooting performance in the first half of the interventions ($p = 0.968$). By the second half of the interventions, however, superior performance was evident for the EFA imagery condition with a very large effect size, [$F_{(1, 24)} = 12.85$] $MSE = 0.02$, $p < 0.001$, $\eta^2 = 0.349$.

Moreover, pairwise comparisons within the IFA technique condition indicated no significant differences between any test points (p's $= 0.131$–0.786). Pairwise comparisons within the EFA imagery condition showed a significant improvement between the performance on the baseline shots and performance at the second half of the intervention [$F_{(1, 24)} = 12.46$ $MSE = 0.05$, $p = 0.001$, $\eta^2 = 0.342$], as well as between performance during the first and latter halves of the intervention [$F_{(1, 24)} = 298\ 22.78$ $MSE = 0.01$, $p < 0.001$, $\eta^2 = 0.487$].

Turning to **Table 1**, there was a positive relationship between the scores from the Flow State Scale-2 administered after the final shots in the IFA technique condition and performance in both conditions, *r's* $= 0.470$–0.477. A similar relationship was not seen for the Flow State Scale-2 administered after the EFA imagery condition; this flow measure was not significantly correlated with shooting performance although the trend was approaching significance ($p = 0.145$). A repeated-measures analysis of variance was also conducted to examine the effect of imagery condition on Flow State Scale-2 scores. The main effect of condition was not significant, [$F_{(1, 24)} = 0.650$], $MSE = 0.06$, $p = 0.801$, indicating that athletes reported relatively high flow states after training within each condition.

DISCUSSION

The present study examined the effect of an athlete's focus of attention during a basketball free shooting training session in an ecologically valid implementation of a counterbalanced within-participant experimental design. The comparison of interest was the immediate effects on shooting accuracy brought about by a mode of instruction borrowed from imagery interventions with the purpose of directing the athlete to an EFA vs. a more traditional technique-oriented session that by definition would have a high IFA. Effects on immediate flow state were also evaluated within each instructional condition. Results showed that the EFA imagery condition produced better free-throw shooting than the IFA technique comparison, with the improvement in shooting accuracy becoming apparent by the latter half of the training session. These findings demonstrate that imagery techniques can be implemented within a sport practice environment and support the contention that an EFA is beneficial

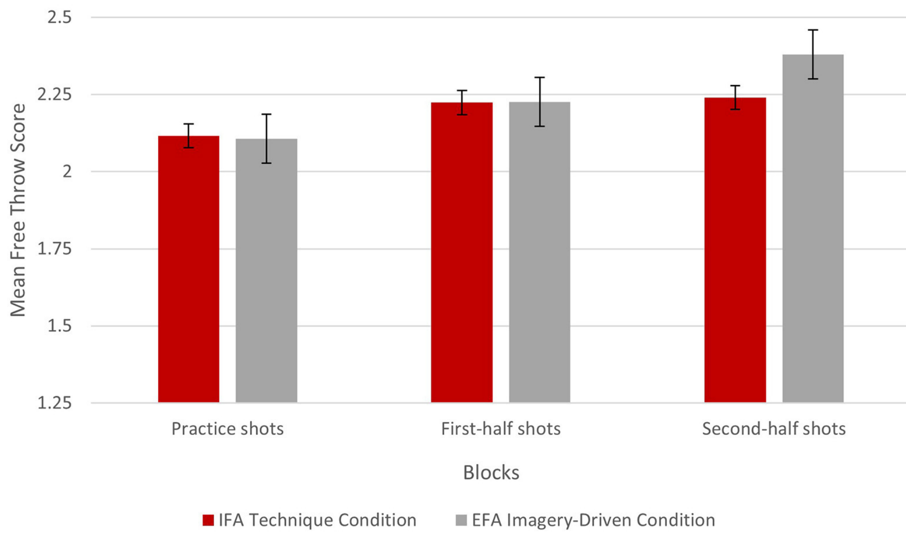

FIGURE 1 | Mean free-throw scores across blocks and conditions.

over an IFA for sport performance, at least in the short term. The results regarding flow, however, were more convoluted; contrary to theory that links an EFA to flow, there was no significant difference in flow state between conditions; yet it should be noted that a high flow state score was reported in both.

Free-Throw Performance

The results of the current study align with the limited research involving the use of imagery techniques to elicit an EFA (Guillot et al., 2013). However, unlike previous research, the current study involved older, highly experienced athletes with the goal of maximizing immediate performance in a short duration. It is notable that there was a significant difference in free-throw shooting performance between conditions considering that the training conditions of the current study were each conducted over a single session with a duration not exceeding 30 minutes. In the meta-analysis of imagery interventions by Cooley et al. (2013), studies that were <5 days in duration did not meet criteria to be included in the study given the expectation that imagery interventions are more long term by nature. Yet, in competitive sport there are many situations in which techniques derived from imagery interventions may be beneficial to an athlete facing time constraints (e.g., half-time, during a substitution, immediately before a match, etc.); hence, it is especially noteworthy that the EFA condition devised for the present study induced improved performance outcomes over such a short time period. This may well speak to the power of a brief EFA imagery approach to coaching instruction to maximize the performance of experienced, competitive athletes.

Flow

Flow experience has been linked to performance across multiple sports (Bakker et al., 2011; Koehn, 2017). The current study found only partial support for this relationship as flow state was correlated with performance in the IFA condition, but not within the EFA training condition. However, this was approaching significance within the EFA condition and the lack of statistical significance is likely an artifact of sample size and power. It is also noteworthy that no difference in flow state scores was found across conditions; flow states were high within both conditions, as evidenced by mean scores reported within the conditions. Note that the interpretation of the flow measure, as guided by the test material, is that higher values (maximum of five) indicate a strong agreement of flow experience. Hence, it may well be that while the EFA training condition succeeded in improving shooting accuracy, it did not increase the flow state of the participants relative to the IFA technique comparison condition due to the overall high flow states of these athletes in general.

The constrained-action hypothesis has been proposed to explain why an EFA may be preferable to an IFA when it comes to motor learning and performance (Wulf, 2013). In particular, it is thought that an IFA may interfere with more efficient, automatic processing by triggering self-evaluative processes (Wulf et al., 2001). Given that self-evaluative processes are counter to establishing and maintaining flow states (Harris et al., 2018), the high flow state scores within our IFA training condition may seem surprising. Indeed, Harris et al. (2018) reported that an EFA increased flow but not performance in their study involving a driving simulation, which is opposite to the pattern reported here. This discrepancy may result from the high experience and skill level of participants included in the present study, in conjunction with what was a familiar task in a low-pressure environment. Memmert et al. (2009) observed that experts were better than novices at switching between attentional modalities; their experience allowed them to pay attention to what was most important during a sport task. Therefore, the extensive basketball experience of the high-level athletes included in the current study may have made them less susceptible to self-evaluative processes during the preparation or completion of a motor action, thereby protecting against any threat to flow associated with an IFA.

The IFA technique condition employed here also likely provided participants with an optimal skill-challenge zone as they engaged in technical behaviors within their realm of expertise and ability. Indeed, expert musicians experienced flow as a function of certain self-regulated practice behaviors (Araújo and Hein, 2016). It is possible that experienced individuals can self-regulate the demands of a familiar task in a practice environment, thereby promoting flow. Interestingly, an optimal skill-challenge environment is a dimension of flow described by Jackson (1995). It is possible that the design of the study did not provoke external stressors, which would have likely been detrimental to flow (Baumeister and Showers, 1986), and instead encouraged a skill-challenge balance, which may have served to maintain the flow state of participants during the IFA condition.

Limitations and Directions for Future Research

The present results demonstrate a significant improvement in free-throw shooting following a single, brief session that employed imagery techniques to elicit an EFA. Despite the encouraging results of our intervention, it is difficult to precisely isolate the underlying mechanisms driving the effect reported here. As previously described, while performance increased more with the EFA imagery instruction, flow did not (resulting in a lesser correlation between flow and performance within this condition). Given the performance benefits seen over the IFA technique condition, the shift to an EFA would thus seem to be implicated as the driving factor.

Yet, as acknowledged earlier we prioritized ecological validity in comparing an EFA condition that included guided imagery to an IFA condition that focused on technique, as our interest was to have a comparison condition that would resemble more typical coaching (as per Guillot et al., 2013). While this provides a valuable comparison for practical applications, it does limit our ability to isolate a single causal factor precisely; in this respect, more research in this important area is warranted. It would be informative in future research, for instance, to manipulate attentional focus within different imagery interventions; this is especially relevant given that the role of attentional focus is near-absent from both the RAMI and PETTLEP models. Thus, while recent research has supported the use of imagery within coaching (Leong et al., 2019), the current study highlights the need to better elucidate EFA and IFA coaching instruction embedded within imagery. Future research may also target differential effects on athletes of different ages and levels of ability, and compare performance within the training study paradigm itself with performance within subsequent game-level competition.

Distinguishing the underlying mechanisms is further complicated by research that has documented beneficial outcomes following motor imagery practice, which may well invoke an IFA through covert movement rehearsal (see Moran and O'Shea, 2020). However, it is important to note that the kinesthetic sensations involved in motor imagery are not necessarily inherent to an IFA. When a particular skill is well-practiced, external visual cues may prime the kinesthetic sensations associated with a task. This may well lead to more effective and efficient consolidation of kinesthetic stimuli in accordance with demands of the task, while avoiding any detriments associated with an IFA. In this way, we speculate that our findings do not directly contradict those of much motor imagery literature but instead highlight the importance of investigating how task-relevant implicit and explicit kinesthetic sensations may interact with athlete experience to influence performance.

Nevertheless, the results of our short-term intervention are suggestive in terms of coaching applications. Our results align with the body of research demonstrating the benefits of an EFA over an IFA and show how this can be brought about within a single training session by employing techniques borrowed from imagery interventions. While more work is required to clarify the theoretical basis of the current results, the practical applications are certainly intriguing.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by REB Mount Allison University. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

KM devised/compiled the materials, recruited the participants, and oversaw the interventions and data collection. Both authors were involved in the data analysis, preparation of this manuscript, conceptualization, and design of the research presented here.

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ORIGINAL RESEARCH
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A Comparison in Physical Fitness Attributes, Physical Activity Behaviors, Nutritional Habits, and Nutritional Knowledge Between Elite Male and Female Youth Basketball Players

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Background: Limited evidence exists comprehensively assessing physical fitness attributes, physical activity behaviors, nutritional habits, and nutritional knowledge according to sex in basketball players during early adolescence. Insight of this nature could be used to optimize the training process and lifestyles in young basketball players.

Objective: To compare physical fitness attributes, physical activity levels, nutritional habits, and nutritional knowledge between elite male and female basketball players under 14 years of age (U-14).

Methods: Twenty-three U-14 basketball players (male, $n = 13$ and female, $n = 10$) from the same elite basketball academy (Spanish Asociación de Clubes de Baloncesto [ACB] League) participated in this study. Physical fitness attributes were assessed using a basketball-specific test battery (countermovement jump, drop jump, linear sprint, Lane Agility Drill, 505 change-of-direction, and repeated-change-of-direction tests), while physical activity levels (Physical Activity Questionnaire for Adolescents, PAQ-A), nutritional habits (Turconi questionnaire), and nutritional knowledge (Turconi questionnaire) were assessed using questionnaires.

Results: Male players exhibited better physical fitness in all tests ($p < 0.001$ to 0.036, effect size $= -0.44$ to -0.76, intermediate to strong) compared to female players. Male players also performed more physical activity in their leisure time ($p = 0.036$) than females. No significant differences in nutritional habits and nutritional knowledge were evident between sexes ($p > 0.05$). Of note, a high proportion of players declared never or only sometimes eating fruit (males: 23%; females: 40%) and vegetables (males: 46%; females: 70%). In addition, relatively poor nutritional knowledge was evident in all players with the group correctly answering <50% of nutritional questions overall (4.57 ± 1.88 out of 11 points, 42%) and according to sex (males: 4.07 ± 2.10, 37%; females: 5.20 ± 1.40, 47%).

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Conclusion: These findings emphasize the necessity to perform individualized prescription of training stimuli across sexes to optimize the physical preparedness and development of youth basketball players. Additionally, strategies such as nutrition-focused education interventions may be necessary in this population given the low consumption of fruits and vegetables, as well as the poor nutritional knowledge observed in players.

Keywords: team sports, eating, diet, performance, health, adolescent, gender

INTRODUCTION

Basketball is a highly demanding team sport, requiring players to adequately develop various physical fitness attributes for successful on-court performance (Castillo et al., 2021). In this sense, quantifying physical fitness attributes is important in the training process to detect deficits in players and consequently prescribe appropriate training strategies (Mancha-Triguero et al., 2019). Quantifying physical fitness attributes is especially important in basketball players during early adolescence (i.e., 12–14 years of age) who undergo dramatic body changes, such as sudden increases in height and body mass as well as alterations in motor control (Faigenbaum et al., 2009). Nevertheless, only one study has compared physical fitness attributes in basketball players under 14 years of age (U-14) according to sex. Specifically, Mancha-Triguero et al. (2021) observed that U-14 male basketball players who participated in the Spanish national championship performed better in single (male: 32.6 ± 2.6 cm; female: 25.5 ± 4.0 cm) and repeated (male: 26.4 ± 5.8 cm; female: 20.7 ± 4.3 cm) jumping tests while their U-14 female counterparts had better repeated-sprint ability (male: 14.1 ± 1.1 s; female: 13.8 ± 0.6 s). Given the limited evidence base to draw from, future studies on this topic seem necessary to facilitate the training process in basketball players during early adolescence for optimal progression into and across elite basketball academies.

Despite the known effect of training strategies on improving physical fitness in young basketball players (Schelling and Torres-Ronda, 2016), the importance of "invisible" training to optimize short- and long-term sports performance has also been highlighted (Mujika et al., 2018). "Invisible" training involves the application of strategies other than physical training, such as the physical activity performed during leisure time and nutritional habits (Mujika et al., 2018). In this sense, the physical activity performed outside of regulated sports training and competition can develop healthy lifestyle habits in young basketball players (López Villalba et al., 2016). Considering physical activity data recorded in German adolescents (*n*: 3,505, age: 12.0 ± 3.3 years) according to sex, a greater proportion of males have been shown to engage in self-reported physical activity in different domains outside the context of sports clubs (leisure-time physical activity outside of sports clubs, extracurricular physical activity and outdoor play) than females (52.6 vs. 46.9%, $p = 0.010$) (Reimers et al., 2019). Similarly, Barja-Fernández et al. (2020) observed males undertake significantly more leisure-time physical activity (e.g., aerobic, cycling, handball) than females (3.01 ± 0.84 vs. 2.79 ± 0.75, $p = 0.04$) among young Spanish adolescents (*n*: 662, age: 12.4 ± 0.9 years). Despite these trends in physical activity behaviors reported in European adolescents, no data exist demonstrating variations in physical activity between sexes specifically in young basketball players. Therefore, future research comparing physical activity levels during leisure time between sexes in U-14 basketball players are necessary to better understand lifestyle behaviors and further individualize training plans in this population.

Another fundamental aspect comprising "invisible" training is nutrition, which is not only vital for adequate growth and development, but also contributes to optimal recovery, performance, and injury risk in young athletes (Jeukendrup and Cronin, 2010). In addition, suitable nutritional habits can also positively affect psychological aspects such as self-concept and self-efficacy in young athletes (Balsalobre et al., 2014; Zaccagni et al., 2020). Thus, understanding the nutritional habits of basketball players during early adolescence, as well as sex-based differences in these behaviors, seems essential for the application of specific and effective nutritional strategies in young male and female basketball players. In this sense, several factors may contribute to poor nutritional habits in young athletes, including a lack of nutritional knowledge. In fact, Trakman et al. (2016) identified nutritional knowledge as a key modifiable determinant of dietary behaviors. Consequently, it is important to also understand the nutritional knowledge, and any underlying sex-based differences in knowledge, to explain nutritional habits in young basketball players and best inform specific intervention strategies to optimize their nutritional habits (e.g., nutrition education programs). However, no studies have explored nutritional habits and nutritional knowledge according to sex in young basketball players.

Given the importance of developing suitable fitness attributes and adopting appropriate activity and nutritional habits outside of training and competition in youth sports, it is essential to examine these aspects and quantify differences between males and females in young basketball players to best develop sex-specific training and lifestyle interventions in this population. Consequently, to address the gaps on this topic in youth basketball, this study aimed to quantify and compare physical fitness attributes, physical activity levels, nutritional habits, and nutritional knowledge between elite U-14 male and female basketball players. Based on findings in previous studies examining U-14 basketball players (Mancha-Triguero et al., 2021) and students during early adolescence (Reimers et al., 2019), we hypothesized that male U-14 players would possess better physical fitness and perform more physical activity outside of regular training and competition than females, and that U-14 females would have better nutritional habits and knowledge than males.

METHODS

Study Design

A cross-sectional, observational study design was followed. In a single testing session, players had anthropometric measurements taken and completed a basketball-specific fitness test battery including jumping tests [countermovement jump (CMJ) and drop jump (DJ)], linear sprint tests, Lane Agility Drill test, 505 change-of-direction (COD) test, and repeated change-of-direction (RCOD) sprint test on an indoor basketball court (15–18°C, 60–70% relative humidity), with 5 min of passive, standing recovery applied between tests. Prior to testing, all players performed a standardized warm-up consisting of running at a moderate intensity for 5 min, followed by 5 min of jumps performed at progressively increasing intensities, 5 min of dynamic stretching exercises, and 3 min of 20-m running bouts performed at increasing intensities. Passive, standing recoveries were administered between efforts during the different warm-up tasks. All tests were carried out 3 days following official competition in the afternoon between 16:00 h and 19:00 h. Players were advised not to perform any physical exercise in the 2 days prior to testing and were given advice to ensure adequate hydration and nutritional status upon arrival for testing. Physical testing was conducted in groups of 3–4 players to ensure consistent recovery times could be administered between tasks across players during testing. Also, before physical testing, players completed questionnaires regarding physical activity behaviors, nutritional habits, and nutritional knowledge on their own and not in the presence of peers. Players were familiarized with the study protocol during training sessions across the month before the start of the study, including all physical fitness tests and questionnaires. Completion of the physical fitness testing and questionnaires took place during the same session during the in-season phase (October) of the 2020–2021 competitive season.

Participants

Twenty-three U-14 basketball players (male, $n = 13$, age: 13.5 ± 0.3 yr, height: 168.1 ± 6.7 cm, body mass: 56.6 ± 12.5 kg, body fat composition: 14.6 ± 5.2%, muscle composition: 37.4 ± 7.7%, training experience: 6.0 ± 3.1 yr; and female, $n = 10$, age: 12.7 ± 0.5 yr, height: 161.1 ± 4.7 cm, body mass: 52.1 ± 7.2 kg, body fat composition: 24.1 ± 5.5%, muscle composition: 33.9 ± 1.7%, training experience: 5.0 ± 2.1 yr) participated in this study. All players belonged to the same elite basketball academy (i.e., Spanish Asociación de Clubes de Baloncesto [ACB] League) being members of teams competing at the highest competitive level in Spain for the U-14 age category. Players were included in the study if they completed all fitness assessments and questionnaires and had not missed $\geq$4 weeks of participation continuously in training during the 2 months prior to testing. All players were not consuming any medications or ergogenic supplements that may have altered performance. All players were undertaking on-court team training consisting of games-based and conditioning drills three times per week with each session typically lasting 75–90 min, as well as participating in one official match per week when testing took place. All players and their legal guardians were informed of the procedures, potential risks, and benefits of participation in the study before giving written informed assent (players) and consent (guardians). The study was performed in accordance with the Declaration of Helsinki (World Medical Association Declaration of Helsinki, 2013) and approved by the Ethics Committee of the University (Code: FUi1-P007).

Physical Fitness Tests

Jumping Tests

Players performed two trials each of the CMJ and DJ to assess lower-limb power (Marshall and Moran, 2013). Each jump trial was separated by 45 s of passive, standing recovery. During CMJ trials, players were instructed to perform a downward movement followed by a complete, explosive extension of the lower-limbs, maintaining their hands on their hips while jumping as high as possible (Heishman et al., 2020). For DJ trials, players were instructed to step from a wooden box (30 cm high) and immediately following ground contact, jump for maximal height as quickly as possible (Marshall and Moran, 2013). A photocell system (Optojump, Microgate™, Bolzano, Italy) was used to measure jump height (cm) for each CMJ and DJ trial with the highest jump used for subsequent analysis in each test. The between-trial intraclass correlation coefficients (ICCs) for jump height attained during both tests was 0.97 in the current sample of players.

Linear Sprint Test

Players completed two trials of 20-m linear sprints at maximal effort to assess linear speed. Each sprint trial was separated by 120 s of passive, standing rest. Four pairs of photoelectric cells (Microgate™ Polifemo, Bolzano, Italy) were used to record sprint split times at 5, 10, and 20 m. The starting position was placed 0.5 m behind the first timing gate to avoid inadvertent triggering of timing, with players commencing each sprint on their own volition. The fastest time (s) for each split (irrespective of the trial) was used for subsequent analysis. The between-trial ICCs were 0.70, 0.67, and 0.75 for 5, 10, and 20-m sprint times in the current sample of players.

Change-Of-Direction (COD) Speed Tests

The Lane Agility Drill test and the 505 COD test were used to assess COD speed in players. In the Lane Agility Drill test, players started at the top left corner of the key, 0.2 m behind the free-throw line to avoid inadvertent triggering of timing, with players commencing each sprint on their own volition. Players faced the baseline throughout the entirety of the test. Initially, players ran 5.8 m to the baseline from the starting point. Players then side-shuffled 4.9 m to the right across the baseline before running backward to the top right corner of the free-throw line. Players then side-shuffled 4.9 m to the left where they touched the floor with their foot at the corner of the key (starting point), and then immediately completed the same circuit in the opposite direction (Raya-González et al., 2021). In the 505 COD test, players ran 15 m linearly from the starting position and performed a 180° turn, self-selecting the preferred lower-limb to initiate the change in direction. After changing direction, players ran as quickly as possible for a further 5 m back toward the starting position (Castillo et al., 2021). A photocell timing gate (Microgate™ Polifemo, Bolzano, Italy) was positioned 10 m from the starting position to capture performance time (s) across the 5 m immediately prior to and the 5 m immediately following the change in direction. Players completed two trials of each test with 90 s of passive, standing rest applied between trials. The fastest trial was used for subsequent analysis in each test. The ICCs were 0.90 for the Lane Agility Drill test and 0.74 for the 505 COD test in the current sample of players.

Repeated Change-Of-Direction (RCOD) Sprint Test

A single trial of the RCOD sprint test was administered consisting of 5 × 30-m shuttle sprints (15 + 15 m) interspersed with 30 s of passive, standing recovery between each sprint. Players started 0.5 m before the first timing gate and sprinted for 15 m, before touching a line on the floor with their preferred foot and returning to the starting position as fast as possible (Castillo et al., 2021). A single pair of photoelectric cells (Microgate™ Polifemo, Bolzano, Italy) were placed at the start line to record performance time (s) during each shuttle. The sum of all shuttle sprint times (total performance time during the RCOD sprint test) was calculated and used for subsequent analysis.

Questionnaires

The questionnaires were conducted following a typical week in which players maintained their normal daily routines involving attendance at school on 5 days, three on-court training sessions, and participation in an official match during the weekend.

Physical Activity Questionnaire for Adolescents (PAQ-A)

The PAQ-A was applied to assess the physical activity behaviors of players outside of regular basketball training and competition across the entire week (Monday to Sunday) prior to testing. The PAQ-A consists of nine questions, each using 5-point Likert scales. The first six questions in the questionnaire assess the physical activity carried out in the last 7 days during leisure time, during physical education classes, during specific times on school days (lunch, afternoon, and night), and during the weekend. The last two questions of the questionnaire assess the level of physical activity carried out during the week and how often physical activity occurred on each day of the week. The final score attained in the PAQ-A is the average of the scores obtained in the first eight questions, while the final question is used to identify whether any circumstances that prevented usual physical activity occurred in the week that was analyzed. The PAQ-A was designed for and validated (ICC = 0.71 for total score) in males ($n = 46$) and females ($n = 36$) aged 13–18 years (Martínez-Gómez et al., 2009).

Dietary Questionnaire

The dietary questionnaire was applied to identify the nutritional habits and nutritional knowledge of players (Turconi et al., 2003). The dietary questionnaire was originally composed of 10 sections; however only three sections (i.e., B, C, and H) were deemed relevant for this study and thus used to assess player nutritional habits and nutritional knowledge. Furthermore, each section was slightly modified with the addition of a "non-reported" option for each item in each section for players to select if they did not feel compelled, were not comfortable, or did not know the precise amounts when answering a question. The three sections from the dietary questionnaire used in this study included:

- *Section B* is focused on the consumption frequency of common foods and beverages, consisting of 28 questions. The questions must be answered using categorical variables based on the perceived frequency of consumption by each player (i.e., always, often, sometimes, never).
- *Section C* is focused on nutritional habits related to breakfast contents, number of meals consumed in a day, daily consumption of fruit and vegetables, and daily consumption of soft drinks and alcoholic beverages. This section contains 14 questions with categorical variables based on the perceived frequency of consumption for 10 questions (i.e., always, often, sometimes, never) and open-ended responses able to be given for four questions. The maximum total score able to be attained in this section is 54.
- *Section H* is focused on nutritional knowledge, consisting of 11 questions. Each question is focused on important nutritional aspects including the function of specific macronutrients and micronutrients as well as the relevance of nutrition. Four answers are available for players to select in each question with only one answer being correct. A point is awarded for each correct answer, with no points awarded for incorrect answers. The maximum total score able to be attained in this section is 11.

Statistical Analysis

Data are presented as mean ± standard deviations (SD) for quantitative variables or frequencies and percentages for qualitative variables. Considering the non-normal distribution of data detected by the Shapiro-Wilk test, Mann Whitney tests were used to examine differences in each physical fitness attribute, questions 1, 8, and the total score in the PAQ-A, and total scores in sections C and H in the dietary questionnaire between male and female groups. Practical significance was assessed by calculating Cohen's r effect size (ES) (Cohen, 1988), which were interpreted in magnitude as: small, $\leq$0.1; trivial, 0.11–0.30; intermediate, 0.31–0.50; and strong, >0.50 (Hopkins et al., 2009). Also, chi squared goodness-of-fit tests were used to examine the distribution of players for each item in the PAQ-A (questions 2–7) as well as sections B, C (questions 1–14), and H (questions 1–11) in the dietary questionnaire. Data analysis was carried out using the Statistical Package for Social Science (SPSS Statistics for Windows, version 25.0, IBM Corp., Armonk, N.Y., USA), with statistical significance set at $p < 0.05$.

RESULTS

The mean ± SD physical fitness attributes in the entire sample, as well as separately for male and female U-14 basketball players are shown in **Table 1**. Male players demonstrated significantly better jump heights (CMJ: $p < 0.001$, strong; DJ: $p < 0.001$, strong), linear sprint times ($p < 0.001$, strong), COD speed (Lane Agility Drill: $p < 0.001$, strong; 505 COD test: $p = 0.001$, intermediate), and RCOD time ($p = 0.04$, intermediate) than female players.

Responses to the PAQ-A in the entire sample, as well as separately for male and female U-14 basketball players are presented in **Table 2**. While male players reported significantly higher physical activity during leisure time compared to female players ($p = 0.036$), no significant differences were evident between sexes in all other questionnaire items nor PAQ_{total}.

Results from the dietary questionnaire regarding the nutritional habits and nutritional knowledge of the entire sample as well as separately for male and female U-14 basketball players are shown in **Table 3** and **Table 4**, respectively. No significant differences ($p > 0.05$) were found between sexes in nutritional habits or nutritional knowledge. However, descriptive data showed a high proportion of players never or only sometimes eat fruit (males: 23%; females: 40%) and vegetables (males: 46%; females: 70%). Furthermore, players demonstrated relatively poor nutritional knowledge with <50% of questions being answered correctly across the entire sample (4.57 ± 1.88 out of 11 points, 42%) and in each sex (males: 4.07 ± 2.10, 37%; females: 5.20 ± 1.40, 47%).

DISCUSSION

A better understanding of the physical fitness attributes, physical activity behaviors, nutritional habits, and nutritional knowledge of elite male and female basketball players participating in a youth basketball academy is essential to optimize their health and development in prescribing specific and effective training and nutritional strategies. In this regard, elite U-14 male basketball players exhibited better physical fitness across all tests (i.e., a test battery consisting of jumping, linear sprint, and change-of-direction tests) and performed more physical activity in their leisure time compared to elite U-14 female basketball players. In contrast, no significant differences were observed between sexes in nutritional habits and nutritional knowledge; however, male and female players reported a low consumption of fruit and vegetables and demonstrated relatively poor nutritional knowledge across a range of nutritional concepts.

Regarding physical fitness, the results of this study showed that elite male U-14 basketball players had superior jump heights (i.e., CMJ and DJ), linear speed (i.e., 5, 10, and 20 m- sprint times), COD speed (i.e., Lane Agility Drill and 505 COD tests), and RCOD speed (i.e., RCODAtotal) than female players. These results coincide with those reported in U-14 Spanish national basketball players revealing that male players ($n = 33$) possess superior lower-body power (i.e., abalakov jump and multi-jump test) and repeated-sprint capacity (i.e., repeat sprint ability test) compared to U-14 female players ($n = 12$) (Mancha-Triguero et al., 2021). This finding is supported with previous literature since sex differences in athletic performances start to increase around the age associated with the onset of puberty in males (12–13 years) (Handelsman, 2017). Also, the superior physical fitness in U-14 male players across many of the fitness tests we examined may be attributed to them possessing greater absolute and relative fat-free mass than females in early adolescence as females have been shown to experience a decline in relative fat-free mass prior to puberty (McCarthy et al., 2014). Furthermore, physical fitness attributes (linear sprint time and RCOD ability) have been shown to be significantly associated ($p < 0.05$; $r = -0.60$ to -0.63) with external load variables (total distance, high-speed running distance, and number of jumps performed) during simulated matches in elite U-14 male basketball players (Castillo et al., 2021) and with performance index rating during matches in elite U-14 male (CMJ height, 20-m linear sprint time, and Agility T-test time, $r = -0.25$ to 0.23, $p < 0.01$) and female (CMJ power, $r = 0.16$, $p < 0.05$) basketball players (Ramos et al., 2019). Given this demonstrated importance of physical fitness attributes for in-match activity and performance, a thorough understanding of differences in physical fitness between male and female U-14 players may inform the development of training stimuli to optimize the physical preparedness of players across both sexes to meet the demands of competition.

While the players in the present study underwent a rigorous training routine participating in an elite basketball academy, an understanding of their physical activity level outside the sports context is also of interest given its positive effects on athletic performance (Mujika et al., 2018). In this way, identifying discrepancies in physical activity performed during leisure time between sexes during early adolescence is needed to understand specific trends in lifestyle behaviors during this phase of life and for the development of specific training strategies. In this study, no significant differences were reported in most items contained in the PAQ-A. Only higher $PAQ1_{mean}$ activities, that is, how often players engaged in activities identified in the PAQ-A (skipping rope, cycling, jogging, racket sports, soccer, etc.) during their leisure time, were evident in male players compared to female players. Similar to these findings, higher participation in physical activity outside of sports clubs has been reported in males compared to females in German adolescents ($n = 2{,}117$, age: 12.0 ± 3.3 years, 52.6 vs. 46.9%, $p = 0.01$) (Reimers et al., 2019) and in Spanish adolescents ($n = 662$, age: 12.4 ± 0.9 years, 3.01 ± 0.84 AU vs. 2.79 ± 0.75 AU, $p = 0.04$) (Barja-Fernández et al., 2020). The greater leisure-time physical activity we observed in elite U-14 male basketball players compared to female players might be attributed to males experiencing greater encouragement from significant reference people (i.e., parental models) to engage in physical activity than females during early adolescence (Dixon et al., 2008). However, we observed no significant differences between sexes in physical activity behaviors during physical education classes, on school days, and during the weekend, suggesting

TABLE 1 | Comparisons in physical fitness attributes between elite, male and female under 14 basketball players.

Variable	Entire sample ($n = 23$)	Male players ($n = 13$)	Female players ($n = 10$)	Mean difference (%)	p-value	Effect size, magnitude
Jump tests						
Countermovement jump height (cm)	24.7 ± 5.6	27.6 ± 4.9	20.7 ± 3.8	25.1	**<0.001**	0.62, strong
Drop jump height (cm)	26.1 ± 6.4	30.0 ± 4.8	20.5 ± 3.6	31.7	**<0.001**	0.75, strong
Linear Sprint test						
5-m sprint time (s)	1.12 ± 0.08	1.07 ± 0.04	1.19 ± 0.06	−10.8	**<0.001**	−0.76, strong
10-m sprint time (s)	2.00 ± 0.14	1.92 ± 0.09	2.12 ± 0.12	−10.1	**<0.001**	−0.68, strong
20-m sprint time (s)	3.46 ± 0.40	3.23 ± 0.34	3.79 ± 0.23	−17.1	**<0.001**	−0.70, strong
Change-of-direction (COD) speed tests						
Lane Agility Drill time (s)	15.31 ± 1.00	14.76 ± 0.58	16.10 ± 0.97	−9.1	**<0.001**	−0.66, strong
505 COD test time (s)	2.68 ± 0.20	2.60 ± 0.15	2.80 ± 0.22	−7.7	**0.001**	−0.48, intermediate
Repeated change-of-direction (RCOD) sprint test						
RCOD sprint test time (s)	34.13 ± 2.06	33.36 ± 1.56	35.23 ± 2.27	−5.6	**0.036**	−0.44, intermediate

Bolded p-value indicates statistical significance at $p < 0.05$.

participation in an elite basketball academy may lessen the differences in leisure-time physical activity between males and females compared to the wider population as shown in European adolescents (Reimers et al., 2019; Barja-Fernández et al., 2020). As such, it seems that basketball practice in an elite academy may have had a positive influence on equating the practice of physical activity in wider social contexts across sexes in young players.

In addition to adequate physical fitness, a balanced and appropriate diet is essential to ensure optimal growth and performance are attained in adolescent basketball players (Iglesias-Gutiérrez et al., 2005, 2012). This is the first study to analyze differences in nutritional habits according to sex in basketball players during early adolescence, with no significant differences in nutritional habits observed between males and females. However, closer examination of the nutritional habits of the players examined in this study reveal some notable findings. Specifically, 30% of the entire sample (23% of males and 40% of females) never or sometimes eat fruit, while 57% of the entire sample (46% of males and 70% of females) never or sometimes eat vegetables. As such, considering the global recommendation of consuming 5 fruits and vegetables daily to prevent chronic diseases such as overweight, obesity, diabetes, or cardiovascular diseases (World Health Organization, 2003), the limited consumption of fruit and vegetables we observed in elite U-14 basketball players is concerning from a health perspective. From a performance perspective, consumption of fruits and vegetables has been shown to influence body composition (fat mass and fruit intake, $r = -0.21$, $p < 0.01$; fat free mass and vegetable intake, $r = 0.25$, $p < 0.01$) and physical fitness (progressive aerobic cardiovascular endurance run performance and vegetable intake, $r = 0.22$, $p < 0.01$) in University students (21.5 ± 1.5 years) (López-Sánchez et al., 2019). Research has indicated that the consumption of fruits and vegetables can delay or prevent the appearance of chronic non-communicable diseases, that is, diseases associated with unhealthy lifestyle habits (e.g., obesity, type II diabetes) (Lampe, 1999; Tian et al., 2018). These benefits are mainly related to the nutritional composition of foods, including vitamins, minerals (essential nutrients), and dietary fiber. By incorporating fruits and vegetables into the daily diet in adolescents, the intake of fats, sugars, and salt are typically reduced, which can help prevent weight gain and reduce the risk of developing overweight or obesity later in adulthood (World Health Organization/Food and Agriculture Organization, 2003).

Like our findings regarding player nutritional habits, no significant differences in nutritional knowledge were found between sexes in elite U-14 basketball players. These insights are novel for youth basketball players and are necessary to identify knowledge deficits regarding nutritional concepts that can be addressed in targeted educational interventions tailored to both sexes (Bird and Rushton, 2020). While these data are the first on this topic in basketball players, contradictory findings have been reported in other athletic populations. For instance, Ali et al. (2015) observed greater nutritional knowledge ($p < 0.05$) in female (19.3 ± 0.7 years) compared to male athletes (21.0 ± 1.8 years) who were involved in football, volleyball, cross-country, basketball, swimming, and other sports activities than males (21.0 ± 1.8 years) using a nutrition knowledge and dietary habits questionnaire. In contrast, Manore et al. (2017) reported no significant differences in nutritional knowledge ($p = 0.08$; females = 45%, males = 56% correct answers) between sexes in high school soccer players under 15 years of age using a nutritional knowledge questionnaire. Irrespective of sex, relatively poor nutritional knowledge was demonstrated across the entire sample of elite U-14 basketball players we examined (42% correct responses). Likewise, some relevant nutrition concepts such as fiber, fat, vitamins, minerals, balanced diet, and transgenic foods were poorly understood across players. Taking

TABLE 2 | Comparisons in Physical Activity Questionnaire for Adolescents (PAQ-A) results between elite, male and female, under 14 basketball players.

Question	Entire sample (n = 23)					Males (n = 13)					Females (n = 10)					p-value
$PAQ1_{mean}$ Activities	0.48 ± 0.27					0.59 ± 0.31					0.34 ± 0.14					**0.04**
PAQ2 Physical education	Never	Hardly ever	Sometimes	Often	Always	Never	Hardly ever	Sometimes	Often	Always	Never	Hardly ever	Sometimes	Often	Always	
	0	0	8.7	56.5	34.8	0	0	0	61.5	38.5	0	0	20	50	30	0.24
PAQ3 Lunch	Sit	Walk	Play little	Play a lot	Play intensely	Sit	Walk	Play little	Play a lot	Play intensely	Sit	Walk	Play little	Play a lot	Play intensely	
	69.6	21.7	4.3	4.3	0	76.9	15.4	7.7	0	0	60	30	0	10	0	0.41
	None	Once a week	2–3 a week	4 a week	>4 a week	None	Once a week	2–3 a week	4 a week	>4 a week	None	Once a week	2–3 a week	4 a week	>4 a week	
PAQ4 4–6 pm	21.7	13	30.4	21.7	13	23.1	0	30.8	38.5	7.7	20	30	30	0	20	0.08
PAQ5 6–10 pm	13	13	47.8	17.4	8.7	7.7	7.7	61.5	15.4	7.7	20	20	30	20	10	0.63
PAQ6 Weekend	8.7	22.7	43.5	17.4	8.7	7.7	15.4	38.5	23.1	15.4	10	30	50	10	0	0.58
PAQ7 Week intensity	Little	1–2 a week	3–4 a week	5–6 a week	>6 a week	Little	1–2 a week	3–4 a week	5–6 a week	>6 a week	Little	1–2 a week	3–4 a week	5–6 a week	>6 a week	
	21.7	39.1	34.8	4.3	0	23.1	30.8	38.5	7.7	0	20	50	30	0	0	0.70
$PAQ8_{mean}$ Diary frequency	1.80 ± 0.63					1.84 ± 0.69					1.74 ± 0.57					0.66
PAQ_{total}	1.63 ± 0.52					1.73 ± 0.60					1.50 ± 0.40					0.32

$PAQ1_{mean}$ Activities, Frequency of physical activities during leisure time across the last 7 days; PAQ2 Physical education, Frequency of being physically active during physical education sessions at school across the last 7 days; PAQ3 Lunch, Type of physical activity before and after lunch across the last 7 days; PAQ4 4–6 pm, Frequency of being physically active immediately after school during the last 7 days; PAQ5 6–10 pm, Frequency of being physically active between 6 and 10 pm across the last 7 days; PAQ6 Weekend, Frequency of being physically active during the last weekend; PAQ7 Week intensity, Weekly frequency of performing physical activity in leisure time; $PAQ8_{mean}$ Diary frequency, Frequency of daily physical activity for each day of the week; PAQ_{total}, Total score obtained across the first eight questions in the questionnaire; Mann-Whitney U-tests were applied to questions 1, 8, and total score, which contain data presented as mean ± standard deviation, while Chi-squared tests were applied to all other questions which contain data presented as percentages. Bold value indicates significance at $p < 0.05$.

TABLE 3 | Comparisons in nutritional habits between elite, male, and female, U-14 basketball players.

Question	Entire sample (n = 23)					Male players (n = 13)					Female players (n = 10)					p-value
C1 Breakfast	Never	Sometimes	Often	Always	NR	Never	Sometimes	Often	Always	NR	Never	Sometimes	Often	Always	NR	
	4.3	0	0	95.7	0	7.7	0	0	92.3	0	0	0	0	100	0	0.37
C2 Beverage breakfast	Tea	Juice	Chocolate	Milk	NR	Tea	Juice	Chocolate	Milk	NR	Tea	Juice	Chocolate	Milk	NR	
	0	0	0	95.7	4.3	0	0	0	92.3	7.7	0	0	0	100	0	0.37
C3 Eat breakfast	Cheese	Pizza	Bread	Fruit	NR	Cheese	Pizza	Bread	Fruit	NR	Cheese	Pizza	Bread	Fruit	NR	
	0	0	95.7	0	4.3	0	0	92.3	0	7.7	0	0	100	0	0	0.37
	Never	Sometimes	Often	Always	NR	Never	Sometimes	Often	Always	NR	Never	Sometimes	Often	Always	NR	
C4 Fruit	13	17.4	30.4	34.8	4.3	7.7	15.4	30.8	46.2	0	20	20	30	20	10	0.54
C5 Vegetables	8.7	47.8	26.1	13	4.3	15.4	30.8	23.1	23.1	7.7	0	70	30	0	0	0.16
C6 Cake	21.7	52.2	13	8.7	4.3	23.1	53.8	7.7	7.7	7.7	20	50	20	10	0	0.83
C7 Wine, beer	60.9	30.4	0	8.7	0	61.5	23.1	0	15.4	0	60	40	0	0	0	0.36
C8 Three meals	0	0	21.7	78.3	0	0	0	15.4	84.6	0	0	0	30	70	0	0.40
C9 Diet	Monotony	Different on weekend	Different sometimes	Different all days	NR	Monotony	Different on weekend	Different sometimes	Different all days	NR	Monotony	Different on weekend	Different sometimes	Different all days	NR	
	4.3	0	8.7	87.0	0	7.7	0	0	92.3	0	0	0	20	80	0	0.18
C10 Diet based on	Different all days	Carbohydrate	Lipids	Protein	NR	Different all days	Carbohydrate	Lipids	Protein	NR	Different all days	Carbohydrate	Lipids	Protein	NR	
	56.5	0	4.3	34.8	4.3	61.5	0	7.7	30.8	0	50	0	0	40	10	0.51
C11 Snacks	Sweets	Fried	Bread	Fruit	NR	Sweets	Fried	Bread	Fruit	NR	Sweets	Fried	Bread	Fruit	NR	
	8.7	21.7	26.1	30.4	13	7.7	23.1	30.8	15.4	23.1	10	20	20	50	0	0.30
C12 Beverages	Juice	Wine, beer	Refresh	Water	NR	Juice	Wine, beer	Refresh	Water	NR	Juice	Wine, beer	Refresh	Water	NR	
	0	0	8.7	91.3	0	0	0	15.4	84.6	0	0	0	0	100	0	0.19
	Never	Sometimes	Often	Always	NR	Never	Sometimes	Often	Always	NR	Never	Sometimes	Often	Always	NR	
C13 Milk	0	0	4.3	95.7	0	0	0	0	100	0	0	0	10	90	0	0.24
C14 Water	0	13	26.1	56.5	4.3	0	7.7	15.4	69.2	7.7	0	20	40	40	0	0.31
C Total	44.78 ± 3.70					45.39 ± 3.86					44.00 ± 3.53					0.45

All questions were obtained from section C in the Turconi questionnaire; NR, not reported; Chi-squared tests were applied to questions 1–14, while a Mann-Whitney U test was applied to the total score.

TABLE 4 | Comparisons in nutritional knowledge between elite, male and female, U-14 basketball players.

Question	Entire sample ($n = 23$)		Male players ($n = 13$)		Female players ($n = 10$)		*p*-value
	Correct (%)	*Incorrect (%)*	*Correct (%)*	*Incorrect (%)*	*Correct (%)*	*Incorrect (%)*	
H1 Carbohydrates	56.5	43.5	61.5	38.5	50.0	50.0	0.58
H2 Fiber	17.4	82.6	7.7	92.3	30.0	70.0	0.16
H3 Fat	8.7	91.3	7.7	92.3	10.0	90.0	0.85
H4 Protein	56.5	43.5	46.2	53.9	70.0	30.0	0.25
H5 Calories	56.5	43.5	61.5	38.5	50.0	50.0	0.58
H6 Energy	47.83	52.17	53.85	46.15	40.0	60.0	0.51
H7 Vitamins and minerals	4.3	95.7	0	100	10.0	90.0	0.24
H8 Balanced diet	21.74	78.26	76.9	23.1	80.0	20.0	0.86
H9 Daily energy expenditure	65.2	34.8	53.8	46.2	80.0	20.0	0.19
H10 Biological foods	56.5	43.5	46.2	53.8	70.0	30.0	0.25
H11 Transgenic foods	21.7	78.3	15.4	84.6	30.0	70.0	0.40
H Total	4.57 ± 1.88		4.07 ± 2.10		5.20 ± 1.40		0.24

All questions were obtained from section H in the Turconi questionnaire; total score is presented as mean ± standard deviation for the number of correctly answered questions.

into account that an adequate nutritional knowledge could promote better nutrional habits (Muderedzwa and Matsungo, 2020) and consequently better health and physical conditioning (Nikolaidis and Theodoropoulou, 2014), nutrition education interventions are likely needed in elite U-14 basketball players to enhance nutritional habits. Further research on this topic is encouraged to identify whether the poor nutritional knowledge we observed represents that of the wider elite adolescent basketball player population.

This study is not exempt from limitations, which should be acknowledged. First, given U-14 players from a single elite basketball academy were strictly recruited in this study, a relatively small sample size was used in each group (males and females). Accordingly, future studies should expand on this work examining larger samples of players and adolescent players from other age categories and levels of play (i.e., international). Secondly, endurance capacity was not measured in this study. Due to the documented importance of aerobic fitness in accomplishing high-intensity running distances during matches in elite, adolescent (18.2 ± 0.5 years) male basketball players (Ben Abdelkrim et al., 2010), further studies comparing fitness attributes between sexes in youth basketball players should include aerobic fitness testing protocols (e.g., Yo-Yo Intermittent Recovery Test, 30–15 Intermittent Fitness Test). Thirdly, data were acquired at a single timepoint in the season and does not capture changes in fitness, physical activity behaviors, or nutritional habits across the season. Consequently, future research should conduct fitness testing and questionnaire assessments at different timepoints throughout the season to understand temporal changes in fitness, physical activity behaviors, and nutritional habits to implement specific strategies at different phases across the competitive season. Fourthly, analysis of nutritional habits was limited to broad patterns of dietary behaviors, whereas further understanding of daily energy expenditure and macronutrient intake would allow for more detailed insight to develop comprehensive nutrition intervention strategies promoting healthy nutritional habits in adolescent basketball players. Finally, maturity status was not able to be measured in this study. Future research on this topic is encouraged to identify the maturity status of players where permissible to understand its role on the variables measured in this study.

CONCLUSIONS

Elite U-14 male basketball players had greater physical fitness and underwent more physical activity during leisure time compared to female players, suggesting individualized prescription of training stimuli across sexes should be adopted to optimize the physical preparedness and development of players. Additionally, while nutritional habits and nutritional knowledge were similar between sexes, players exhibited low consumption of fruits and vegetables as well as relatively poor nutritional knowledge. Consequently, strategies such as education interventions may be necessary to improve the nutritional knowledge of elite basketball players in early adolescence.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Universidad Isabel I. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

SS-D led the project and developed and revised the original manuscript. DC and JR-G analyzed and interpreted the data and developed and revised the original manuscript. AS revised the original manuscript. JY developed the statistical report and revised the original manuscript. All authors contributed to the article and approved the submitted version.

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Modeling the Keys to Team's Success in the Women's Chinese Basketball Association

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The technical characteristics of women's basketball may differ from men's basketball, and there is a need to identify the key performance indicators (KPIs) that contribute to the success of women's teams. The aim of the current study was to examine and quantify the relationships between technical performance indicators and match outcome in elite women's basketball using both linear and non-linear statistical methods, the effectiveness of the two methods was compared as well. A total of 136 matches (n = 272 teams' observations) in the regular season of Women's Chinese Basketball Association (WCBA; season 2020–2021) were analyzed using multiple linear regression (MLR) and quantile regression (QR). Results showed that two-point percentage, offensive rebounds, assists and turnovers had significant effects on the match outcome for both MLR and QR analysis. No significant relationships were observed between match outcome and three-point percentage, steals, and fouls. The results between MLR and QR analysis were different in free-throw percentage, defensive rebounds and blocks. Current results highlighted QR analysis is an advanced statistical model more powerful than the traditional linear method for the identification of KPIs. The identified KPIs may help coaches to develop more specific training interventions and match strategies during match play.

Keywords: women, team sports, performance analysis, match analysis, quantile regression

INTRODUCTION

One of the most important tasks of performance analysis in basketball is to interpret and quantify the dynamical interactions among technical, tactical, physical and psychological factors during matches (Drust, 2010). Over the years, researchers have paid more attention on the technical match performance of men's basketball, especially in the identification of key performance indicators (KPIs) (Gómez-Ruano et al., 2008; Lorenzo et al., 2010) and tactical patterns (Kempe et al., 2015), the effect of situational variables (Sampaio et al., 2010; García et al., 2014), and the use of performance profiling (Zhang et al., 2017, 2019). However, the available literature regarding the exploration of women's technical match performance is scarce (Gómez-Ruano et al., 2006, 2013; Leicht et al., 2017a). The sex differences should not be ignored when choosing the research object, as differences in technical (Sampaio et al., 2004), anthropometric (Garcia-Gil et al., 2018), and physiological (Scanlan et al., 2012) characteristics may exist between men and women's players. Previous research has reported that women differ from men in the effectiveness of collective movement patterns during match play (Gómez-Ruano et al., 2013), and women's teams obtained higher unsuccessful two-point field-goals and steals, and lower blocks than men's teams (Sampaio et al., 2004).

The technical match performance could be interpreted and quantified by a set of technical performance indicators (Liu et al., 2016), and the technical performance indicators is a combination of match actions and events that aims to explain some or all aspects of a successful match performance (Hughes and Bartlett, 2002). Therefore, in light of the gender differences in technical performance indicators (e.g., steal and block) and well-documented literature for men's basketball, it would be of interest to identify the KPIs that best can explain the match characteristics of women's basketball. Gómez-Ruano et al. (2006) employed the discriminant analysis to identify the KPIs that better differentiate winning and losing teams, where successful two-point field-goals, defensive rebounds and assists were identified as the key predictors for women's basketball matches. Another study from Leicht et al. (2017a) employed both linear and non-linear statistical models to examine the relationships between technical performance indicators and the match outcome for women's basketball matches at the Olympic Games. Field-goal percentage, defensive rebounds, steals, and turnovers were considered as the key indicators of match outcome, concluding that the combination of distinctive KPIs with the non-linear modeling could provide teams with a greater likelihood of winning a match. It is therefore suggested that the non-linear statistical techniques could be useful tools for coaches and performance analysts in the evaluation of teams' and players' match performances.

The current study proposed a novel non-linear statistical model called quantile regression (QR), developed by Koenker and Bassett (Koenker and Bassett, 1978; Koenker, 1994), to identify the relationships between technical performance indicators and match outcome, these relationships were considered as linear and estimated by linear equations in the previous studies. However, the technical data collected from basketball matches cannot meet the conditions of traditional linear regression (e.g., linearity, homoscedasticity, independence, or normality) in most cases, especially for analyses with a limited sample size (Montgomery et al., 2021), whereas QR modeling provides that capability. Besides, traditional linear regression summarizes the average relationship between a set of independent variables and dependent variable based on the conditional mean function (Bilgili et al., 2021), but fails to fully capture the patterns in the data and may only provide a partial view of the relationships. Conversely, the QR modeling performs a stratified analysis and describes the relationships at different points in the conditional distribution of the dependent variable, enabling examination of the relationships between various conditional quantiles (e.g., 10th, 25th, 50th, 75th, and 90th quantiles) of the dependent variable and independent variables (Koenker et al., 2017). Therefore, the heterogeneities among the relationships could be revealed with QR modeling. Zhang et al. (2020) compared the effectiveness between multiple linear regression (MLR) and quantile regression for identifying the KPIs of men's basketball matches at the FIBA Basketball World Cup, reporting that QR modeling explored additional KPIs (mid-range score at 10th quantile and offensive rebounds at 90th quantile) than MLR modeling. Therefore, QR modeling could be considered as a potentially superior tool for performance analysts to explain the match performance based on multivariate datasets.

The aim of this study was to identify the relationships between match-related statistics and match outcome in elite Women's basketball teams (Women's Chinese Basketball Association, WCBA), using linear and non-linear modeling. We hypothesized that QR modeling would allow us to identify the KPIs that can better explain the technical characteristics within matches and provide more detailed information for quantifying the relationships between KPIs and match outcome in elite women's basketball.

MATERIALS AND METHODS

Data Source and Reliability

Technical match performance data of teams from the regular season of the WCBA in the season 2020–2021 were acquired from the official website of the Chinese Basketball Association[1]. The reliability and accuracy of data were tested by two experienced analysts with more than 5 years of experience in basketball performance analysis using a randomly selected sub-sample of 10 matches. The test results were compared with the corresponding data from the official website and acceptable Intra-Class Correlation Coefficients (ICC = 0.87–0.98) were obtained for all variables. This study used a observational design and all the analyzed data were de-identified and available in the public domain, no stipulations were in place from the WCBA regarding re-use of the data for production of scientific manuscripts without permission, so ethics approval was not required, but the study design and procedures were in accordance with the ethical guidelines of the authors' affiliated institutions.

Sample and Technical Variables

There were 17 teams participating in the regular season of WCBA in season 2020–2021, with each team played against the other 16 teams one time. The teams' technical match-related statistics of all 136 matches (n = 272 team observations) were selected as the sample. After disregarding the effect of multicollinearity among the explanatory variables, ten technical variables were analyzed and classified into two groups, offensive and defensive variables, according to previous studies (Gómez-Ruano et al., 2009; Sampaio et al., 2015; Zhang et al., 2020). The grouping information and operational definitions of these technical variables are presented in **Table 1**. The normalization of all variables was performed using the number of ball possessions (Ibáñez et al., 2009b; Gómez-Ruano et al., 2015).

[1]https://www.cba.net.cn

TABLE 1 | Selected technical performance-related match variables.

Groups	Variables: operational definitions
Offensive variables	**Two-point percentage:** the percentage of two-point field goal attempts that were successful during the match
	Three-point percentage: the percentage of three-point field goal attempts that were successful during the match
	Free throw percentage: the percentage of free throws that were successful during the match
	Offensive rebound: the number of rebounds a player or team collected while on offense
	Assist: an assist occurs when a player completes a pass to a teammate that directly leads to a field goal score
	Turnover: a turnover occurs when the player or team on offense loses the ball to the defense
Defensive variables	**Defensive rebound:** the number of rebounds a player or team collected while on defense
	Steal: a steal occurs when a defensive player takes the ball away from a player on offense
	Block: a block occurs when the defense player tips the ball and prevents an offensive player's shot from scoring
	Foul: any infringement that is penalized as foul play by a referee

Ball possession was defined as a period of play between when one team gains the control of the ball and when another team gains the control of the ball (Sampaio and Janeira, 2003). The equation for calculating the ball possessions was as follows: ball possessions = field goals attempted – offensive rebounds + turnovers + 0.44 $\times$ free throws attempted (Oliver, 2004; Kubatko et al., 2007).

Statistical Analysis

Previously, the MLR has widely been used by researchers to identify the relationships between KPIs and the match performance of players and teams (Liu et al., 2016; Yi et al., 2019a,b). However, the traditional MLR method was modeled based on the average relationships between the dependent variable and a set of independent variables using the conditional mean function (Koenker and Bassett, 1978). This kind of mean regression modeling presumes that the dependent variable could be interpreted as a linear combination of a set of independent variables, but the level of the dependent variable has not been considered. It cannot estimate the overall impact of explanatory variables on the explained variables, only an average effect provided. QR describes the relationships between dependent and independent variables at different points of the conditional cumulative distribution of the dependent variable, and produces different coefficients for each prespecified quantile (decile or centile) of the error distribution (Koenker and Bassett, 1978). It enables researchers to understand the entire distribution of measured correlations conditional on a set of explanatory variables. Given that the sample contains non-normal disturbances, applying the conditional mean estimators to the main equation would not be suitable because these estimators are not robust to departures from normality or long tail error distributions. Hence, MLR is likely to produce inefficient and biased estimates. In contrast, the QR as a conditional median approach is robust to departures from normality and skewed tails (Bilgili et al., 2021).

In the current study, MLR and QR were both employed to identify the relationships between technical variables and match outcome, and the results between these approaches were compared. The examination of data distribution and multicollinearity were conducted before analyzing the effects of KPIs on the match outcome (final point differential) using MLR and QR models, respectively. The MLR and QR modeling were performed using R software (R project version 3.5.1). QR modeling was denoted as $Qq(y/x)$, where q is the quantile or percentile, the median is the 50th percentile of the empirical distribution with no zero values for the dependent variable (Koenker, 1994). The relationships were interpreted by the positive and negative regression coefficients, which indicate a greater/lower propensity to increase/decrease the match outcome (Sampaio et al., 2010). The current study selected five quantile levels (Q10, Q25, Q50, Q75, and Q90) for the QR model. Q10 and Q25 represent the lower tail distribution and Q75 and Q90 represent the higher tail distribution. The statistical significance was set at $p < 0.05$.

RESULTS

The parameter estimates of the MLR and QR with five quantile levels (Q10, Q25, Q50, Q75, and Q90) are shown in **Table 2**. **Figure 1** is the visualization combining the results of MLR and QR modeling, and the significant technical indicators for both approaches are summarized and compared in **Figure 2**.

The horizontal axis presents the different quantiles, the vertical axis lists the regression coefficients. The black line with yellow dots is the estimate of the regression coefficient for quantiles (10th, 25th, 50th, 75th, and 90th), the red line represents the corresponding regression coefficient of MLR. The light orange and deep gray shaded areas represent the 95% confidence intervals of the regression coefficients for QR and MLR, respectively.

Offensive Variables

There was a significantly positive relationship between two-point percentage and the match outcome (regression coefficient, RC = 0.517) for MLR, while the significantly positive relationships were only found at the quantile of 75th and 90th (RC = 0.668 and 0.662) in the QR analysis. No significant relationship was detected between three-point percentage and match outcome for both MLR and QR modeling. Free-throw percentage also had no evident impact on the match outcome

TABLE 2 | Parameter estimates from multiple linear regression (MLR) and quantile regression (QR) on the difference quantiles of final score.

Variables	Multiple linear regression	Quantile regression (QR)				
		Q10 (*n* = 272)	**Q25 (*n* = 272)**	**Q50 (*n* = 272)**	**Q75 (*n* = 272)**	**Q90 (*n* = 272)**
Constant	0.175 (0.152)	−0.129 (0.189)	−0.187 (0.205)	0.284 (0.179)	0.411* (0.201)	0.492** (0.132)
Two-point percentage	0.517** (0.173)	0.246 (0.200)	0.413 (0.229)	0.206 (0.202)	0.668** (0.216)	0.662** (0.193)
Three-point percentage	0.001 (0.002)	0.001 (0.002)	0.0004 (0.002)	−0.0004 (0.002)	0.001 (0.002)	−0.001 (0.001)
Free-throw percentage	0.001 (0.001)	0.001 (0.002)	0.004* (0.002)	0.001 (0.001)	−0.0001 (0.001)	−0.0003 (0.001)
Offensive rebound	0.011** (0.003)	0.008 (0.005)	0.008 (0.005)	0.014** (0.003)	0.009* (0.004)	0.010** (0.004)
Assist	0.011** (0.003)	0.016** (0.006)	0.018** (0.004)	0.015** (0.003)	0.007 (0.004)	0.0005 (0.004)
Defensive rebound	−0.006 (0.003)	−0.003 (0.003)	−0.007* (0.003)	−0.007* (0.003)	−0.007* (0.003)	−0.001 (0.003)
Turnover	−0.013** (0.003)	−0.009* (0.004)	−0.013** (0.003)	−0.016** (0.004)	−0.013** (0.004)	−0.010** (0.003)
Steal	0.0001 (0.004)	0.001 (0.006)	0.003 (0.005)	0.001 (0.004)	−0.001 (0.005)	0.002 (0.004)
Block	0.012 (0.007)	0.002 (0.014)	0.016 (0.010)	0.019** (0.007)	0.015* (0.007)	0.012 (0.010)
Foul	−0.002 (0.003)	−0.004 (0.004)	−0.003 (0.004)	0.0001 (0.004)	0.0004 (0.004)	0.0003 (0.003)

*Standard errors are shown within parentheses; * $p < 0.05$ and ** $p < 0.01$.*

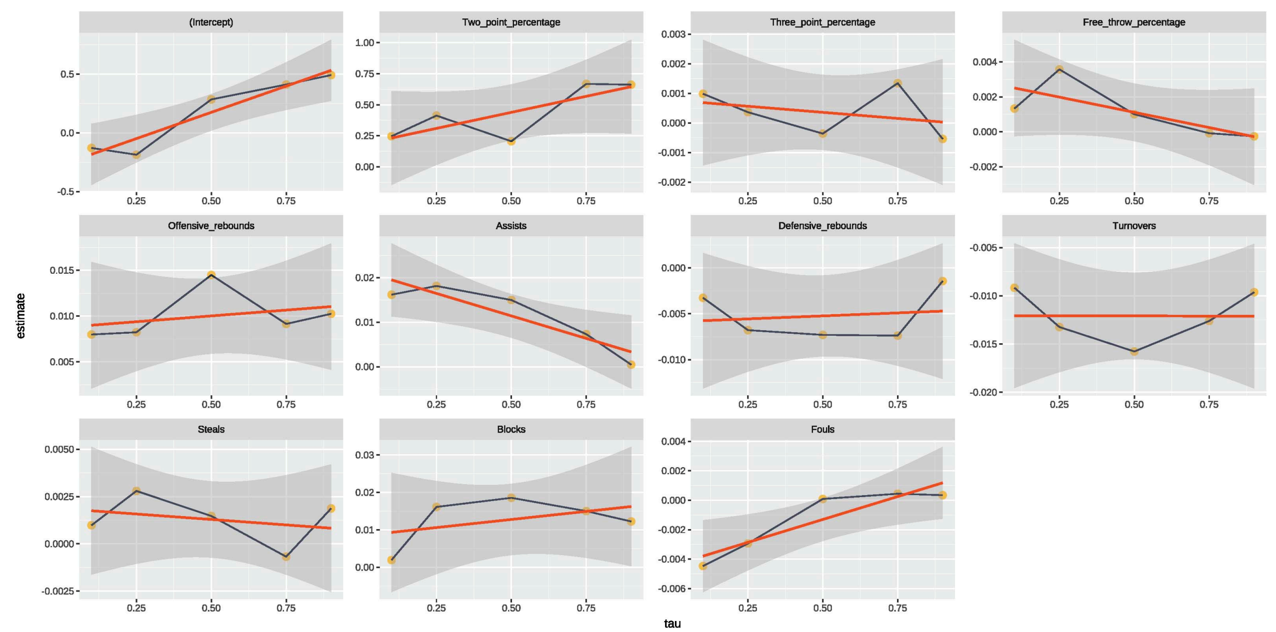
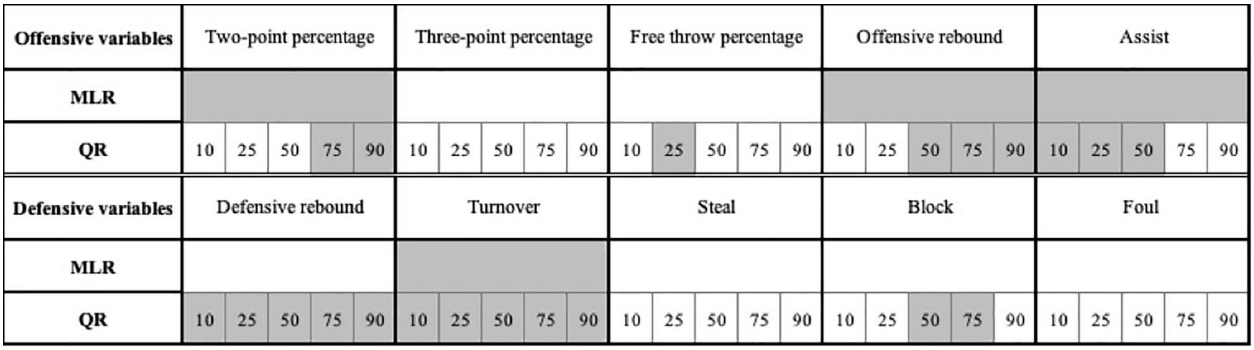


FIGURE 1 | Regression coefficients of MLR and QR modeling for the effects of key performance indicators on match outcome.

for both models, except for the 25th quantile (RC = 0.004). Offensive rebounds showed significantly positive relationships with match outcome for MLR (RC = 0.011) and QR with quantiles of 50th, 75th, and 90th (RC = 0.014, 0.009, and 0.010). A significantly positive relationship between assists and match result was identified for MLR (RC = 0.011) and QR with the quantiles of 10th, 25th, and 50th (RC = 0.016, 0.018, and 0.015).

Defensive Variables

There was no significant relationship between defensive rebounds and match outcome for MLR, but the significantly negative relationships were found for QR analysis with the quantiles of 25th, 50th, and 75th (RC = −0.007, −0.007, and −0.007). Turnovers showed significantly negative relationships with the match result for MLR (RC = −0.013) and all QR quantiles (RC = −0.009, −0.013, −0.016, −0.013, and −0.010). No significant relationships between steals and match result were found for MLR or QR analyses with all quantiles. Blocks showed significantly positive relationships with match result at the quantiles of 50th and 75th for QR analysis (RC = 0.019 and 0.015), while no significant relationship could be detected for the MLR analysis. Fouls had no evident effect on the match result based on the results from both statistical approaches.



Offensive variables	Two-point percentage					Three-point percentage					Free throw percentage					Offensive rebound					Assist				
MLR																									
QR	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90
Defensive variables	Defensive rebound					Turnover					Steal					Block					Foul				
MLR																									
QR	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90

FIGURE 2 | Comparison between MLR and QR modeling for the identified key performance indicators.

DISCUSSION

This study aimed to identify the relationships between technical performance indicators and match outcome in the WCBA, quantifying the effects of KPIs on the match outcome using MLR and QR models. Our results showed that offensive variables (two-point percentage, free-throw percentage, offensive rebound, and assist) had positive effects on the match outcome, while the defensive variables showed both positive and negative effects on the match outcome. The differences in the results between MLR and QR were identified, with QR analysis providing more detailed information for the quantification of the relationships between KPIs and match outcome.

Previous studies have reported that two-point percentage is the critical indicator for basketball match performance (Lorenzo Calvo et al., 2010; Parejo et al., 2013), and most of the points scored in a basketball game through two-point field goals (Ibáñez et al., 2009a). Our results indicated that two-point percentage had the greatest impact on the match result for MLR and QR analysis, a one-unit increase in two-point percentage would bring an increase of 0.517 units (MLR), 0.668 units (75th quantile) and 0.662 (90th quantile), respectively, for the match outcome. Scoring in the paint and mid-range area means that more offensive actions need to perform, and more physical contact with defenders would face (Gasperi et al., 2020; Reina et al., 2020). Therefore, more effective offensive actions that lead to two-point field goals, such as dribble penetration or post play, and greater physical ability would heighten the likelihood of team success. Unexpectedly, we found that three-point percentage had no significant relationship with the match outcome, which is inconsistent with a prior study from Zhang et al. (2020) who reported that three-point score was a KPI that significantly associated with match outcome for men's basketball matches at the FIBA World Cup. This may be partly explained by the differences in the anthropometrical characteristics between men's and women's players (Garcia-Gil et al., 2018). The relative less strength and height may be a disadvantage for women's players to reach higher accuracy in the three-point field goal given the longer distance that must be covered with shots compared to two-point field goals (Miller and Bartlett, 1996). The positive effect of strength on the accuracy of three-point field goals has been confirmed by previous studies (Tang and Shung, 2005; Justin et al., 2006). Therefore, frequency of occurrence of three-point field goal in women's matches may be relatively lower than in men's matches. Free-throw is executed under much more controlled and stable conditions than field goals, and the shooting accuracy is influenced by limited factors. It was considered as one of the most effective scoring methods, especially the importance at the last 5 min in close matches has been previous highlighted (Kozar et al., 1994). A prior study of women's basketball from Gómez-Ruano et al. (2006) identified that free-throw percentage was not a KPI associated with match outcome for all matches and unbalanced matches, but it can effectively differentiate the winning teams and losing in balanced matches. Our findings were in line with this study that identified free-throw percentage had no significant effect on the match result for MLR analysis, while this indicator was positively associated with the lower distribution (25th quantile, close matches) of final-match outcome. This may indicate that use of linear statistical approaches may underestimate the influence of free-throw percentage on the match outcome. However, differences between sexes may exist as a previous study for men's basketball reported that free-throw percentage was not the KPI that can significantly affect the match result based on both linear and non-linear approaches (Zhang et al., 2020), In this regard, differences in motor abilities between women and men basketball players may be a plausible reasons for the different trends regarding the relationship between free-throw percentage and match outcome.

Offensive rebounds and assists showed significant positive effects on the match outcome for MLR analysis, but the results of QR analysis showed an opposite trend that offensive rebounds and assists had a significant impact on the upper and lower distribution of match result, respectively. This result may indicate that QR analysis as a non-linear statistical approach can provide more detailed information for the explanation of the relationships between technical performance indicators and match performance. Besides, the importance of offensive rebounds is well documented (Ibáñez et al., 2009b; García et al., 2014; Zhang et al., 2020) and has been verified again in this study, and assist as match action that directly impacts scoring is naturally closely related to the match outcome. Defensive rebounds and blocks, especially the defensive rebound, have been confirmed as the keys for teams' success in previous studies (Gómez-Ruano et al., 2006; Summers, 2013; Leicht et al., 2017a). However, the results of MLR analysis demonstrated that defensive rebounds and blocks had no significant impact on match outcome, but the significant negative (defensive rebounds) and positive (blocks) effects on the match result were found using QR analysis. These disparities among two approaches may indicate that the effects of defensive rebounds and blocks on match outcome are sensitive. Therefore, caution should be paid by coaches on these indicators when developing the defensive strategies for women's basketball competition.

Steals and fouls are widely used as performance indicators for the evaluation of defensive performance during match play. The execution of a successful steal can help the teams to recover of ball possession and more steals may contribute the probability of winning (Gómez-Ruano et al., 2013). Committing fouls will provide an easy scoring opportunity (i.e., free throws) for opponents and it has a negative impact on the match outcome. However, the current study identified that steals and fouls were not significantly associated with the match outcome, which is insistent with previous studies regarding both men's (Leicht et al., 2017b) and women's (Gómez-Ruano et al., 2006; Leicht et al., 2017a) basketball matches. This disparity may be due to differences in the application of statistical methods. Turnovers were the only indicator that showed significant relationships with match outcome for both MLR analysis and the entire range of quantiles of QR analysis which was in line with the result reported by Teramoto and Cross (2010) who found that turnover is a key predictor of teams' success in the regular season games in the National Basketball Association (NBA). Others have also reported the importance of turnovers for basketball match success for both men's and women's matches in elite competitions (Olympic Games and FIBA Basketball World Cup) (Leicht et al., 2017a; Zhang et al., 2020). Passing errors were considered as the most common turnover in women's basketball, and most of the turnovers happened during set plays (Fylaktakidou et al., 2011). The occurrence of a turnover is the result of good defensive decisions of opponents, leading to the loss of ball possession. Therefore, improving the ability to manage ball possession, and incorporating specific decision-making tasks into the training sessions with the consideration of specific situations (i.e., involving group-tactical situations) may potentially decrease the number of turnovers during the match play and increase the likelihood of team success.

CONCLUSION

The current study has identified the key technical performance indicators that associated with match outcome in women's basketball using linear and non-linear statistical methods. Our results indicated that QR analysis is more powerful when identifying the keys for teams' success. The traditional linear modeling only describes the relationship between independent variables and the mean conditional distribution of dependent variables, while the QR analysis provides more detailed and practical information for understanding the relationships between technical performance indicators and various levels of distribution of match outcome. This may avoid the underestimation or overestimation of the effects of technical indicators on the match outcome. Additionally, our findings highlighted the KPIs in elite women's basketball matches. The importance of two-point percentage, offensive rebounds, assists and turnover were confirmed by both MLR and QR. The significant effects of free-throw percentage, defensive rebounds and blocks on the match outcome were detected by MLR, while these were not the case in the results of QR. Three-throw percentage, steals and fouls were considered as non-critical indicators in women's matches. This finding may allow coaches to get a better understanding of match success of women's basketball matches and to control for technical–tactical strategies during match-play.

STUDY LIMITATIONS

The limitations of the current study should be noted. First, the situational factors, such as match location and quality of opponent have not been considered in the analysis. Future research is recommended to take these situational variables and their interactions into account to improve the practical applications of the findings. Second, only one season was included in the analysis, the limited sample size could be one potential reason of the existing differences between this research and previous studies. Future research could expand the sample to identify the KPIs based on a longitudinal design across multiple seasons.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

QY and WF: conceptualization. SZ: methodology, formal analysis, software, and visualization. QY: data collection and writing – original draft preparation. SZ, WF, and M-ÁG-R: writing – review and editing. M-ÁG-R: supervision. QY and WF: funding acquisition. All authors have read and agreed to the published version of the manuscript.

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The Association Between Facial Width-to-Height Ratio (fWHR) and Sporting Performances: Evidence From Professional Basketball Players in Japan

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Previous research in evolutionary psychology has highlighted the potential role of facial structures in explaining human behavior. The facial width-to-height ratio (fWHR) was found to be associated with testosterone-driven behavioral tendencies like achievement drive, aggression, and sporting success. The current study aimed to replicate such relationships using real-world data (i.e., professional basketball players; $N = 482$). Achievement drive, aggression, and sporting success were operationalized as field-goal attempts (FGA), the number of fouls committed (Foul), and player performance rating (EFF), respectively. The results indicated that fWHR was significantly associated with FGA and EFF, controlling for minutes of play and body-mass-index. The same results were obtained for separate analyses focusing on outsider players. However, analyses of inside players demonstrated that fWHR was associated only with EFF. The current research further provides empirical evidence supporting the effects of fWHR on achievement drive and sporting successes, although the effect sizes are notably small.

Keywords: facial structure, fWHR, achievement drive, aggression, athletic performance

INTRODUCTION

Faces play an important role in society as individuals communicate with facial expressions and draw inferences about others' personalities and behavioral tendencies based on their faces (Zebrowitz, 2018). Although such inferences are often inaccurate and undesirable, various research has highlighted that faces could be a predictor of human traits and behavior (Wong et al., 2011; Short et al., 2012). In this research stream, facial width-to-height ratio (fWHR; calculated by dividing the length between the left and right zygomatic arches by the length between the top of the lip and the bottom of the eyebrows) has commonly been utilized to better understand the relationships between facial characteristics and various outcomes (Geniole et al., 2015). For example, fWHR is positively associated with achievement drive (Lewis et al., 2012), psychopathic personality traits (Geniole et al., 2015; Anderl et al., 2016), and anti-social behavior (Stirrat and Perrett, 2010). The common explanation underlying such relationships is related to the testosterone level (Lefevre et al., 2013). It has been theorized that increased testosterone exposure during puberty can contribute to forming wider faces—greater fWHR, which in turn leads to aggressive traits and behavior (Marečková et al., 2011; Lefevre et al., 2013; Haselhuhn et al., 2015).

Based on the testosterone hypothesis explained above, fWHR could be a useful tool in certain contexts—Sport. Sporting success can be associated with testosterone-driven attributes (e.g., achievement drive, aggression; Tamiya et al., 2012; Tsujimura and Banissy, 2013). Indeed, previous literature highlighted the associations between fWHR and testosterone-driven attributes in sport (Carré and McCormick, 2008). Carré and McCormick (2008) found that fWHR is predictive of ice hockey penalties and aggressive behavior in a laboratory setting. Similarly, fWHR is associated with aggressive behavior (measured by the number of penalty cards received and fouls committed) among football players (Welker et al., 2015; Fujii et al., 2016). Trebický et al. (2014) demonstrated that fWHR is significantly associated with fighting success among mixed martial arts (MMA) athletes. Tsujimura and Banissy (2013) demonstrated that Japanese professional baseball players' fWHR is associated with their home run performance in two consecutive seasons. Although various scholars operationalized outcome variables differently, it seems warranted that fWHR is associated with sporting performances backed by achievement drive, aggression, and actual performances.

Nevertheless, previous literature has also reported inconsistent findings regarding fWHR (Haselhuhn et al., 2015; Kramer, 2015; Kosinski, 2017; Wang et al., 2019). For example, a large-scale study conducted by Kosinski (2017) found that fWHR was not associated with self-reported behavioral tendencies such as cooperativeness, impulsiveness, and impression management. Wang et al. (2019) indicated little evidence regarding the relationship between fWHR and anti-social behavioral tendencies. Similarly, some studies focused on athletes' fWHR have provided no support for the association between fWHR and testosterone-related outcomes. Kramer's (2015) study showed that commonwealth game athletes who compete in contact sports (e.g., boxing, judo) have greater fWHR than those who compete in non-contact sports (e.g., badminton, swimming), but the effect was negated when controlling for body-mass-index (BMI).

The replicability of published fWHR findings has recently been a primary concern.

Although some meta-analyses indicated significant results of fWHR (e.g., Haselhuhn et al., 2015; Giacomin and Rule, 2020), studies that obtained null findings have commonly used real-world small sample data (Wang et al., 2019). Hence, it is essential to further examine the robustness of the associations between fWHR and sporting performances by using real-world data with relatively large observations.

Accordingly, the current study assessed the relationship between fWHR and sporting performances by using actual professional basketball players who compete in Japan Professional Basketball League (B-League). In accordance with previous literature, we focus on (1) achievement drive, (2) aggression, and (3) sporting successes as outcome variables. Achievement drive has been defined as a mentality that encourages individuals to stand out in competition (Singh, 2011). Athletes who strongly pursue achievement can demonstrate certain behaviors that help them stand out from the crowd. In the context of basketball, scoring is one of the most crucial indicators that can influence the level of fame that athletes may receive. In fact, Berri et al. (2011) found that the scoring record can predict the draft order in NBA. Since achievement drive itself cannot guarantee that such behaviors end up successes, the current study operationalized achievement drive as field-goal-attempts (FGA). Aggression refers to actions that are intended to harm other people to achieve their results (Husman and Silva, 1984). The construct of aggression has been operationalized as the number of penalties received (e.g., fouls, yellow/red cards received, penalty minutes; Carré and McCormick, 2008; Goetz et al., 2013; Welker et al., 2015; Fujii et al., 2016). The current study also follows the previous literature and operationalized aggression as the number of fouls (Foul). Lastly, sporting successes can be viewed from various perspectives. However, previous literature has commonly focused on on-field performances of athletes or teams (Beedie et al., 2000; Wicker et al., 2012). Considering that the current study aimed to investigate the relationship between fWHR and sporting successes at the individual athlete level, the authors operationalized sporting success using player efficiency ratings (EFF). The current research can further provide evidence regarding the associations between fWHR and behavioral tendencies explained above in sport by utilizing real-world data.

METHODS

Materials

To measure fWHR, photographs were obtained *via* the official player directory book for the 2019–2020 season published by B-League. After confirming that all the player images are forward-facing, two research assistants independently measured vertical and horizontal lengths by following the established approach (Weston et al., 2007; Özener, 2012; Lefevre et al., 2013). Specifically, we measured the vertical lengths between the highest point of the upper lip to brow. Face width was measured based on the horizontal distance from the left to the right zygomatic arch.

With regard to dependent measures, we obtained each player's performance statistics (i.e., FGA, Foul, and EFF) published by each team's official web pages. FGA and Foul are the total number of shots attempted and fouls committed throughout the season. EFF was calculated using the formula:

$$\begin{aligned} \text{EFF} &= (\text{Points} + \text{Rebounds} + \text{Assists} + \text{Steals} + \text{Blocks}) \\ &\quad - (\text{Missed Field Goals} + \text{Missed Free Throws} \\ &\quad + \text{Turnovers})/\text{the number of games played.} \end{aligned}$$

It is common to use EFF to understand the contribution of players to a game in the National Basketball Association (NBA). EFF has been frequently used as a performance measurement of basketball players in previous empirical studies (e.g., Staunton et al., 2017; Kingsley et al., 2021). Ninety players were excluded from the further analyses due to unavailability of performance data. Twenty seven players who competed in <10 games were excluded from further analyses (Tsujimura and Banissy, 2013), leaving 482 observations.

It is also important to control variables that can potentially influence the association between fWHR and sporting

TABLE 1 | Descriptive statistics.

		All players (n = 482)				Outside players (n = 318)				Inside players (n = 164)			
		M	*SD*	Min	Max	*M*	*SD*	Min	Max	*M*	*SD*	Min	Max
1	Minutes of Play	685.53	385.79	17.70	1780.82	664.78	353.30	23.55	1737.73	725.76	440.43	17.70	1780.82
2	BMI	24.59	1.65	20.45	32.03	24.02	1.25	20.45	29.19	25.70	1.78	21.04	32.03
3	fWHR	1.96	0.18	1.56	2.67	1.94	0.16	1.56	0.67	2.00	0.21	1.56	2.50
4	FGA	217.91	166.55	3.00	1030.00	195.07	134.65	9.00	904.00	262.21	208.80	3.00	1030.00
5	Foul	60.86	29.54	0.00	135.00	59.18	29.03	0.00	133.00	64.12	30.33	0.00	135.00
6	EFF	8.39	7.57	0.00	33.00	5.86	4.36	0.00	33.00	13.29	9.77	1.00	32.00

BMI, body mass index; fWHR, facial width-to-height ratio; FGA, field goal attempt; Foul, number of fouls committed; EFF, performance efficiency rating.

performance. Based on previous literature, we controlled minutes of play (Krenn and Meier, 2018) and BMI (Mayew, 2013; Kramer, 2015; Fujii et al., 2016). Krenn and Meier (2018) suggested that sporting successes can be strongly influenced by each player's playing time. Their study found no evidence of fWHR when controlling for minutes of gameplay. For the same reason, we also controlled BMI. Deaner et al. (2012) found that the effect of fWHR on aggression among ice hockey players was canceled when controlling for body weight. The official webpage of B-league makes players' minutes of play, height, and weight data available, being calculated to develop BMI data for each player.

Statistical Analyses

We first ran descriptive analyses to assess mean, standard deviation, minimum and maximum scores for all variables included in this study. Pearson correlation was then employed to evaluate inter-correlations among variables. We then performed a series of hierarchical regression models to investigate the associations between fWHR and professional basketball players' performance. Specifically, the first step included minutes of play and BMI in the model as control variables. In the second step, we included fWHR as a predictor variable. The effect size was interpreted based on the R^2 changes.

After the omnibus analyses above, we also conducted separate analyses for outside versus inside players based on previous literature, suggesting that athletes' playing positions can influence their performance statistics (Welker et al., 2015; Fujii et al., 2016; Krenn and Meier, 2018). Indeed, a study conducted by Ferioli et al. (2018) also demonstrated that basketball players' physical profile is heterogeneous depending on playing positions. Players' positions were determined based on the information available on the official B-league webpage. Specifically, we categorized point guard (PG), shooting guard (SG), and small forward (SF) as outside players, whereas power forward (PF) and center (C) as inside players.

RESULTS

Descriptive analyses indicated that players' minutes of play ranged between 17.70 and 1780.82 minutes, with an average of 685.53 (SD = 385.79). BMI ranged from 20.45 to 32.03 with a mean of 24.59 (SD = 1.65). With regard to the dependent measure, fWHR scores in this study ranged from 1.56 to 2.67, with a mean of 1.96 (SD = 0.18). It is important to note that the inter-coder consistency of fWHR was 97.2%, ensuring the reliability of fWHR data in this study (Deaner et al., 2012). FGA fell between 3 and 1030 with a mean of 217.91 (SD = 166.55). Regarding Foul, the score ranged from 0 to 135, whose average score was 60.86 (SD = 29.54). EFF scores were in the range of 0 to 33, with an average of 8.39 (SD = 7.57). The official webpage of the league also published players' age, which ranged from 20 to 49 years old, and the mean was 28.42. Descriptive statistics and correlations among variables are shown in **Tables 1**, **2**. The visual summary of the results can be found in **Figure 1**.

TABLE 2 | Correlations.

		1	2	3	4	5
1	Minutes of play	–				
2	BMI	0.14**	–			
3	fWHR	0.07	0.23**	–		
4	FGA (field goal attempt)	0.90**	0.12**	0.20**	–	
5	Foul (number of fouls committed)	0.80**	0.02	0.11*	0.64**	–
6	EFF (performance efficiency rating)	0.68**	0.25**	0.33**	0.81**	0.45**

*$p < 0.05$. **$p < 0.01$.

The results of the regression analyses are represented in **Table 3**. In the first step, minutes of play and BMI explained 80.7, 63.4, and 52.2% of variances in FGA, Foul, and EFF of overall players. In Step 2, fWHR significantly predicted FGA ($B = 39.06$, 95% CIs [2.11, 76.01], $p < 0.05$, $\beta = 0.04$, $\Delta R^2 = 0.002$) and EFF ($B = 6.37$, 95% CIs [3.78, 8.97], $p < 0.001$, $\beta = 0.15$, $\Delta R^2 = 0.02$). In addition to the minutes of play and BMI, fWHR explained 0.2 and 2.2 % of the variances in FGA and EFF, respectively. However, we did not find evidence in Foul ($B = -6.70$, 95% CIs [−15.73, 2.33], $p = 0.15$, $\beta = -0.04$, ΔR^2 =0.002).

With regard to the position-based separate analyses, minutes of play and BMI explained 79.9, 63.1, and 56.2% of variances in FGA, Foul, and EFF of outside players in step 1. In Step 2, the results showed that fWHR was positively associated with FGA ($B = 65.35$, 95% CIs [24.79, 105.91], $p < 0.01$, $\beta = 0.08$, $\Delta R^2 = 0.006$) and EFF ($B = 4.71$, 95% CIs [2.81, 6.61], $p < 0.001$, $\beta = 0.18$, $\Delta R^2 = 0.03$) in the outside players group while Foul was not predicted by fWHR ($B = -8.55$, 95% CIs [−20.55, 3.44], $p = 0.16$, $\beta = -0.05$, ΔR^2 =0.002). Thus, fWHR significantly explained 0.6

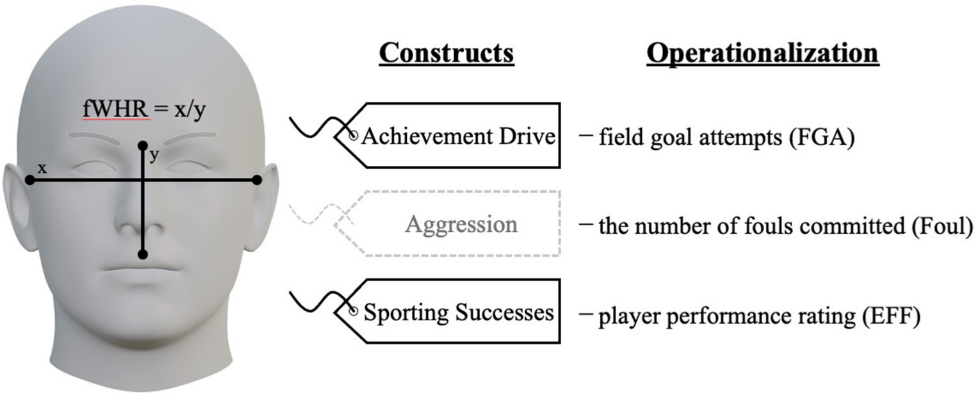

FIGURE 1 | The summary of the results.

and 3.1 % of the variances in FGA and EFF, respectively. Lastly, we found that minutes of play and BMI explained 83.9, 64.7, and 59.7% of variances in FGA, Foul, and EFF of inside players. Only EFF ($B = 6.29$, 95% CIs [1.61, 10.97], $p < 0.01$, $\beta = 0.13$, $\Delta R^2 = 0.02$) was significantly predicted by fWHR while no evidence was shown in FGA ($B = -13.79$, 95% CIs [−78.37, 50.78], $p = 0.67$, $\beta = -0.01$, $\Delta R^2 = 0.001$) and Foul ($B = 3.45$, 95% CIs [−17.35, 10.45], $p = 0.63$, $\beta = -0.02$, $\Delta R^2 = 0.001$) in the inside player group. The R^2 change for EFF of inside players was 1.7%.

DISCUSSION

Previous literature has provided mixed findings regarding the association of fWHR on sporting performances (Carré and McCormick, 2008; Deaner et al., 2012; Tsujimura and Banissy, 2013; Kramer, 2015; Welker et al., 2015; Fujii et al., 2016). The present study was conducted to investigate the relationship between fWHR and testosterone-driven outcomes such as professional basketball players' achievement drive (i.e., FGA), aggression (i.e., Foul), and sporting successes (i.e., EFF) by utilizing real-world data (i.e., professional basketball players). The results indicated that fWHR was significantly related to FGA and EFF in the total samples, although the effect size was trivial. Such findings were consistent for the group of outside players, whereas fWHR only predicted EFF for the inside player group. Inconsistent with the previous literature, the association between fWHR and aggression was not supported. Overall, it is concluded that the testosterone hypothesis was partially supported.

There are several theoretical implications from the above findings. First, fWHR could be considered a meaningful predictor of achievement drive ($\beta = 0.04$, 95% CIs [2.11, 76.01], $p < 0.05$, $\Delta R^2 = 0.002$) and sporting successes ($\beta = 0.15$, 95% CIs [3.78, 8.97], $p < 0.001$) in professional basketball in Japan. Based on the testosterone hypothesis, scholars found that individuals with large fWHR are more competitive and successful (Wong et al., 2011; Lewis et al., 2012; Stirrat and Perrett, 2012). Previous literature focused on sport performances also yielded similar findings. For example, fWHR is significantly associated with MMA athletes' fighting successes (Trebický et al., 2014), baseball players' home runs (Tsujimura and Banissy, 2013), and football players' goals and assists (Welker et al., 2015). Nevertheless, some empirical studies demonstrated very little or null effects of fWHR (Haselhuhn et al., 2015; Kramer, 2015; Kosinski, 2017; Wang et al., 2019). In particular, the refuting evidence has been reported when controlling for various characteristics of players (e.g., BMI, minutes of play; Mayew, 2013; Kramer, 2015; Krenn and Meier, 2018). In this sense, since we also controlled for BMI and minutes of play, it deemed acceptable to conclude that the effect of fWHR on achievement drive as well as performance in basketball players is—while small—replicated.

Second, the relationship between fWHR and aggression did not turn out statistically significant ($\beta = -0.04$, 95% CIs [−15.73, 2.33], $p = 0.15$). The results of the current study were somewhat inconsistent because the relationship between fWHR and aggression has been relatively oft-supported with various operationalizations (e.g., fouls, yellow/red cards received, penalty minutes; Carré and McCormick, 2008; Goetz et al., 2013; Welker et al., 2015; Fujii et al., 2016) and even in meta-analytic projects (Geniole et al., 2015; Haselhuhn et al., 2015). However, some prior studies have also reported the null findings of fWHR on aggression (e.g., Deaner et al., 2012; Kramer, 2015; Krenn and Meier, 2018). Moreover, it is imperative to note that the supporting evidence reported in previous literature was small in effect sizes with somewhat inconsistent findings when separate analyses based on players' positions were conducted (e.g., Fujii et al., 2016). In this sense, the current research further added to the empirical evidence refuting the effect of fWHR on aggression. A possible interpretation for this non-significant finding is our operationalization of aggression. Based on previous literature, fouls could be an appropriate variable that operationalizes aggression. Nevertheless, committing fouls in basketball is highly strategic (Ángel et al., 2006). Hence, players might commit fouls outside of the influence of aggression. Although FGA, Foul, and EFF could be appropriate operationalizations in basketball among publicly available data, it would have been more desirable to obtain more detailed player statistics. One example could be the number of technical or unsportsmanlike fouls, which could be linked more to aggressive traits.

TABLE 3 | Results of regression analyses for FGA, Foul, and EFF.

	FGA					Foul					Efficiency				
	B	**95% CI**	β	ΔR^2	***p***	***B***	**95% CI**	β	ΔR^2	***p***	***B***	**95% CI**	β	ΔR^2	***p***
All players (*n* = 482)															
Step 1				0.807***	<0.001				0.634***	<0.001				0.522***	<0.001
Minutes of play	0.38***	[0.36, 0.40]	0.88***		<0.001	0.06***	[0.06, 0.07]	0.80***		<0.001	0.01***	[0.011,0.014]	0.65***		<0.001
BMI	7.98***	[3.96, 11.99]	0.08***		<0.001	−0.03	[−1.01, 0.95]	−0.01		0.95	1.13***	[0.84, 1.41]	0.25***		<0.001
Step 2				0.002*	<0.05				0.002	0.15				0.022***	<0.001
Minutes of play	0.38***	[0.36, 0.40]	0.88***		<0.001	0.06***	[0.06, 0.07]	0.80***		<0.001	0.01***	[0.011,0.014]	0.64***		<0.001
BMI	7.01***	[2.91, 11.12]	0.07***		<0.001	0.13	[−0.87, 1.14]	0.01		0.80	0.97***	[0.68, 1.26]	0.21***		<0.001
FWHR	39.06*	[2.11, 76.01]	0.04*		<0.05	−6.699	[−15.73, 2.33]	−0.04		0.15	6.37***	[3.78, 8.97]	0.15***		<0.001
Outside players (*n* = 318)															
Step 1				0.799***	<0.001				0.631***	<0.001				0.562***	<0.001
Minutes of play	0.341***	[0.32, 0.36]	0.89***		<0.001	0.07***	[0.06, 0.07]	0.80***		<0.001	0.01***	[0.008, 0.01]	0.75***		<0.001
BMI	−0.13	[−5.49, 5.24]	−0.001		0.963	−0.13	[−1.70, 1.43]	−0.01		0.87	0.07	[−0.16, 0.35]	0.03		0.46
Step 2				0.006**	<0.01				0.002	0.16				0.031***	<0.001
Minutes of play	0.34***	[0.32, 0.36]	0.90***		<0.001	0.07***	[0.06, 0.07]	0.79***		<0.001	0.01***	[0.008, 0.10]	0.75***		<0.001
BMI	−1.49	[−6.85, 3.86]	−0.01		0.584	0.04	[−1.54, 1.63]	0.01		0.96	−0.01	[−0.25, 0.25]	−0.01		0.99
FWHR	65.35**	[24.79, 105.91]	0.08**		<0.01	−8.55	[−20.55, 3.44]	−0.05		0.16	4.71***	[2.81, 6.61]	0.18***		<0.001
Inside players (*n* = 164)															
Step 1				0.839	<0.001				0.647	<0.001				0.597***	<0.001
Minutes of play	0.43***	[0.40, 0.46]	0.91***		<0.001	0.06***	[0.05, 0.06]	0.81***		<0.001	0.02***	[0.015, 0.019]	0.76***		<0.001
BMI	2.83	[−4.66, 10.32]	0.02		0.46	−0.14	[−1.76, 1.47]	−0.01		0.86	0.25	[−0.31, 0.80]	0.05		0.38
Step 2				0.001	0.67				0.001	0.63				0.017**	<0.01
Minutes of play	0.43***	[0.40, 0.46]	0.91***		<0.001	0.06***	[0.05, 0.06]	0.81***		<0.001	0.02***	[0.014, 0.019]	0.75***		<0.001
BMI	3.15	[−4.50, 10.80]	0.03		0.42	−0.06	[−1.71, 1.58]	−0.01		0.94	0.10	[−0.45, 0.66]	0.02		0.72
FWHR	−13.79	[−78.37, 50.78]	−0.01		0.67	−3.45	[−17.35, 10.45]	−0.02		0.63	6.29**	[1.61, 10.97]	0.13**		<0.01

The practical implication that the current study can highlight can be related to the player selection. In basketball, team performance is dependent upon a variety of qualities. Therefore, coaches and sport scientists need to understand the complex player selection dynamics (Balli and Korukoglu, 2014). Consistent with the association between BMI and performances observed in this study, Drinkwater et al. (2008) also emphasized the importance of the size of basketball players. However, it can be challenging to secure a "big-man" even in the professional basketball market. In such situations, incorporating the information about human face structure may contribute to effective player selection.

There were several research limitations in this study. The sample representation and generalizability were the first limitations due to the highly selective sample (i.e., professional basketball players in Japan). It could be possible to include fWHR data of non-professional athletes (e.g., college athletes) from various sports and test the relationship with standardized performance data. By doing so, concerns regarding alternative explanations about the restricted sample and a particular sport would be minimized. Second, although we attempted to investigate the association between fWHR and performances based on players' positions as a potential moderator. Future research should also consider other moderating variables that can alter the relationship between fWHR and focal variables. For example, Goetz et al. (2013) found that social status moderated the relationship between fWHR and aggression with the sample of NHL players. Specifically, fWHR gives a meaningful impact on aggression when the target individuals are low in social status. Social status can be operationalized as players' salaries in sport (Goetz et al., 2013). However, we could not incorporate it into the current study due to data availability issues.

In conclusion, the current research provided valuable additions to the literature. Expressly, this study further provided supporting evidence regarding the relationship between basketball players' fWHR and achievement drive as well as sporting successes. Nevertheless, the relationship between fWHR and aggression should be re-considered. Considering the above limitations, scholars should exercise caution in generalizing the findings. Meanwhile, we welcome future scholarly efforts in extending our research by incorporating various moderators, which will contribute to the growing body of evolutionary psychology literature that focuses on physical characteristics and sporting performances.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

SS: conceptualization, data collection, data analyses, and original draft writing. KK: manuscript writing/editing and data analyses. KS, HA, and YB: data collection. HM: reviewing manuscript and supervision. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.714819/full#supplementary-material

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frontiers in Psychology

ORIGINAL RESEARCH
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The Relationship Between Reactive Agility and Change of Direction Speed in Professional Female Basketball and Handball Players

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Assessing the physical ability of players to perform change of direction and the cognitive and motor abilities revealed in reactive agility (RA) is necessary to understand the physical requirements and capabilities of professional players in handball and basketball. The main aim of this study was to determine the differences between professional female basketball and handball players in terms of anthropometric features, change of direction speed (CODS), and the RA task. Moreover, the relationships among anthropometric features, agility, and parameters of perception were determined. Two scenarios of the Five-Time Shuttle Run to Gates test (planned and unplanned) were used to evaluate the CODS and RA. The response time (RT) was also measured in the unplanned scenario. Additionally, the index of reactivity (REAC-INDEX) was specified as the difference between the RA test result and the measurement of CODS. There was a significant difference found in terms of body height, with basketball players being taller than handball players ($p = 0.032$). Professional female handball players achieved better results than professional female basketball players with regard to RA tasks ($p = 0.01$) and CODS ($p = 0.041$). Significant simple correlations between each anthropometric feature (body height, body mass) and values for CODS and RA were observed ($r = 0.49$–0.53). Applying partial correlation allowed for the assessment of actual relationships among CODS, RA, RT, and REAC-INDEX, without a confounding variable. Detaching the anthropometric parameters from the rest of the relationships resulted in maintenance or changes in r-values and an increased significance in the relationships between each pair: RA vs. RT, RA vs. REAC-INDEX, and RT vs. REAC-INDEX. The strongest associations were related to RT vs. REAC-INDEX ($r = 0.97$ at detaching body height or body mass, $p < 0.001$) and CODS vs. RA ($r = 0.66$ at detaching body height and $r = -0.67$ at detaching body mass, $p < 0.001$). It is recommended to use partial correlations in subsequent studies, as simple correlations are not reliable and may not reveal the apparent relationships between the variables. In addition, when determining the CODS and RA, it is suggested to take anthropometric and perception variables into account, such as reaction time or REAC-INDEX.

Keywords: competitive sport, cognitive motor skills, team sport, performance analysis, motor performance

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INTRODUCTION

The ability to accelerate, stop quickly, turn or change of direction (COD), and accelerate again is an essential part of the motor skills of a handball and basketball player (Scanlan et al., 2015; Bayraktar, 2017; Šimonek et al., 2017; Conte et al., 2020). This ability is referred to as COD if the movement does not require a response to a stimulus, and it is usually classified as a preplanned and closed skill (Brughelli et al., 2008; Sheppard et al., 2014; Young et al., 2015a). During COD maneuvre, the running phase is followed by a slowdown or stopping phase due to eccentric muscle contraction and the COD. This phase includes adjusting the support (foot contact with the ground in the lateral part of the foot/forefoot) in relation to the center of mass (COM) in order to effectively use the external force to accelerate in the new planned direction of movement (Spiteri et al., 2013; Jones et al., 2017; Dos'Santos et al., 2018). This can be carried out at different speeds depending on the situation on the court. The term "change of direction speed" (CODS) is often used, and it is defined as the ability to COD in the shortest possible time into a predetermined location and space on the field, pitch, or the court (Young et al., 2015a).

In many situations during a game, the players cannot usually plan their movement pattern in advance. This is because their movement constitutes a reaction to an unpredictable single or complex external stimulus (e.g., an opponent, a teammate, ball, etc.). Taking this into consideration, fast and accurate reactions in the form of changes of direction movement performed in response to specific external stimuli are defined as reactive agility (RA) and require a significant involvement of the cognitive-perceptual components of decision-making, such as visual processing, recognition of the space, reaction time, perception, and anticipation (Jones et al., 2009; Spasic et al., 2015; Šimonek et al., 2017). However, CODS remains the physiological and mechanical basis underpinning agility in handball and basketball. Biomechanical studies indicate that preplanned COD movements place less load on the knee compared to a reaction to a stimulus requiring sidestepping, which reduces the risk of lower limb injury (Nimphius et al., 2016; Thomas et al., 2018).

The CODS and RA are the important components of motor performance of a team sports player, and therefore the relationships between them, as well as with other components, should be explored (Pehar et al., 2018). The CODS and RA may be impacted by other factors, such as: anthropometric parameters, training experience, playing level or player position, which should be considered when evaluating these attributes (Sekulic et al., 2014b; Scanlan et al., 2015; Coh et al., 2018, 2019; Pehar et al., 2018; Barrera-Domínguez et al., 2020; Popowczak et al., 2020). Elite players should demonstrate a high level of CODS and RA performance, which allows them to act effectively during a game in planned situations and in response to a sudden external stimulus (e.g., passing the ball, approaching an opponent). At the same time, the question arises whether CODS and RA performance are related? If so, are these dependencies direct or spurious, that is, caused by other variables? There are no answers to these questions in available literature on the subject.

Many studies have shown anthropometric parameters to be related to both CODS and RA (Chaouachi et al., 2009; Young et al., 2015b), due to the importance of body dimensions in the results of motor tests, that is, body height or legs length (Koltai et al., 2021). The explanation is, for example, the lower position of the COM, which determines the efficiency of the COD test, and which is lower in the case of shorter players (Young et al., 2002).

There have been numerous attempts to assess CODS and RA under training conditions; however, few of these are based on the same movement pattern. A uniform pattern in planned and unplanned activities allows one to define not only the physical component but also the perceptual-cognitive component. Based on the study conducted by Spasic et al. (2015) and Morral-Yepes et al. (2020), two movement scenarios for RA and CODS were distinguished, which are specific to basketball and handball players, that is, "stop-and-go" and "SpeedCourt©." In turn, based on these scenarios, various tests were carried out, differing in the number of changes of direction, the angle of direction change, execution time, and sprint distance between changes of direction (Scanlan et al., 2015; Born et al., 2016; Šimonek et al., 2016; Coh et al., 2018; Popowczak et al., 2020; Peric et al., 2021). The patterns of such actions are most often presented by players during a game, as evidenced by the number of changes of direction per minute performed by players (Luteberget and Spencer, 2017; Svilar et al., 2019; Salazar et al., 2020). Moreover, additional and very helpful indicators for determining RA have been introduced. The first is the index of perceptual and reactive capacity (P&RC index), as a ratio of the participant's performance in the CODS and RA (Spasic et al., 2015). Another is the reactivity index (REAC-INDEX), as the difference between the RA and CODS scores (Fiorilli et al., 2017).

Assessment of the physical abilities in COD and the cognitive motor skills in RA tests is important to understand the ability of players to "read and react" to sport-specific stimuli. Moreover, it is necessary for understanding the physical requirements and capabilities of professional handball and basketball players (Pereira et al., 2018). Nonetheless, at present, there is limited information on COD ability and RA in professional level handball and basketball players, especially regarding differences in the level of these abilities depending on one's sports discipline. Very slight differences in the level of agility (using the Fitro Agility Check test) among young basketball and handball players were observed in the study by Šimonek et al. (2017). In addition, in the aforementioned study, as well as in the study by Silva et al. (2013), there were very small or no differences ($p > 0.05$) in the level of CODS (using the 4 m Shuttle Run test) among the players of these sports. Different results were obtained by Bilge et al. (2020), who concluded that young basketball players achieved shorter times of CODS ($p < 0.001$) than their peers, which was also seen in handball training (as shown by the T-test). However, in a study performed by Freitas et al. (2020), it was found that female handball players were faster in the Zig-Zag CODS test ($p < 0.05$) than players of other team sports (for rugby: effect size (ES) = 1.19, for soccer: ES = 1.14). On the other hand, there are no studies that measure CODS and RA in professional basketball and handball players based on tests of specific stop-and-go movement patterns.

Taking into consideration the importance of COD ability and RA in the aforementioned sports, coaches and practitioners have become interested in valid and reliable assessments of these abilities to determine the strengths and weaknesses of their athletes, so that informed decisions can be made regarding the future training proposed for a given player (Thomas et al., 2018). Thus, the main goal of this study was to determine the differences between professional female basketball and handball players in anthropometric features, CODS, and RA task. Moreover, we attempted to determine the relationship among anthropometric variables, CODS, RA, and perceptual parameters. We hypothesized that basketball and handball require athletes to have different performance in terms of CODS, RA, and REAC-INDEX in a task based on a "stop-and-go" movement patterns. As a result, the level of the aforementioned features between professional groups of basketball and handball players will be differentiated.

MATERIALS AND METHODS

Participants

The study group consisted of 31 professional female athletes, including 12 basketball players (mean age: 24.98 ± 3.38; 95%: 22.83 – 27.14) and 19 handball players (mean age: 27.34 ± 4.68; 95%: 25.09–29.6). All the basketball players belonged to the same team, competing in two basketball leagues, that is, the Polish Basketball League (EnergaBasket Liga, 1st League in Poland) and EuroCup Women, in the 2018–19 season. On the other hand, all the handball players belonged to the same team, competing in two handball leagues, that is, the Polish Women's Super League (1st League in Poland) and the Women's EHF Cup, in the 2018-19 season. The study was carried out 1 week after the end of the preseason and was approved by the Research Bioethics Committee of the Faculty Senate of the University School of Physical Education in Wrocław, Poland (reference number: USPE-2013-06-07). The study was conducted in accordance with the ethical principles for medical research involving human subjects contained in the Declaration of Helsinki, developed by the World Medical Association. The study also met the "ethical standards in sport and exercise science research" (Harriss and Atkinson, 2015). All participants were asked to provide written informed consent prior to participation in the study.

Measures and Procedures

All tests were performed in sports hall facilities, where the athletes participate in league matches and train. Prior to the commencement of physical tests, anthropometric parameters were measured in the morning. All the anthropometric measurements were performed by the same experienced researchers. The height of the participants was measured with a GPM 101 anthropometer (DKSH, Zurich, Switzerland) with a precision of 1 mm. Body mass was measured when the participants were shoeless and wearing minimal clothes using the InBody 230 system (Tanita Corp., Tokyo, Japan).

The physical tests were all performed between 10:00 and 12:00 p.m. Before the measurements, the participants underwent a standardized 15-min warm-up procedure consisting of 5 min of low-intensity running, 5 min of dynamic stretching, and 5 min submaximal running plus COD exercises, multi-jump exercises, and sprints. The participants were then familiarized with the Five-Time Shuttle Run to Gates test.

A Fusion Smart Speed System (Fusion Sport, Coopers Plains, QLD, Australia) was used during the Five-Time Shuttle Run to Gates test (to measure the CODS and RA times). The system is comprised of five gates, each equipped with a photocell with an infrared transmitter and a light reflector, a Smart Jump mat integrated with a photocell and a radio frequency identification reader (RFID) for identification of the participants, as well as computer software (Fusion Smart Speed System application). The layout of the gates, the mat, and the RFID in the Five-Time Shuttle Run to Gates test was adopted on the basis of the previous article (Popowczak et al., 2016). The Fusion Smart Speed System application was used for fixed (preplanned) or random (unplanned) selection of a gate, where the lamp was turned on according to the procedures proposed by Popowczak et al. (2016). The "stop-and-go" scenario of tests as a reaction to a light signal is characterized by reliability levels at an intra-class correlation coefficient (ICC) > 70% (Paul et al., 2016; Morral-Yepes et al., 2020).

The participant had to run the distance from the starting point on the mat to the gate line (placed between the photocells with reflectors, 1 m long) five times and return to the mat. As soon as both feet were in contact with the central part of the mat, the participant received a light signal indicating the gate they should run to. The start to the gates was not delayed. The participant then ran to the line in the gate with a light signal. After crossing it with both feet, the participant returned to the mat. Again, when both feet touched the mat, the participant received another light signal indicating the gate to which they should run. They then repeated the run with a COD four more times. After crossing the last (fifth) gate line, the participant returned to the mat and finished the test. The testing apparatus measured the running time with an accuracy of 0.001 s. The data from the tests was recorded in a personal digital assistant (PDA, HP iPAQ 112).

In the first scenario of the Five-Time Shuttle Run to Gates Test (preplanned), which determines CODS, the participant ran to the gates in an order that was the same for all participants (1-2-3-4-5). The angle of COD was ≅ 180°, while the action on the Mat Jump was performed at an angle of ≅ 135°. The CODS test was repeated twice, and the best result (overall duration) of the run was used in the analysis of the results.

On the other hand, in the second scenario of the Five-Time Shuttle Run to Gates Test (unplanned), determining RA, the run to randomly selected goals was investigated. Their order was different for every participant, but they all covered the same distance. During the RA, participants were instructed not to try to predict which exit gate they would be required to sprint through. The RA test was repeated twice, and the best result (overall duration) of the run (RA) was used in the analysis of the results.

In addition, the REAC-INDEX, which represents the time differences between the RA test result and the measurement of CODS of a similar pattern and for similar distances (Fiorilli et al., 2017), was determined.

$$\text{REAC} - \text{INDEX}[s] = \text{RA}[s] - \text{CODS}\ [s]$$

The average response time (RT) to the first light signal in each RA test was also calculated.

Statistical Analysis

The Shapiro–Wilk test was used to evaluate the normality of the distribution of the continuous variables. All the variables showed a normal distribution. Descriptive statistics are presented as means, SDs, and 95% CIs.

Unpaired *t*-tests of students were used to evaluate the differences between the two groups of athletes. Cohen's *d* effect size (ES) and respective 95% confidence intervals were also calculated to assess the observed effects (Cohen, 1998). The thresholds of ES were: ≤0.2, trivial; 0.2–0.59, small; 0.6–1.19, moderate; 1.2–1.99, large; and ≥2.0, very large (Hopkins et al., 2009).

Pearson's product-moment correlations were used to examine which variables were correlated. The magnitude of the correlation (r) between test measurements was interpreted as: ≤0.1–trivial; >0.1–0.3—small; >0.3–0.5—moderate; >0.5–0.7—large; >0.7–0.9—very large; and >0.9–1.0—almost perfect (Hopkins et al., 2009).

Additionally, partial correlations were computed for more insight into the relationships between variables statistically significantly correlating with each other. In this publication, partial correlation was computed for a statistically significant relationship between anthropometric variables and CODS, RA, RT, and REAC-INDEX. Thus, for example, the relationships between both tests (CODS or RA) and body height were determined using partial correlation controlling the effect of body mass; on the other hand, the relationships between both tests (CODS or RA) and body mass were determined using partial correlation controlling the effect of body height. In addition, the relationships between CODS vs. RA, RA vs. RT, RA vs. REAC-INDEX, and RT vs. REAC-INDEX were determined using partial correlation controlling the effect of body height and body mass.

The significance level was set at $\alpha = 0.05$. Statistical analysis was performed using the application Statistica v.13.0 (StatSoft Polska, Kraków, Poland).

RESULTS

Descriptive statistics of the parameters for basketball and handball players, as well as *t*-values and *p*-values from the unpaired *t*-test of students, are presented in **Table 1**. The analysis revealed statistically significant differences between sports in terms of body height, CODS time, and RA time.

Handball players displayed a significantly lower total time in both CODS ($p = 0.041$, ES = 0.789) and RA ($p = 0.014$, ES = 0.972) tests compared to basketball players. However, the height difference was statistically significant. Therefore, it is interesting to analyze the relationship between height and the results of CODS and RA tests. The presence of such a relationship would have a decisive influence on the direction of the result interpretation. In the next step of the study, the correlation coefficients between individual variables were presented (**Table 2**).

Pearson's product-moment correlation coefficient showed large associations between the anthropometric parameters (body height and body mass: $r = 0.81$, $p < 0.001$; body mass and BMI: $r = 0.71$, $p < 0.001$), as well as between CODS and RA ($r = 0.76$, $p < 0.001$), RT and REAC-INDEX (r = 0.97, $p < 0.001$; **Table 2**). Moderate correlations between both anthropometric parameters and CODS time and RA time were also observed (CODS vs. body height: r = 0.49, $p = 0.005$; CODS vs. body mass: $r = 0.55$, $p = 0.001$; RA vs. body height: $r = 0.53$, $p = 0.002$; RA vs. body mass: $r = 0.52$, $p = 0.003$). Moreover, there was a small correlation between RA and RT on a light signal ($r = 0.48$, $p = 0.006$), as well as between RA and REAC-INDEX ($r = 0.48$, $p = 0.007$).

Based on the results of the simple correlation, strong relationships of anthropometric parameters with the maneuvrability variables of CODS and RA tests were found (**Table 2**). In order to perform a deeper analysis aimed at determining the importance of each of the two anthropometric parameters in shaping the strength of dependencies between anthropometric, as well as agility and perceptual parameters, a series of partial correlation analyses was performed (**Table 3**). It was found that close first-order correlations, between one morphological feature and CODS time or RA time, excluding the second morphological feature, are not significant. When controlling the effect of body height, significant moderate-almost perfect correlations were found between CODS and RA ($r = 0.67$; $p < 0.001$), RA and RT ($r = 0.47$; $p = 0.009$), RA and REAC-INDEX ($r = 0.49$; $p = 0.006$), and RT and REAC-INDEX ($r = 0.97$; $p < 0.001$). Controlling the effect of body mass, significant moderate-almost perfect correlations were found between CODS and RA ($r = 0.66$; $p < 0.001$), RA and RT ($r = 0.47$; $p = 0.004$), RA and REAC-INDEX ($r = 0.49$; $p = 0.002$), and RT and REAC-INDEX ($r = 0.97$; $p < 0.001$).

As moderate total correlations were found between RA and RT or REAC-INDEX, the partial correlation was investigated in order to rule out a false relationship. It was found that the analysis of the relationships of each pair of variables does not produce a complete picture of the actual relationships. The analysis of the partial correlations confirms that the study of the relationships of two variables, e.g., RA vs. RT, without considering the related variable REAC-INDEX ($r = 0.08$; $p = 0.67$), produces spurious correlations. This is similar for the relationship RA vs. REAC-INDEX, without considering RT ($r = 0.06$; $p = 0.77$).

DISCUSSIONS

The aim of this study was to determine the differences between professional basketball players and handball players in terms of CODS and RA using the "stop-and-go" test scenario. It should be mentioned that this is the first study of professional female basketball and handball teams concerning planned and unplanned changes in running directions using the "stop-and-go" scenario. Moreover, the obtained results cannot be compared to previous studies in which CODS and RA times in team sports were measured.

TABLE 1 | Characteristics of participants by sport disciplines with means, SDs, and 95% CIs.

Variables		Sport		*t* value	*p*	Effect size
		Basketball	Handball			
Body height [cm]	Mean ± SD	181.67 ± 7.41	175.77 ± 6.93	2.25	**0.032**	0.829
	(95% CI)	(176.96–186.38)	(172.44–179.11)			0.078–1.581
Body mass [kg]	Mean ± SD	74.38 ± 8.54	71.13 ± 8.35	1.05	0.304	0.386
	(95% CI)	(68.95–79.8)	(67.1–75.15)			−0.343–1.115
CODS [s]	Mean ± SD	15.92 ± 0.55	15.31 ± 0.87	2.14	**0.041**	0.798
	(95% CI)	(15.57–16.26)	(14.89–15.73)			0.048–1.547
RA [s]	Mean ± SD	18.37 ± 0.74	17.57 ± 0.87	2.63	**0.014**	0.972
	(95% CI)	(17.9–18.84)	(17.15–17.99)			0.21–1.734
RT [s]	Mean ± SD	0.48 ± 0.15	0.45 ± 0.11	0.54	0.590	0.237
	(95% CI)	(0.38–0.57)	(0.4–0.5)			−0.488–0.962
REAC-INDEX [s]	Mean ± SD	2.45 ± 0.69	2.26 ± 0.54	0.87	0.391	0.316
	(95% CI)	(2.01–2.89)	(1.99–2.52)			−0.411–1.043

CODS, change of direction speed; RA, reactive agility; RT, reaction time; REAC-INDEX, difference CODS vs. RA, bolded p-value represents significant difference (p < 0.05).

TABLE 2 | Matrix of correlation between measured variables.

		Body mass	CODS	RA	RT	REAC-INDEX
Body height	*r*	0.81	0.49	0.53	0.17	0.12
	p	**<0.001**	**0.005**	**0.002**	0.37	0.52
	Body mass	*r*	0.55	0.52	0.09	0.04
		p	**0.001**	**0.003**	0.65	0.84
		CODS	*r*	0.76	−0.19	−0.21
			p	**<0.001**	0.31	0.25
			RA	*r*	0.48	0.48
				p	**0.006**	**0.007**
				RT	*r*	0.97
					p	**<0.001**

CODS, change of direction speed; RA, reactive agility; RT, reaction time; REAC-INDEX, difference CODS vs. RA; r, Pearson r coefficient, bolded p-value represents significant correlation (p < 0.05).

Based on the obtained results, differences in height ($p = 0.032$, ES $= 0.829$) were found between professional female basketball players and handball players. Statistically significant differences were observed in terms of CODS ($p = 0.041$, ES $= 0.798$), as well as RA ($p = 0.014$, ES $= 0.972$). Handball players obtained better results in tests examining both parameters. Moreover, simple correlation indicated that the taller the player, the longer the execution time of the tests performed to determine CODS and RA. Anthropometric parameters, such as height or leg length, can affect the characteristics of CODS, as shorter individuals take less time to lower their COM (Barrera-Domínguez et al., 2020). Therefore, the involvement of anthropometric parameters in CODS time and RA time were observed. Height specifically affected the results of tests engaging perceptual skills. This observation is of great importance from the point of view of both selection and training itself, and the morphological component seems to be very important for both motor skills.

The results of the analysis clearly demonstrate the correlation between the two morphological variables and CODS. Similarly, morphological variables were correlated with RA. This suggests the need to study the differences in the results of motor ability tests between groups of athletes of various sports disciplines, considering the control of anthropometric parameters (body height and body mass, in our case). The first-order correlations between one morphological feature and CODS or RA, excluding the second morphological feature, are significantly lower than the total correlations. However, a greater role in the formation of a correlation with CODS is played by body mass, or its control consisting of shortening the step and lowering the COM in planned movements (Sattler et al., 2015). In the case of the correlation with RA, the contribution of both anthropometric parameters is similar.

In contrast, Garcia-Gil et al. (2018) observed a non-significant relationship between anthropometric parameters (body height and body mass) and CODS using the *t*-test in professional Spanish female basketball players. The variations in the study findings may concern the movement patterns performed in the respective analyzed tests. In our CODS test, there is a nine-fold

TABLE 3 | Partial correlations for the measured variables.

Relations	Correlation between variables	Controlling variable	*r*	*p*
CODS vs. body height or body mass,	CODS vs. body height	Body mass	0.10	0.59
controlling body height or body mass.	CODS vs. body mass	Body height	0.29	0.12
RA vs. body height or body mass,	RA vs. body height	Body mass	0.21	0.27
controlling body height or body mass.	RA vs. body mass	Body height	0.20	0.31
CODS vs. RA,	CODS vs. RA	Body height	0.67	**<0.001**
controlling body height or body mass.	CODS vs. RA	Body mass	0,66	**<0.001**
RA vs. RT,	RA vs. RT	Body height	0.47	**0.009**
controlling body height or body mass.	RA vs. RT	Body mass	0.51	**0.004**
RA vs. REAC-INDEX,	RA vs. REAC-INDEX	Body height	0.49	**0.006**
controlling body height or body mass.	RA vs. REAC-INDEX	Body mass	0.54	**0.002**
RT vs. REAC-INDEX,	RT vs. REAC-INDEX	Body height	0.97	**<0.001**
controlling body height or body mass.	RT vs. REAC-INDEX	Body mass	0.97	**<0.001**
RA vs. RT or REAC-INDEX,	RA vs. RT	REAC-INDEX	0.08	0.67
controlling RT or REAC-INDEX	RA vs. REAC-INDEX	RT	0.06	0.77

CODS, change of direction speed; RA, reactive agility; RT, reaction time; REAC-INDEX, difference CODS vs. RA; r, Pearson r coefficient, bolded p-value represents significant correlation ($p < 0.05$).

COD that lowers the COM, and body height and body mass may have had a significant role in the maneuvring speed and overall test duration. That is why it is so important to select a test for the determination of CODS according to the specific nature of sports disciplines and their dominating movements (maneuvres). Considering the situational and general nature of the Five-Time Shuttle Run to Gates Test for team sports games, future research should continue to investigate the relationship of the test result and various anthropometric parameters in order to determine whether the anthropometric parameters determine the result of CODS during the run more than the type and the specificity of the discipline, as well as the position on the court.

Despite numerous similarities in the performance of actions to COD in a game as previously planned movements, and as a result of a reaction to unpredictable single or complex external stimuli (e.g., an opponent, ball, etc.), athletes of both disciplines showed differences in the time of performing the COD test.

The applied RA test can be classified as a general test measuring the situational ability of athletes of various sports disciplines to COD quickly. This is not a test specific for a given team sport, as it measures the reaction to a light signal and not to the ball or an opponent or a teammate. The differences in the results obtained in RA tests with different reaction stimuli were presented by Scanlan et al. (2016) and Kovacikova and Zemková (2020). Nevertheless, an increase in the level of the ability to COD in response to a light signal may lead to an increase in the level of these abilities in another COD and RA task (Nygaard Falch et al., 2019).

A high correlation coefficient ($r = 0.76$, $p < 0.001$) between RA and CODS was obtained in the present study. Similar results (r from 0.62 and 0.68, $p \leq 0.05$) were found in the study by Sekulic et al. (2014a) representing various sports, including college-age basketball and handball players. Moderate correlations between CODS and RA ($r = 0.51$ and 0.65, $p < 0.05$) were also observed by Sattler et al. (2015) in college-age athletes (females and males; 21.9 ± 1.9 years of age) representing team sports (football, basketball, volleyball, and handball). On the other hand, weak to moderate correlations (r from 40 to 56, $p < 0.01$) between basketball-specific COD tests and basketball-specific non-planned agility tests were found by Sekulic et al. (2017) in high-level male basketball athletes from Bosnia and Herzegovina (professional/semiprofessional players). Lockie et al. (2014) found weak correlations ($r = 0.28$ and 0.48, $p < 0.05$) or no significant correlations between CODS and RA by examining semiprofessional and amateur male basketball players (22.30 ± 3.97 years of age). However, the large diversity of the information obtained based on research concerning the relationship between CODS and RA and the increasing number of proposed tests require a search for the best correlations between the results obtained in the tests and the results determining COD, accelerations, and deaccelerations during games. Although physical activities (with regard to redirecting total body momentum in a new direction as quickly as possible) constitute a large proportion of the time needed to complete RA and CODS tasks, perceptual decision-making processes may alter the level of correlation between tests (Pehar et al., 2018; Krolo et al., 2020). This should affect the level of correlations between CODS and RA. Information concerning the variables in CODS and RA tests may be of high importance in training and conditioning, since this will allow for specific and targeted development of important qualities that will, consequently, improve specific RA or CODS results.

In the present study, a significant relationship ($r = 0.97$, $p < 0.001$) between RT and REAC-INDEX was found, which may indicate that REAC-INDEX is an important factor determining the reaction time to a stimulus during CODS. The increasing time difference between a CODS test and RA test will be strongly related to the reaction time to the light stimulus, that is, to the perceptual factor. Similar conclusions were reported by Zemková and Hamar (2018), who investigated athletes of different sports (ball hockey and soccer), finding an almost perfect influence ($r = 0.933$, $p = 0{,}001$) of perception, reaction, and decision-making (measured by the reaction time of the double choice) on agility performance. This almost perfect correlation suggests that improving perceptual skills and, at the same time, decision-making speed may be beneficial for increasing RA in athletes. Moreover, the strong relationship between RT and REAC-INDEX may suggest the need to introduce a new variable determining visual perception skills (as a substitute for response time), which is important for the effectiveness of COD actions. However, this requires further research on the information processing speed of an individual, which is an important component of RA (Lockie et al., 2014). In the present study, the presence of false relationships between RA and RT or REAC-INDEX was also noticed based on partial correlations. This may indicate the need to include reaction time in RA tasks and to analyze REAC-INDEX as the difference between RA and CODS results, as well as the need to study partial correlations instead of total correlations.

The study is limited by the absence of an analysis concerning the COD angle in a run during RA tasks and the strength of the lower limbs as predictors of the characteristics of CODS. Different COD angles could result in a different level of involvement of basic motor components, namely force or speed, when changing the direction of movement. Therefore, it seems important to distinguish those tests in which there were numerous changes of direction based on speed (angle $\cong 0°$ to $\cong 90°$) or force (angle $\cong 135°$ to $\cong 180°$; Bourgeois et al., 2017; Nygaard Falch et al., 2019).

Second, our sample was limited to European clubs; therefore, large cohort studies are required to confirm these results across other regions. A diversity in the results of motor ability parameters in female and male basketball players from different regions of the world was indicated by Milanović et al. (2020) and Stojanović et al. (2018).

In addition, our data were limited to anthropometric parameters and results of CODS and RA tests. Exploring other factors (e.g., playing position of athletes, training experience, playing level), which may influence main findings, should also be included (Scanlan et al., 2015; Young et al., 2015a; Sekulic et al., 2017).

The approach adopted in the present study, although very practical, shows only the time measurements of COD in a run based on the "stop-and-go" scenario. In contrast, further research requires the biomechanical study of this complex ability related to the functioning of the neuromuscular system (Sarvestan et al., 2020). Moreover, these outcomes can be used by basketball players to refine their training and assessment methods in order to optimize RA and COD performance.

Conclusions

Based on the present study, it was observed that professional female handball players achieve better results than professional female basketball players in COD and RA. It is necessary to perform further research concerning the variables that determine these differences. It is assumed that they would include height and body mass. Moreover, it can be concluded that ordinary (total) correlations constitute false relationships and are not reliable. The relationship among CODS, RA, and basic physical traits treated as an entirety should be explored, while eliminating one of these parameters. This lays out new directions for multidimensional research and analysis. In this paper, it was suggested to use two strongly interdependent predictors (RT vs. REAC-INDEX) in the analysis of RA. Their effect on RA is best assessed using partial correlations. We believe that while the present study is not the final word on the issue, it will extend the knowledge in this field and initiate further research. As a result, coaches and sports scientists should consider these relevant and specific differences when designing specific COD and reactive training programs for professional female handball or basketball players.

DATA AVAILABILITY STATEMENT

The data analyzed in this study are subject to the following licenses/restrictions: The data are owned by Laboratory for Ball Game Studies, Wroclaw University of Health and Sport Sciences, Poland (certificate PCC-CERT No. PW-06305-19X). Requests to access these datasets should be directed to Marek Popowczak, marek.popowczak@awf.wroc.pl.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Research Bioethics Committee of the Faculty Senate of the University School of Physical Education in Wrocław, Poland. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MP and JD drafted and revised the manuscript. IC and AR revised the manuscript. All authors contributed to the article and approved the submitted version.

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Quantifying Training and Game Demands of a National Basketball Association Season

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Purpose: There are currently no data describing combined practice and game load demands throughout a National Basketball Association (NBA) season. The primary objective of this study was to integrate external load data garnered from all on-court activity throughout an NBA season, according to different activity and player characteristics.

Methods: Data from 14 professional male basketball players (mean ± SD; age, 27.3 ± 4.8 years; height, 201.0 ± 7.2 cm; body mass, 104.9 ± 10.6 kg) playing for the same club during the 2017–2018 NBA season were retrospectively analyzed. Game and training data were integrated to create a consolidated external load measure, which was termed *integrated load*. Players were categorized by years of NBA experience (1-2y, 3-5y, 6-9y, and 10 + y), position (frontcourt and backcourt), and playing rotation status (starter, rotation, and bench).

Results: Total weekly duration was significantly different ($p < 0.001$) between years of NBA playing experience, with *duration* highest in 3–5 year players, compared with 6–9 ($d = 0.46$) and 10+ ($d = 0.78$) year players. Starters experienced the highest *integrated load,* compared with bench ($d = 0.77$) players. There were no significant differences in *integrated load* or duration between positions.

Conclusion: This is the first study to describe the seasonal training loads of NBA players for an entire season and shows that a most training load is accumulated in non-game activities. This study highlights the need for integrated and unobtrusive training load monitoring, with engagement of all stakeholders to develop well-informed individualized training prescription to optimize preparation of NBA players.

Keywords: team sports, load monitoring, wearable technology, physical demands, NBA

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INTRODUCTION

In basketball, external training load data can inform decision-making regarding periodization (Schelling and Torres-Ronda, 2013) and injury reduction strategies (Caparrós et al., 2018), which may lead to optimized player health and physical performance (Halson, 2014). External "training load" is a construct encompassing the training stimulus imposed on players by both practices and competitions, and its quantification can be achieved using various proxy measures, such as distance or accelerometer load (Impellizzeri et al., 2019). In team sports, such as basketball, where different modes of training are often completed, practitioners may be required to use several different measures to quantify the overall training load in practice and competition (Buchheit et al., 2014). For instance, players in the National Basketball Association (NBA) may wear technology/devices during practices that are not permitted during games (McLean et al., 2018), while optical tracking (OT) technology (Second Spectrum Los Angeles, United States) is used during games to quantify external load, but these systems are not available in practice settings.

While a variety of technologies (e.g., wearables and OT in basketball) may report similar load metrics, limited understanding about agreeability of these systems can lead to issues when combining data, particularly considering how raw data is collected and analyzed, which may affect the final metrics. Because the relationship among multiple systems is poorly understood, much of the current basketball literature reports external load data isolated to either practice or competition (Teramoto et al., 2017; Caparrós et al., 2018; Lewis, 2018), with limited research describing integrated, season-long load demands. For NBA players specifically, current research on the external load demands has been limited to competition only (Caparrós et al., 2018; Lewis, 2018). Over a 6-month regular season, NBA teams play 82 games at an average frequency of 3.4 games/week (McLean et al., 2018), which is considerably higher than other professional basketball leagues. As only half of the days in the regular season include games, there is a significant amount of time available for non-game court work or recovery. Despite this significant amount of time available for non-game activity, there is currently no study that describes the combined practice and game load demands in professional basketball throughout an entire season.

Describing external load based on individual player characteristics is also important in better understanding the training dose-response relationship over time. Differences in basketball player characteristics that have been previously investigated include position (Svilar et al., 2018; Salazar et al., 2020a) and playing rotation status (Conte et al., 2018; Vazquez-Guerrero et al., 2018). Professional basketball can employ a wide range of experience levels, from draftees right out of college to veteran players who have been in the NBA for decades. The differences in age and years of experience may affect loading demands and therefore impact preparation strategies. However, these characteristics have never been examined and reported in the NBA across an entire season.

Quantification of the holistic on-court demands is needed to better understand training stimuli in professional basketball players. Therefore, the primary objective of this study was to integrate external load data garnered from practices and games to describe the physical demands of an NBA season. Additionally, this study described the seasonal training load according to player's playing position, years in the league, and game rotation status.

MATERIALS AND METHODS

Participants

Data from 14 professional male basketball players (mean ± SD; age, 27.3 ± 4.8 years; height, 201.0 ± 7.2 cm; body mass, 104.9 ± 10.6 kg) from the same NBA club were retrospectively analyzed for this study. Data were included for players who were under contract with the same club for the entire regular season and excluded if they had a two-way contract (e.g., player is contracted to play for both NBA team and its developmental team affiliate). The study was approved by the Human Research Ethics Committee of the University of Technology Sydney (UTS; HREC # ETH18-2658), and consent was granted by the NBA and the NBA Players Association as per the guidelines and requirements for "NBA related health research" governed by the NBA Collective Bargaining Agreement (CBA; NBA.com, 2017).

Experimental Design

A longitudinal, observational design was employed for this study. External training load and duration data were collected during the 2017–2018 NBA season (September to April), which included 3 weeks of pre-season and 26 weeks of the regular season. Post-season data were excluded from this analysis.

Methodology

All practices and games were included and assigned to the following activity categories: team training (basketball-specific court work done as a team), official NBA games ("games"), and individual training (basketball-specific court work not done with the team). Court work was further categorized by drill type, including (1) Skill drills, which are predominantly scripted drills with limited physical contact, focused on skill development, (2) Simulated play, which are predominantly non-scripted drills, focused on game-like physical contact, pace, and situations, and (3) official NBA game play. Court work was also characterized by tactical emphasis of the drill (offensive, defensive, both), and players were characterized by playing position, years of NBA experience, and playing rotation (**Table 1**).

External training load data from an ultrawideband (UWB) local positioning system (Catapult ClearSky, Catapult Sports, Melbourne, Australia) and inertial measurement unit (Catapult T6, Catapult sports, Melbourne, Australia) were integrated with external game day load data from an OT system (Second Spectrum, Los Angeles, United States) to quantify external load across all on-court activities. The process of merging external load data from two different measurement systems has been evaluated in professional soccer (Buchheit et al., 2014; Taberner et al., 2020; Ellens et al., 2021), with findings that suggest positional data can be interchanged between different systems to confidently quantify external load (Buchheit et al., 2014; Taberner et al., 2020; Ellens et al., 2021). The two systems used for load quantification in this study were evaluated simultaneously during basketball-specific activity (e.g., running, change of direction, and 5 on 5 basketball play) to determine the level of agreement, *via*

TABLE 1 | Categorization of activities and participants.

	Category	Definition
Activity categories		
Drill Type	Skill*	Predominantly scripted drills with limited physical contact, focused on skill development or team tactics.
	Simulated play**	Predominantly non-scripted drills, focused on game-like physical contact, pace, and situations.
	Game play***	Any league mandated competitive event.
Tactical Emphasis	Offensive	Predominantly offensive emphasis and physical demands.
	Defensive	Predominantly defensive emphasis and physical demands.
	Both	Approximately equal offensive and defensive strategy and physical demands.
Participant categories		
Playing Position	Backcourt	Point guards; Shooting guards
	Frontcourt	Small forwards; Power forwards; Centers
Playing rotation	Starter	Started ≥90% of games played with mean of ≥25 min per game.
	Rotation	Played in ≥70% of regular season games with mean of 13–22 min per game.
	Non-Rotation	Mean of <5 min per game over the course of the season.
Years in NBA	1–2	Defines number of years active on an NBA or NBA G-League affiliate roster.
	3–5	
	6–9	
	10 +	

**Entire activity duration collected for all players participating at any point in activity; **Activity duration collected only during "live" parts of the drill (i.e., excluding breaks), for only the participants actively in the drill; ***Activity duration collected only when game clock is running and during inbounds plays after referee hands basketball to player to inbound.*

regression analysis, of external load metrics. On an individual player basis, regression equations were generated between the OT system and UWB system. These equations indicated strong relationships for each subject (R^2 ranging from 0.93 to 0.99) for total distance and PlayerLoad™ (PL). The resulting regression equations were used to convert OT distance from NBA games to an equivalent PL metric. While this type of load quantification in team sports with similar technology has a level of error associated with merging data, the error is not expected to outweigh the practical implications of weekly load monitoring (Taberner et al., 2020). Indeed, this novel approach to integrating external load demands from NBA practices and games is the only approach that allows for a consistent external load measure throughout an entire season based on league restrictions around load monitoring (NBA, 2017; McLean et al., 2018).

During training sessions, external load data were collected by players wearing a microsensor device (Catapult T6, Catapult Sports, Melbourne, Australia) voluntarily, as per NBA CBA stipulations (NBA.com, 2017). The microsensor was worn in a tight-fitting manufacturer-provided garment, positioned between the scapulae according to manufacturer specifications, sampling inertial data at 100 Hz. Throughout the season, 10 players elected to wear the device, and participation in non-game court activities was recorded using microsensor manufacturer software (Catapult Openfield, Version 1.18, Catapult Sports, Melbourne, Australia). Data collected from court work were included in *integrated load* analyses if players wore their device for at least 95% of the non-game court work sessions (except for pre-game court work). Pre-game court work remained relatively consistent for each player across all 82 regular season games; therefore, small samples taken of each player's pre-game session were used to estimate individual pre-game training load. For situations in which microsensor data were not collected during non-game court work for the players that elected to wear the unit (e.g., system errors, unit malfunction, and pre-game), *integrated load* was estimated per drill on an individual basis, using measured duration and historical load per minute values from each player for similar drill categories (Bowen et al., 2017). As a result, approximately 18.8% of the *integrated load* data used in this study was estimated (1857 ± 422 min).

If a player did not wear the microsensor unit regularly ($n = 4$), a device was assigned to that player, and their non-game court activities were recorded with the same methods outlined above. The resulting data were included in duration analyses only. After all training sessions, wearable data were downloaded using the manufacturer software package, then exported to Microsoft Excel (Microsoft Office, 2016, Washington, United States) for integration. Game data were collected *via* the NBA contracted OT system (Second Spectrum, Los Angeles, United States), sampling at a rate of 25 frames per second. The data were then processed and exported in a JavaScript Object Notation file by the company which manages the optical tracking cameras (Second Spectrum, Los Angeles, United States), converted to Comma-Separated Value format using a customized script in R (R Foundation for Statistical Computing, Vienna, Austria) and imported locally to Microsoft Excel for integration. Once these data streams were integrated, all data were exported to SPSS (IBM SPSS Statistics for Macintosh, Version 26.0., IBM Corp., New York, United States) for analysis.

Statistical Analysis

Dependent variables (*integrated load*, duration) were summed in weekly blocks from Monday to Sunday per player and described descriptively (mean, SD, 95% confidence intervals (CI)). While the NBA game schedule does not follow a consistent weekly schedule, planning and periodization of court work

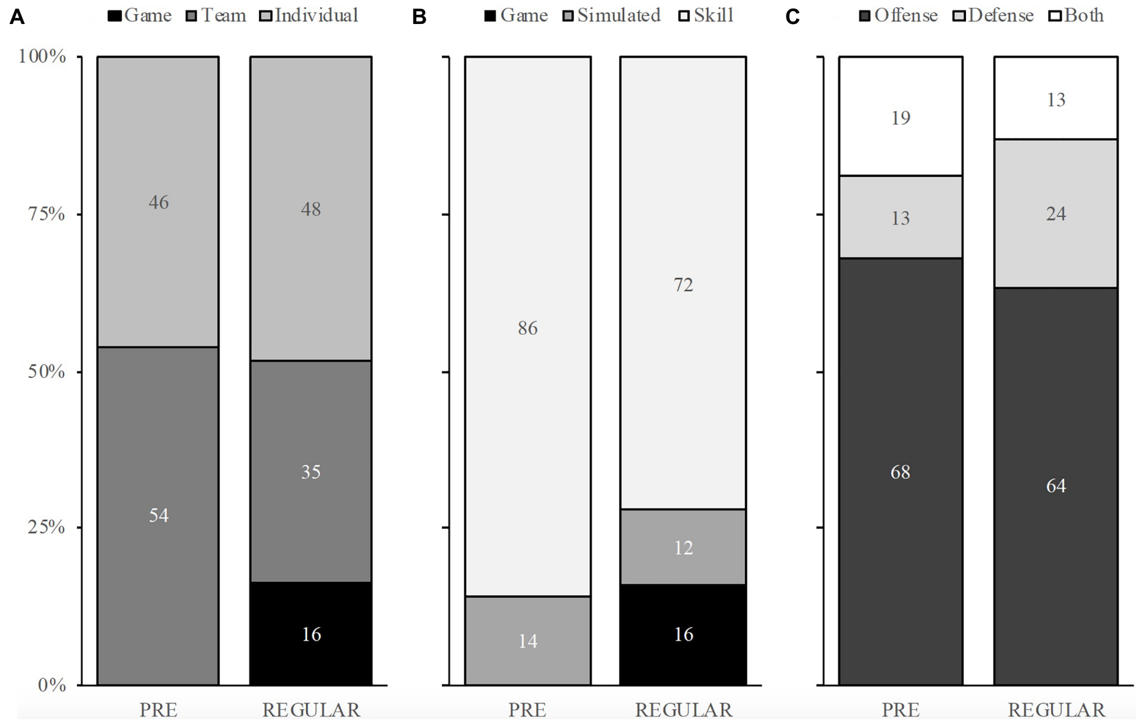

FIGURE 1 | Percentage duration spent on-court work in pre-season (PRE) and regular season (REGULAR) based on activity category **(A)**, drill type **(B)**, and tactical emphasis **(C)**. Game = any league competitive event; Team = basketball-specific court work done as a team, Individual = basketball-specific court work not done with the team, Simulated = predominantly non-scripted drills, focused on game-like physical contact, pace, and situations, Skill = predominantly scripted drills with limited physical contact, focused on skill development, Offense = basketball activity with predominantly offensive emphasis, Defense = basketball activity with predominantly defensive emphasis, Both = basketball activity with equal offensive and defensive emphasis.

for this team was conducted on a weekly basis following a Monday-Sunday block. From the 29 available weeks, 14 players duration data ($n = 406$ player weeks) and 10 players *integrated load* data ($n = 290$ player weeks) was included in the final analyses. Data were included in weekly sum analyses if the daily collection time was greater than 30 s. Differences in dependent variables based on activity categories, drill types, and tactical emphasis were also analyzed descriptively. Mixed models were used to compare means of total weekly integrated load and duration, between playing position, years in the league, and game rotation status. Players were treated as a random effect with scaled identity covariance matrix. Mixed models were used for their ability to model possible correlations of residual errors within each player over time. Model's residuals were visually inspected for normality and outliers (± 3 SD) and the predictors estimated marginal means were compared between groups with a Bonferroni correction.

Effect sizes were calculated to assess practical significance of differences and were considered: ≤0.2, trivial; >0.2–0.6, small; >0.6–1.2, moderate; >1.2–2.0, large; 2.0–4.0, very large (Hopkins et al., 2009). Years playing in the NBA were binned together (seasons 1–2, seasons 3–5, seasons 6–9, and seasons 10+). Only one participant who agreed to wear the microsensor device played in the NBA for 10+ and was excluded from the years in the NBA analysis due to insufficient sample size. All statistical analyses were performed in SPSS Version 22.

RESULTS

Descriptions of mean weekly duration spent in different activity categories, drill types, and tactical emphasis are shown in **Figure 1** based on seasonal phase and shown in **Figure 2** based on player rotation status, respectively.

Mixed Models showed significant effects for rotation status on *integrated load* ($F(2, 7.41) = 15.19$, $p = 0.002$). Post-hoc comparisons showed bench players had notably lower integrated load than starters ($p = 0.003$, $d = 0.77$) and rotation players ($p = 0.013$, $d = 0.46$). Comparisons between starters and rotation players were insignificant ($p = 0.20$, $d = 0.28$). Models showed insignificant effects for years in NBA ($F(2, 6.01) = 2.25$, $p = 0.19$) and position ($F(1, 7.92) = 0.02$, $p = 0.89$) on *integrated load*.

Mixed models showed significant effects for years in the NBA on duration ($F(3, 95.14) = 19.06$, $p < 0.001$). Post-hoc comparisons showed that those played 10+ years had significantly lower duration than those that played 6–8 years ($p = 0.043$, $d = 0.32$), 3–5 years ($p < 0.001$, $d = 0.78$) and those that played between 1 and 2 years ($p < 0.001$, $d = 0.61$). Those that played 6–8 years had significantly lower duration than those who played 3–5 years ($p = 0.001$, $d = 0.46$). Models showed insignificant effects for Rotation status ($F(2, 10.91) = 0.70$, $p = 0.52$) and position ($F(1, 11.95) = 0.42$, $p = 0.53$) on duration.

Estimated marginal means, standard deviations and 95% confidence intervals can be seen in **Table 2**.

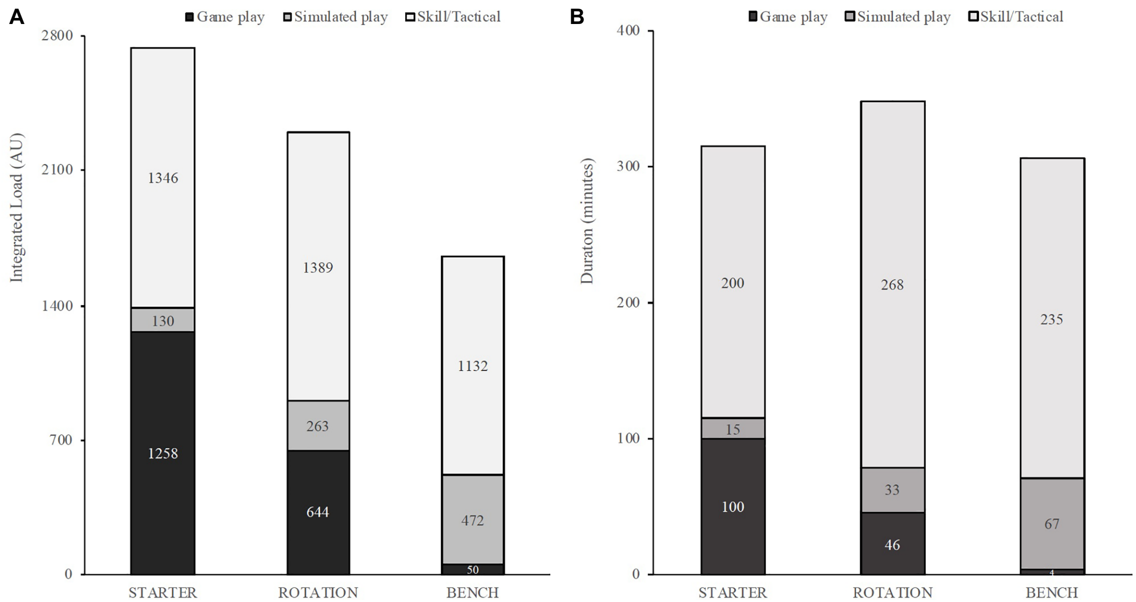

FIGURE 2 | Average weekly *integrated load* **(A)** and duration **(B)** during the regular season, by rotation status.

TABLE 2 | Descriptive statistics of total player weeks of *integrated load* and duration across participant categories.

	***Integrated Load* (AU)**				**Duration (minutes)**			
	n	**EMMean**	**95% CI**	**ES, Interpretation**	**n**	**EMMean**	**95% CI**	**ES, Interpretation**
Total	278[1]	2,192	1899, 2,485		394[2]	340	314, 365	
Frontcourt	220	2182.548	1829, 2,536	0.01, Trivial	278	345	314, 376	0.06, Trivial
Backcourt	58	2230.396	1,524, 2,937		116	327	278, 377	
1–2 years[A]	87	2134.934	1708, 2,562	0.18, Trivial[A-B]	86	365	342, 388	0.17, Trivial[A-B]
3–5 years[B]	104	2504.795	2,135, 2,875	0.06, Trivial[B-C]	105	388	367, 409	0.46, Small[B-C]
6–9 years[C]	58	2006.12	1,483, 2,529	0.26, Small[C-A]	87	327	304, 350	0.32, Small[C-D]
10+ years[D]	–	–	–	–	116	284	264, 304	0.61, Moderate[D-A]
								0.78, Moderate[D-B]
								0.29, Small[C-A]
Starter[E]	46	2664.792	2,328, 3,002	0.28, Small[E-F]	134	329	285, 374	0.09, Trivial[E-F]
Rotation[F]	145	2302.679	2092, 2,513	0.46, Small[F-G]	174	356	316, 397	0.1, Trivial [F-G]
Bench[G]	87	1699.125	1,427, 1971	0.77, Moderate[E-G]	86	324	267, 382	0.01, Trivial[E-G]

EMMean, Estimated Marginal Mean; ES, Cohen's D effect size (Hopkins et al., 2009); n, number of player weeks; CI, confidence interval; AU, arbitrary units. 1,2: Number of outliers removed.

DISCUSSION

This study described the weekly load and duration demands for NBA players throughout an entire season (i.e., game and practice). NBA players spend a large proportion of time in non-game court work (84% total duration on court), and training load is highest for starters and players with 3–5 years of NBA experience. There were no meaningful differences in training load or duration between different positional groups. This study provides a novel model for integrating load data from practices and games in the NBA. The differences in training requirements between groups according to rotation status highlight the importance of holistic, unobtrusive training load monitoring in the NBA.

This study described the time spent in different on-court training activities across an entire NBA season. Given the congestion of the NBA playing schedule (Esteves et al., 2020; Yang et al., 2021), it is interesting that most active time on-court is spent in non-game activities. Load management strategies in the NBA commonly include reducing game exposure (Scamardella et al., 2020), and the findings of this study suggest that there is ample opportunity to manage exposure during non-game court activity to reduce external load demands over the course of a season. While games themselves regularly have

48 min of clock time when players are actively engaged in basketball, this activity actually takes place over a 2–3 h period. This distinction between "active" time and "total" time is especially important in basketball, where duration quantification methods are often poorly described (Russell et al., 2021). Additionally, while this study was the first to report load and duration measures across an entire NBA season, the rate of load accumulation (i.e., training intensity) was not described, which should be investigated in future studies.

Our findings reveal trivial differences between total time on-court based on playing rotation status, but show *integrated load* was notably higher for starters and rotation players compared to bench players ($d = 0.77$; $d = 0.46$). Further starters had visually higher *integrated load* than rotation players ($d = 0.28$), but this may have occurred by chance. These differences between playing rotation status are interesting given the similar amount of time spent on-court in basketball-related activities (starters = 329 min/week, rotation = 356 min/week, bench = 324 min/week), with meaningful differences evident between the type of activities completed. Logical findings were that starters had more playing time in games than both rotation and bench players (see **Figure 2B**) while bench players spent the most time in simulated play drills, most likely due to attempts to replicate the demands of the game in which they did not participate. Despite the intentional programing of additional simulated play for bench players, they did not accumulate weekly loads similar to starting players. Overall, the weekly *integrated load* of bench players was only about 65% of the starters load (1,699 vs. 2,664 AU, respectively). These findings are unique, as most studies investigating external training load in basketball only include one type of playing group, such as starters (Bishop and Wright, 2006; Moreira et al., 2010), or only players that played the majority of the game minutes (Delextrat et al., 2012; Scanlan et al., 2015; Doeven et al., 2017; Puente et al., 2017; Sanders et al., 2018; Staunton et al., 2018; Vazquez-Guerrero et al., 2018, 2019; Alonso et al., 2020; Ransdell et al., 2020; Fox et al., 2020a). The present results highlight the importance of quantifying non-game activities to physically prepare all members of a basketball team.

Another novel finding of the present study was that players with 3- to 5-year experience spent the most time on court (~388 min/week) and had the highest weekly *integrated loads*. The total weekly durations for players in both the 1–2 and 3–5 year groups were moderately higher ($d = 0.61$ and $d = 0.78$, respectively) compared to players that had 10+ years' experience. In the current study, players spent an average of ~340 min on court each week, which is similar to the ~368 min/week reported in semi-professional basketball players competing in three games per week (Fox et al., 2020b). Increased training load has previously been reported during weeks where 3 games were played, in both semi-professional (Fox et al., 2020b) and European professional (Salazar et al., 2020b) basketball. In this study, only 3/26 regular season weeks involved less than 3 games, meaning that "high game load" weeks in other leagues is normal practice in the NBA. While these differences are important to consider, the absolute volume of training undertaken by these players does not exceed 7 h per week on-court, even in the highest load periods. Therefore, it is likely that periodization of loading and recovery is more important than the absolute training volume. Determining "optimal" training prescription requires the context of other information (e.g., player responsiveness measures and basketball performance outcomes) and ideal periodization is likely different for each individual player (Salazar et al., 2020b).

Identifying differences between training load characteristics based on experience may inform approaches training management when transitioning through developmental pathways (e.g., high school and college) to the professional level better understand the training dose-response relationship over time, which could help plan future training programs and recovery strategies for high-value players. While the results are taken from one small cohort, it is the first study to compare external training load differences based on years of playing experience in NBA players, which we believe is important to consider when developing appropriate individualized training prescription. Previous research in Australian football, comparing external load based on years of experience, found that the most experienced group (7+ years) had the lowest in-season load (Rogalski et al., 2013). These authors suggested that age-related injury risk and resultant risk mitigation strategies could cause these differences (Rogalski et al., 2013). While the differences may be due to chance, our findings were similar in that players with less experience (i.e., ≤5 years in the NBA) had visually higher load than more experienced players, which may be due to an increased emphasis on player development during the early career phase, for these younger players. While development pathways will always be specific to each player, an understanding of physical demands through high school, college, and professional careers, combined with other contextual and individual factors (e.g., anticipated playing rotation) may help better plan training load for individual players beginning and throughout their NBA career.

To evaluate seasonal differences in *integrated load* and duration based on position, we dichotomized players to frontcourt or backcourt groups. While up to five traditional positions exist in basketball (point guard, shooting guard, small forward, power forward, center), previous research (Ribeiro et al., 2015; Vazquez-Guerrero et al., 2018; Reina Román et al., 2019) using such analyses with low samples of players (e.g., single club studies) limits the generalizability of the findings. A further complication of using a five-position classification is that players often play multiple positions during a season or within a single game. These fluid roles are becoming increasingly common in the NBA, where traditional positional classifications have evolved due to tactical changes including "small-ball" line ups (i.e., a line up not including a center) and "stretch 4's" [i.e., a power forward (also referred to as the "4" position) with non-traditional offensive tactics] (Seidl et al., 2018). The present study showed no significant differences for *integrated load* or duration based on playing position. Previous research investigating external load in basketball by position has concluded that acceleration, deceleration, change of direction, and intensity demands varied based on position (i.e., centers, guards, and forwards; Svilar et al., 2018; Salazar et al., 2020a). However, the absence of differences between positions in the present study suggests that positional categorizations may be less important when evaluating global measures of external load (e.g., player load) and developing training plans throughout an NBA season. This is in line with the NBA moving away from traditional position roles and incorporating tactics, such as "small-ball" (Seidl et al., 2018). Although not evaluated in this study, it may still be important to consider individual roles, which are somewhat related to position, when evaluating very specific physical demands (i.e., contact and discrete movements) along with tactical requirements. This could lend insight to the difference in physical demands if players have more of an offensive or defensive role on the team, or provide information on how physical demands may change based on opponent or game strategies.

LIMITATIONS

While this study advances current understanding of the physical demands experienced throughout an entire season, there are challenges in consolidating profiles of physical load in the NBA (McLean et al., 2018). One clear challenge is the investment from the players, highlighted in the current study where 4 players regularly chose not to wear a microsensor during non-game court activity. This contributed to the small number of participants for comparisons between groups, which reduces the statistical power of our analyses. The comparisons we made resulted in some players being included in the same groups across multiple categories (e.g., some starters were also frontcourt players), and the availability of players during practices and games, or lack thereof, could impact results. Overall, the low participant numbers (i.e., one team over one season) and missing data (i.e., no wearable data from 4/14 players) limits the generalizability of recommendations from the current findings.

To overcome these limitations in the NBA, it is important to create collaborative environments around player monitoring, which requires alignment from all stakeholders, including players, team staff, league officials and player unions. However, even with the most collaborative approaches, currently available technologies/systems are likely too cumbersome to apply during all on-court activity. One example of this is pre-game court work, in which players complete short (~15 min), predominantly individual, sessions before each game. The short time frame and technical focus of pre-game work means that collecting wearable data is highly impractical, but these short blocks of work represent a significant training load over an 82-game season, which may be important. As a result, we used *integrated load* estimates for 18.8% of the time spent on court (primarily from pre-game work), which could skew the results. However, we are confident that our estimates were reflective of the actual training load demands and, therefore, more valuable than excluding that training load altogether. While estimated and missing data are not ideal in research settings, missing data are often underreported in high-performance sport practice and research and not unique to basketball. In the NBA specifically, there are concerns from the players about the privacy and ownership of data generated from wearable technology that deters them from participating in team or league initiatives (Zillgitt, 2020). Through openly acknowledging and discussing these limitations we can move closer toward developing better solutions for player support.

Another challenge presented in this work is the need to integrate data from two systems that measure load differently. While we present one solution to integrate load data, this is far less desirable than a one system approach. A significant investment is required to understand the relationship between these systems, a luxury that may not be available to all practitioners facing similar challenges. Additionally, the approach and load measures used in the present study lack gold standard validity and present many logistical and data processing issues. Despite these limitations, the method we present for quantifying load does enable consistent, season-long information regarding the physical demands in the NBA. We again highlight that using only one data stream (e.g., publicly available game data) is insufficient for describing the demands that NBA players experience throughout a season.

Despite these limitations, the present findings provide novel information on physical demands and some of the associated contextual factors of the NBA, which improve current understanding and provide a platform for future work to build upon. Quantifying the individual physical demands is vital for enhancing player management and care in the NBA, where players have diverse training and playing backgrounds.

PRACTICAL APPLICATIONS

The present study provides novel information regarding practice and game load demands in the NBA. By integrating the duration and load demands of both practices and games across an entire NBA season, we highlight several factors that can impact training and recovery planning in NBA basketball. First, a significant portion of time and load accumulated in non-game activities has implications for player load management and periodization of court work throughout an NBA season. The findings related to duration and load demands across player categories emphasize the need for practitioners to develop integrated and consolidated monitoring systems to best inform individualized training prescription and optimize preparation of NBA players. Additionally, this study highlights some limitations to conducting applied research in a high-performance environment (e.g., low participant numbers, missing data, and data from multiple sources) which are often underreported. Reporting these limitations in the NBA is novel and represents one of the major contributions of this work, as it provides additional information and context for stakeholders seeking to improve current systems; we strongly encourage other researchers to acknowledge such limitations in their work. Future studies utilizing multi-center or league-wide approaches would strengthen the depth and breadth of understanding around player and training characteristics so that more generalizable recommendations can be made. Collaborative approaches are imperative within high-performance environments, in order to develop integrated player monitoring solutions and continue to educate stakeholders about the value of training load monitoring, in order to support best practices for player preparation.

CONCLUSION

This is the first study to evaluate the holistic load demands of NBA players across an entire season. This study described the time NBA players spent in basketball-specific activity and highlights that a significant portion of time and load is accumulated in non-game activities. The present results identified that duration was significantly higher for players with 3–5 years of NBA experienced compared to players with <3 years or ≥ 6 years. *Integrated load* was significantly higher for starters compared to bench players, while total load did not appear to be significantly impacted based on playing position.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, in a format whereby individual participants are not identifiable, and without undue reservation.

ETHICS STATEMENT

The study was approved by the Human Research Ethics Committee of the University of Technology Sydney (UTS; HREC # ETH18-2658). Written informed consent from participants was not required for this study. Consent to analyze and publish this data was granted by the NBA and the NBA Players Association as per the guidelines and requirements for "NBA related health research" outlined by the NBA Collective Bargaining Agreement (CBA; NBA.com, 2017).

AUTHOR CONTRIBUTIONS

JR, BM, DS, and AC contributed to conception and design of the study. JR and BM collected and organized the data. SS performed the statistical analysis. JR wrote the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Some authors involved in this work are NBA-affiliated practitioners/researchers. As such, the study design and methods have been required to comply with the NBA Health-Related Research policy. This work has been reviewed by the NBA, NBA Physicians Association, and NBA Players Association. As part of this process, this manuscript was made available for comment from the NBA and NBA Research Committee prior to publication (these contributors are not listed as authors). The authors declare no other conflict of interest.

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Influence of Strength Programs on the Injury Rate and Team Performance of a Professional Basketball Team: A Six-Season Follow-Up Study

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This study aims to determine possible associations between strength parameters, injury rates, and performance outcomes over six seasons in professional basketball settings. Thirty-six male professional basketball players [mean ± standard deviation (SD): age, 30.5 ± 4.7 years; height, 199.5 ± 9.5 cm; body mass, 97.9 ± 12.9 kg; BMI 24.6 ± 2.5 kg/m^2] participated in this retrospective observational study, conducted from the 2008–09 to the 2013–14 season. According to their epidemiological records, each player followed an individual plan designed within different strength training programs: Functional ($n = 16$), Eccentric ($n = 8$), or Resistance ($n = 12$). Seven hundred and fourteen valid records were obtained from 170 individual strength tests during 31 sessions. Tests performed were leg press, squat, and jerk. Parameters recorded were force, power, velocity, peak velocity, and time to peak velocity for strength; time loss injury and muscle injury for injury rate; and games won, games lost, and championships for performance outcomes. All the strength variables and injuries are independent of the strength programs ($p < 0.01$). The correlation analysis showed very significant relationships between muscular injuries and time to peak velocity ($r = 0.94$; $p < 0.01$), significant relationships between force and games lost ($r = 0.85$; $p < 0.05$), and muscular injuries with games lost ($r = -0.81$; $p < 0.05$) per season. Mean values per season described a possible association of force, time to peak velocity, and muscular injuries with performance outcomes ($R^2 = 0.96$; $p < 0.05$). In this specific context, strength variables and injury rate data show no association with a single type of strength training program in this cohort of high-performance basketball players.

Keywords: individualization, periodization, load monitoring, force, time to peak velocity, muscle injuries

INTRODUCTION

Basketball is a team sport with a complex nature (Mallo, 2020), and the competitive outcome is based on multiple performance factors. Therefore, it is almost impossible to know to what extent the physical, technical, tactical, or emotional aspects have contributed to athletic performance. Thus, numerous studies categorize relevant performance factors in the National Basketball Association (NBA) (Huyghe et al., 2021), the EuroLeague (Paulauskas et al., 2018), prestigious European championships, such as the Spanish "Liga ACB" (García et al., 2014), or even National Team competitions like the FIBA World Cup (Zhang et al., 2020), or the Olympic Games (Sampaio et al., 2010). However, these studies focused exclusively on analyzing the technical-tactical aspects, acknowledging that physical, physiological, or mental factors contribute to the player performance but without studying their specific impact on the game.

Other studies have adopted a different approach, monitoring, and assessing the impact of different training methods on basketball players' physical fitness, the impact of physical fitness on the execution of technical and tactical abilities, or the significance of injuries throughout a sports season at an individual and team level. For instance, Naclerio et al. (2013b) observed that high volume resistance training (three sets per exercise and nine sets per muscle group) was the best approach to increase strength in college team sport athletes with no previous resistance training experience during pre-season, while low volume (one set per exercise and three sets per muscle group) seemed to be an interesting in-season strategy for maintaining strength and enhancing lower-body average power. The effects of these different programs were assessed *via* one repetition maximum (1 RM) and maximal average power (AP) on the bench press, upright row, and squat exercises using progressive tests. According to a study comparing professional and semiprofessional male basketball players, a standard preparation period (5–7 weeks, with athletes practicing 5–12 times a week, with 60–120 min practices) can induce improvements in professional players in abilities such as change of direction (COD). However, minimal differences between professional and semi-professional players were reported in the countermovement jump (CMJ) (Ferioli et al., 2018). On the other hand, a meta-analysis published in 2016 on strength training in healthy basketball players highlighted that interventions using external loads and even bodyweight exercises positively affected vertical jump ability (ES: 0.78 LARGE with 95% CI: 0.41, 1.15) (Sperlich et al., 2016). The effect of different circuit-training protocols in vertical jump height and peak power, horizontal jump distance, 3-points percentage, bench-press power output, RSA total and ideal time, and agility *T*-Test in semiprofessional basketball players has also been analyzed (Freitas et al., 2016). The authors found no changes in performance in the group participating in power circuit training (45% 1 RM), while the group using a high-resistance circuit training format (6 RM) presented decrements after 3 weeks. Plyometric training also seems a suitable training method to enhance muscle power, linear sprint speed, change-of-direction speed, balance, and muscle strength in basketball players, according to a recently published meta-analysis (Ramirez-Campillo et al., 2020). Similarly, Santos and Janeira (2012) demonstrated that a 10-week in-season resistance training program with moderate volume and intensity loads significantly increased vertical jump ($p < 0.05$) and medicine ball throw ($p < 0.05$) performances in the experimental group as compared to controls. Nevertheless, the study was conducted on twenty-five young male basketball players.

All the physical capacities improved by the strength and conditioning (S&C) practices mentioned so far are relevant, as research shows a translation between fitness and technical performance. Analyzing this relationship is relevant in highly complex sports such as basketball if we want to understand the reasons why the improvement of physical abilities can to some extent be associated with optimal competitive performance. Thirty-eight first division players from Bosnia-Herzegovina showed an association *via* multiple regression between higher fatigue resistance and free throw performance, preplanned agility, countermovement jump, and fatigue resistance with the two-point shot D2 ($R = 0.44$; $p = 0.03$), and countermovement jump, medicine ball toss, and anaerobic endurance with the three-point shot accuracy ($R = 0.39$; $p = 0.03$) (Pojskic et al., 2018). However, we must clarify that the study evaluated technical performances outside of an actual competitive situation using static and dynamic shooting tests. According to a study with twenty-eight first division basketball players from Turkey, the type of training also seems a significant issue. The results showed that one of the study groups, under a functional training program (core strengthening and specific basketball task-related exercises with/without equipment) lasting 20 weeks with a frequency of two sessions per week, significantly improved upper and lower body strength, flexibility, vertical jump ability, and T-drill agility scores when compared to a control group following a more traditional strength training program consisting of free-weight and machine-based exercises (Usgu et al., 2020). The use of ecological tests to measure the benefits of the different training programs is also relevant since some articles highlight the absence of association between strength measures and results from field tests (Alemdaroglu, 2012). Regarding the use of different exercises, an interesting piece of research surveying soccer, basketball, handball, volleyball, indoor soccer, and field hockey elite Spanish teams (Reverter-Masía et al., 2009) observed that only handball and volleyball coaches used Olympic lifts consistently. Many single-joint exercises were used by indoor and outdoor soccer teams and, especially, basketball teams. Basketball and handball were the sports mainly using weighted squat jumps. Similarly, a study surveying 20 NBA S&C coaches (69% response rate) found that all the respondents used strategies to develop the range of motion, followed some periodization, with Olympic lifts being used by 95% of the coaches ($n = 19$), and reporting that the squat or its variations were used by many of the teams, and all of them employing plyometrics in their practices (Simenz et al., 2005). Therefore, research demonstrates that the variability of methods used in the physical training of team sports is substantial and relevant differences between scientific evidence and what professionals do in the "real world" also exist.

Injuries in basketball are inevitable, as in any other discipline. Starkey reported that ankle sprains were the most frequent injury (9.4%), followed by patellofemoral inflammation (8.1%), lumbar strains (5.0%), and knee sprains (2.3%) in NBA players. Drakos et al. (2010), in a similar fashion, developed a 17-year longitudinal study in the same league, finding again that ankle sprains were the more recurrent medical issue (13.7% of the cases observed), while patellofemoral inflammation was the leading cause of more missed games (17.5%). According to the authors, professional NBA players undergo a high rate of game-related injuries. Contrarily, Rodas et al. (2019), in a study considering injury in an elite Spanish basketball club competing at the highest level of national and European leagues over nine seasons, found that muscle injuries (21.2%) were more commonly observed compared with ankle sprains (11.9%). Thus, prevention and therapeutic approaches to injuries in professional basketball settings are somewhat relevant.

Different authors have also analyzed the relationship between injuries, strength levels, workloads, and team-sport performance. Caparrós et al., 2014 found relations between squat strength (force), better performance (scored points) (rho = –0.81; $p < 0.05$), and fewer time-loss injuries (TLI) (rho = 0.82; $p < 0.05$) in a prospective study conducted on 12 Spanish professional male basketball players. Another study led by the same first author, but this time on NBA players, found that athletes under lower external loads were more prone to TLI (Caparrós et al., 2018). As some leagues present demanding competition schedules (McLean et al., 2018), the benefits of applied load management processes and different monitoring strategies seem relevant to protect professional players' physical integrity (Burgess, 2017). It is hypothesized that strength programs may reduce inter-limb asymmetries, a well-known internal risk factor for injuries (Bahr and Holme, 2003), limiting physical performance (Šarabon et al., 2020) and availability (Gabbett et al., 2018b).

Despite available research, to the best of our knowledge, there has been a limited attempt of examining the relationships between the use of different individualized strength training programs, injury rates, and competitive achievements in basketball longitudinally. This study aimed to determine possible associations between strength parameters, injury rates, and performance outcomes over six seasons in a European professional basketball team.

MATERIALS AND METHODS

Study Design

A retrospective observational study was carried out during six seasons in a professional basketball team (FC Barcelona) that played four main competitions every season. The data collection took place from 2008–09 to 2013–14, and players were allocated in three different strength training groups (functional, eccentric, or resistance training program) on each season, depending on their medical record. The measurements included individual strength assessments for each training group at the beginning and end of the mesocycles and team performance outcomes assessments per season. Baseline medical information was recorded from all participants at the beginning of each season through the FC Barcelona periodic health examination protocol. The protocol consisted of basic medical information (history), anthropometric data (age, height, weight, and ethnicity), physical examination, spirometry, basal 12-lead electrocardiography (ECG), submaximal cardiovascular exercise testing (with ECG and blood pressure monitoring), and cardiac echocardiography. Once a season started, various parameters potentially related to the type and frequency of musculoskeletal injuries (e.g., mechanism of injury) were collected. Athlete exposure and other variables, such as playing position, were recorded. We also collected clinical information and data related to the type of injury, TLI, medical attention (MA), and return to play (RTP) (Hägglund et al., 2005). Before implementing the strength training programs, all participants were required to perform familiarization tests and sessions. The S&C coach recorded all strength and performance data (TC). The Team Physician (GR) was responsible for diagnosis and RTP decision-making for every injury and recorded all the injuries included in the current investigation. Data were recorded daily after every practice and game. All participants took part in another retrospective study previously published (Caparrós et al., 2016).

Participants

Thirty-six professional basketball players [mean ± standard deviation (SD)]: age, 30.5 ± 4.7 years; height, 199.6 ± 9.5 cm; body mass, 97.9 ± 12.9 kg; BMI 24.6 ± 2.5 kg/m^2) from a Spanish basketball club (FC Barcelona) participated in this study. Thirty-two of them were Caucasian, and four were African American. Regarding their playing roles, 10 were guards, 11 were forwards, and 15 were centers. Two players played at the team during the six seasons of this follow up; 1 during 5; 5 players over 4 seasons; 4 over 3, 11 over 2, and 36 of them took part in at least 1 season (1.7 ± 1.2 seasons per player) with a mean value of 13.0 ± 0.9 players per season. The inclusion criteria for all subjects required each participant to be part of the FC Barcelona professional team roster during a complete season and aged >18 years, not being involved in a TLI rehabilitation process, and not to change between training methods during the same season. During the study, 8 of the 44 starting participants were not able to meet the inclusion criteria. All the players and the club (FC Barcelona) were informed of the risks and benefits of the study and gave written informed consent to participate in this study. Players were allowed to decline the inclusion of their data. The study was conducted following the ethical principles for biomedical research with human beings, established in the Declaration of Helsinki of the World Medical Association (amended in 2013), and it was approved by the club Board of directors and the Research Ethics Committee of the University of Vic-Central University of Catalonia (favorable report available upon request).

Strength Measurements

Strength assessments were carried out at the beginning of the first mesocycle and at the end of each mesocycle to evaluate each period's initial and final state (Bangsbo et al., 2006). During the analyzed period, tests were conducted during the training sessions and were non-invasive (Bangsbo et al., 2006) using the main exercises of each program. They were performed during introductory microcycles (Naclerio et al., 2013b), and depending on the strength program and seasonal periodization, the test exercises were: single leg press (LP) (Cuadrado Sáenz et al., 2009) for the eccentric (ECC) and resistance (RES) programs and double-leg squat (SQ) (Caparrós et al., 2014) and jerk (JK) (Andújar Gutiérrez et al., 2015) for the functional (FUNC). Tests were carried out during the morning sessions after a full rest day, beginning with a warm-up consisting of 8 min of submaximal general physical activity, lumbopelvic analytic protocol, and joint mobility. Parameters recorded were force (F), power (P), velocity (V), peak velocity (pV), and time to peak velocity (tpV). They were evaluated indirectly through data gathered using a linear encoder with an accuracy < 0.075 mm (MuscleLab PFMA V.4000e, Ergotest Innovation AS, Norway) (Porta-Benache et al., 2010). Every player performed four series of each exercise with a progressive weight increase of 10 kg and a decreasing number of repetitions in each series (12, 10, 8, and 6) (Naclerio et al., 2013a). Weights were individualized (Bangsbo et al., 2006) and could vary in each test (depending on the previous results and the periodized program), but there was always a minimum of two loads equal to the previous test, and the reference weight was the same throughout the whole season. The variables analyzed (F, P, V, pV, and tpV) in each exercise (LP, SQ, and JK) were determined to be reliable showing the following Guttman's Lamba 6 (G6) and coefficient of variation (CV) interval values at different weights: 115 kg [40–50% of 1 repetition maximum (1 RM)]; for single LP (G6 95 % confidence interval [CI] = 0.86–0.99; CV 95% CI = 0.01–0.29), 90 kg (40–50% 1 RM) for SQ (G6 95% CI = 0.94–0.99; CV 95% CI = 0.01–0.24), and 35 kg (40–50% 1 RM) for JK (G6 95% CI = 0.81–0.94; CV 95% CI = 0.05–0.26).

All the players underwent assessments as part of their training routine, and therefore the possibility of a player being injured because of the participation in the study was not considered. The S&C coach carried out the assessments, and all the players were familiar with the technique and protocol. To ensure that the testing was carried out consistently, the acoustic feedback provided by the encoder software was enabled during the execution of the tests. It was used to determine the minimum individual power level to be achieved.

Injury Measurements

To monitor injuries, we followed the model proposed by Hägglund et al. (2005), as well as the premises of Fuller et al. (2006). The study focused on TLI that caused absence from practices, workouts, or games, and among these, the group of muscular injuries (MI)—rupture, tear, strain, cramps or tendon ruptures, tendinosis or bursitis—were followed up.

Performance Outcomes Measurements

Five Team performance outcomes were considered: the Spanish Super Cup, the King's Cup, the Euroleague Final Four qualification stage, the Euroleague Final Four, and the Spanish League (ACB). Games won (GW), games lost (GL), and championships won (CW) were recorded on each season (Caparrós et al., 2016).

Periodization

To achieve the competitive goals, every season was divided into seven mesocycles, always considering the competition calendar. The first performance outcome fell within mesocycle 1 (Spanish Super Cup). Mesocycle 2 focused on the start of the regular season of the Spanish League (ACB) and the Euroleague season. Most of the first phase of the regular competitions takes place during Mesocycle 3. Mesocycle 4 included the second performance outcome (King's Cup). Mesocycle 5 covered the second phase of the regular competitions and the Euroleague playoffs (third outcome). Mesocycle 6 ended with the Euroleague Final Four (fourth outcome), and Mesocycle 7 comprised ACB playoffs for the championship as the fifth performance outcome (see **Figure 1**).

The duration of each season was 43 ± 2 weeks. Workload planning, both conditional and technical/tactical, was designed with as similar a structure as possible between mesocycles, with a duration of 6 ± 1 weeks. Mesocycle periodization followed the blocked periodization model (Issurin, 2008), and the progression of contents was divided into four orientations (general, directed, specific, and competitive) (Schelling and Torres-Ronda, 2013).

The design of the mesocycles was adapted to the game days, two per week during the regular season phases (31 weeks), except 5 ± 2 weeks with a single game. During the ACB and Euroleague playoffs, and in the King's Cup (8 weeks), three games were played weekly. The usual structure of each of the microcycles in each mesocycle was as follows: 1 day or morning session free with a recovery session in the afternoon; Monday and Tuesday: double session with strength and individual strength workouts in the morning and tactical session in the afternoon; Wednesday: tactical session in the afternoon; Thursday: pre-game session in the morning and game in the afternoon; Friday afternoon: recovery and joint technical/tactical session; Saturday morning: tactical session; and Sunday: game (with a pre-game session if it was in the afternoon) (see **Figure 2**). In addition, each player had an individualized preventive program, a strength workout, or practice to be performed before joint practices or during free days. Players with a lower competitive load had a compensatory practice on Monday morning (Gabbett, 2016; Caparrós et al., 2018).

Strength Programs

An integrative strength training program was designed for each player (Schelling and Torres-Ronda, 2016). In the light of their medical history, the players were distributed into three distinct workgroups. Those with the fewest constraints participated in the FUNC program (Schelling and Torres-Ronda, 2016), consisting of a multi-joint exercise routine, easily transferable to competitive play (Pojskic et al., 2018). These routines were performed with free weights, bodyweight exercises, medicine, weight balls, resistance bands, and mini bands. Those players whose injury records showed a history of tendon or muscle injuries were placed in the ECC program, which included both multi-joint and analytic exercises and was eminently preventive, emphasizing the eccentric component of the exercises

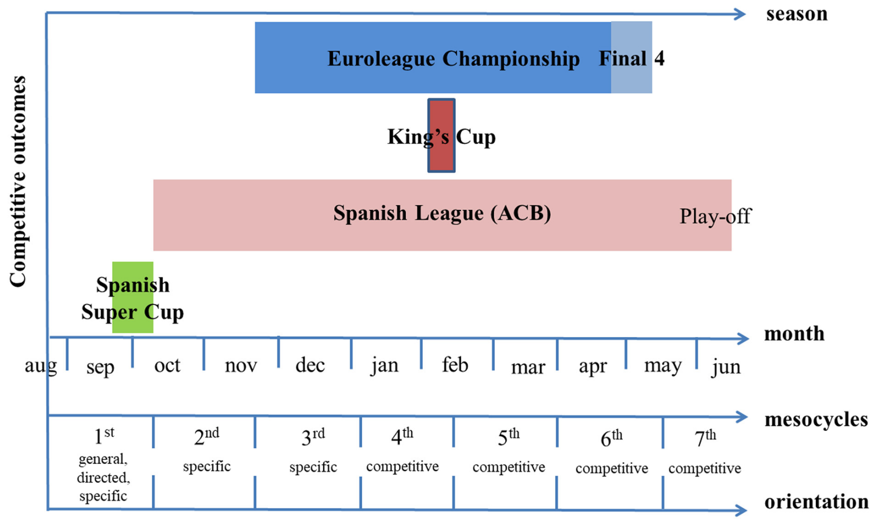

FIGURE 1 | Timeline of season competitive outcomes, mesocycles, and mesocycle orientation.

Microcycle periodization model

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Morning	off	Conditioning: 45 min **Strength*** + 30 min specific	off	Technical Pre-Game 60 min	off	Tactical 90 min	Technical Pre-Game 60 min
Afternoon	off	Tactical 90 min	Tactical 90 min	GAME	Recovery practice: 30 min Strength + 45 min	off	GAME

FIGURE 2 | Microcycle periodization model; * test sessions.

(Roig Pull and Ranson, 2007; Peña et al., 2017). The tools used for this program were strength machines, own bodyweight, medicine ball and weight balls, and resistance bands and mini bands. Finally, those who had chronic joint injuries or were older were assigned to the Resistance (RES) program, oriented to specific muscle groups (Naclerio et al., 2013b). Tools used for this program were weight machines, own body weight, and resistance bands and mini bands. Subsequently, depending on their age and playing characteristics, the exercise program, progression, and workload were adapted individually. The program's degree of specificity (Wen et al., 2018) and the volume and intensity of work were determined by the time of the season and by the orientation of the previous mesocycles. Therefore, strength work was integrated with the team's technical and tactical needs according to the competition calendar (McLean et al., 2018; see **Figure 3**).

Statistical Methods

Data are presented as mean ± standard deviation (SD). After performing a central tendency descriptive study and considering the non-normality of the sample, the Kruskal–Wallis test was used to evaluate the effects of the strength training program (independent variables) on dependent variables (strength and injury rate parameters). For this purpose, we used the values (F, P, V, pV, and tpV) of the best repetition in each series of each test (LP, SQ, and JK) recorded. A Dunn-Bonferroni *post hoc* test was performed in turn. Intrasession reliability of measures was determined using the Guttman's Lambda 6 test with 95% confidence intervals (Oosterwijk et al., 2016). The results were weighted to take account of the number of players in each program. Subsequently, and considering the normality of the average values by season, it was performed Pearson's rho correlation analysis between the variables of the best repetition in each test for the strength, injury, and performance outcome variables. The correlation magnitude was defined according to Hopkins's criteria (Hopkins, 2002): random: 0–0.09; low: 0.10–0.29; moderate: 0.30–0.49; large: 0.50–0.69; very large: 0.70–0.89; nearly perfect 0.90–0.99; perfect: 1. Finally, the multiple linear regression analysis used performance outcomes as the dependent variable, whereas strength and injury rate parameters operated as independent predictors. The statistical analyses were performed with JASP software version 0.11.1 (The Jasp Team, Amsterdam, Holland). The level of significance was set at $p < 0.05$.

Method	Mesocycle Orientation				Progression	
	General	Directed	Specific	Competitive	Sets	Repetitions
Functional	**Squat***	**Squat***			3 or 4	6 to 12
			Clean & Jerk	Clean & Jerk	3 or 4	6 to 12
		Clean	Clean	Clean	3 or 4	6 to 12
			Jerk*	**Jerk***	2 or 3	6 to 10
	Step up	Step up	Step up	Step up	2 or 3	6 to 12
		Lateral step	Lateral step	Lateral step	3 or 4	6 to 12
	Bench press	Bench press	Bench press	Bench press	2 or 3	8 to 12
	Cable row	Cable row	Cable row	Cable row	2 or 3	6 to 15
	Gluteus bridge	Gluteus bridge	Gluteus bridge	Gluteus bridge	2 to 4	10 to 15
	Landmine Press	Landmine Press	Landmine Press	Landmine Press	3 or 4	6 to 12
		Monster walks	Monster walks	Monster walks	3 or 4	8 to 15
	Core workout	Core workout	Core workout	Core workout	3 or 4	10 s to 20 s
		Push ups	Push ups	Push ups	1 to 3	6 to 10
		Pull ups	Pull ups	Pull ups	2 to 4	4 to 8
			Front jumps	Front jumps	2 to 4	4 to 8
			Lateral jumps	Lateral jumps	2 to 4	4 to 8
Eccentric	**Leg Press***				3 or 4	6 to 12
	Russian belt	Russian belt	Russian belt		3 or 4	6 to 12
		Back lunge	Back lunge	Back lunge	3 or 4	6 to 12
	Adductor Slider	Adductor Slider	Adductor Slider	Adductor Slider	2 or 3	6 to 10
	Hamstrings	Hamstrings	Hamstrings	Hamstrings	2 or 3	6 to 12
	Gluteus	Gluteus	Gluteus	Gluteus	3 or 4	6 to 12
	Soleus	Soleus	Soleus	Soleus	2 or 3	8 to 12
	Bench press	Bench press	Bench press	Bench press	2 or 3	6 to 15
	Cable row	Cable row	Cable row	Cable row	2 to 4	10 to 15
	Landmine Press	Landmine Press	Landmine Press	Landmine Press	3 or 4	6 to 12
	Core workout	Core workout	Core workout	Core workout	3 or 4	10 s to 20 s
		Push ups	Push ups	Push ups	3 or 4	10 to 15
		Pull ups	Pull ups	Pull ups	1 to 3	6 to 10
		Step Down	Step Down	Step Down	2 to 4	4 to 8
			Front jumps	Front jumps	2 to 4	4 to 8
			Lateral jumps	Lateral jumps	2 to 4	4 to 8
Resistance	**Leg Press***				2 to 4	6 to 12
	Adductor (slidding or assisted by S&C Coach)				2 or 3	6 to 10
	Hamstrings (Ecc phase Leg Curl or assited by S&C coach)				2 or 3	6 to 12
	Gluteus				3 or 4	6 to 12
	Soleus				2 or 3	8 to 12
	Bench press				3 or 4	10 to 15
	Dorsal Cable row				3 or 4	10 to 15
	Lateral shoulder raises				3 or 4	6 to 10
	Core workout				1 to 3	10 s to 20 s
	Push ups				2 to 4	10 to 15
	Pull ups				2 to 4	6 to 10

FIGURE 3 | Main strength exercises and progression by method and mesocycle orientation; *test exercises.

RESULTS

The 36 players were distributed between the strength training programs: RES: 12; ECC: 8; FUNC: 16. Seven hundred fourteen test valid records were obtained (27.5 ± 3.5 per player), of which 111 were from the RES group, 132 from ECC, and 471 from FUNC. The records were made during 170 individual tests in 31 sessions (5.2 ± 1.9) days of tests per season and (4.9 ± 2.2) tests performed per player. Of these tests, 26 were LP for the RES group, 12 were LP for ECC, 108 were SQ for FUNC, and 24 were JK for FUNC. There was a relevant difference between the numbers of test records in different seasons. The average was 119 records per year, going from a maximum of 228 in the second season (2009–10) to a gradual decline, reaching 29 in the last season (2013–14).

Strength Programs

Regarding the strength values recorded for each program, RES showed the highest F (1196.1 ± 356.8 N) compared to the FUNC with the lowest values (964.3 ± 266.2 N). FUNC showed the highest values for P (842.5 ± 183.1 W), V (0.92 ± 0.29 m/s), and pV (1.39 ± 0.58 m/s), and a lower tpV (0.25 ± 0.08 s). RES showed the worst values in all these cases, except in tpV, where it was ECC (see **Figure 4**).

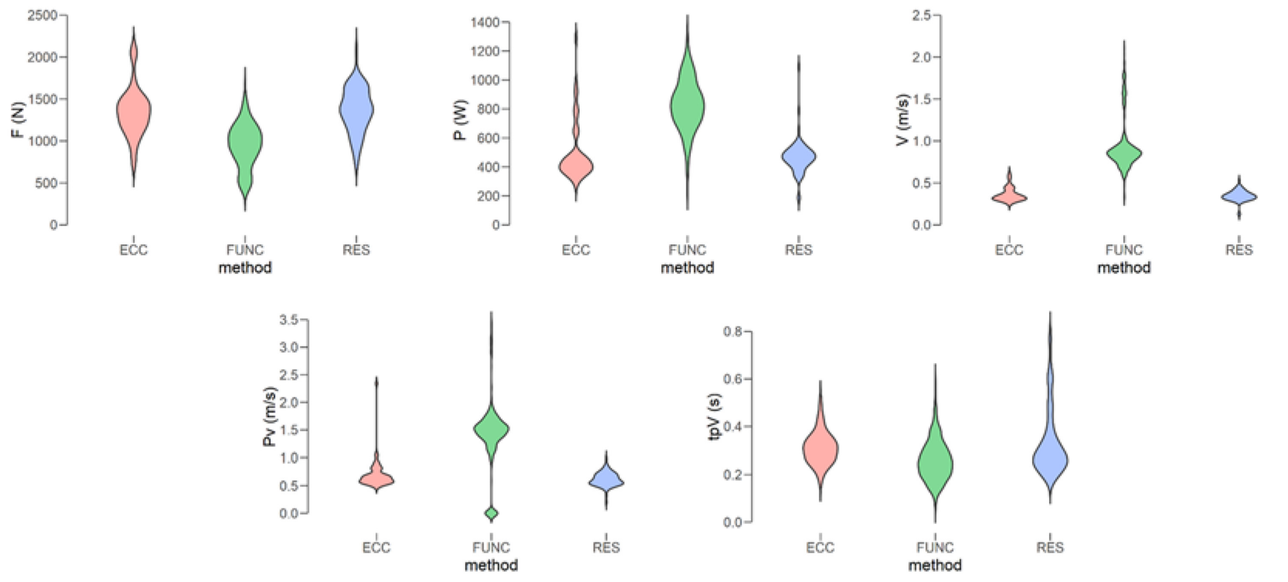

FIGURE 4 | Absolute values of Force (F), Power (P), Velocity (V), peak Velocity (pV), and time to peak Velocity (tpV) by strength training method (Eccentric—ECC—Functional—FUNC—or Resistance—RES). N, newtons; W, watts; m/s, meters per second; s, seconds.

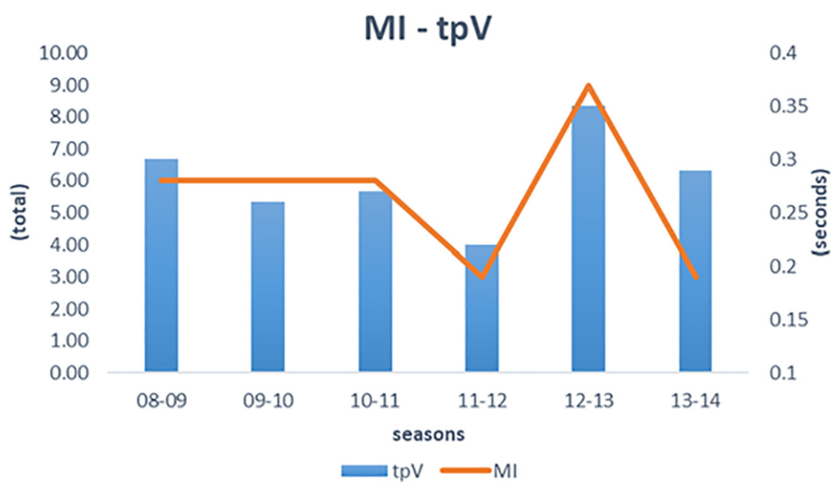

FIGURE 5 | Relationship of Muscle Injuries (MI) and mean season time to peak Velocity (tpV), by season. 08–09: 2008–2009; 09–10: 2009–2010: 10–11: 2010–2011: 11–12: 2011–2012; 12–13: 2012–2013; 13–14: 2013–2014. s, second.

Statistically, the Kruskal-Wallis test enabled us to determine the independence (H = 43.69–146.61; df = 2; p < 0.001) of all the strength variables (F, P, V, pV, and tpV) according to the test performed and considering all the strength programs. The *post hoc* test, in turn, also determined that these differences were present between each of the variables in every training group (z: −10.37 to 7.41; wi: 197.77–467.29; wj: 256.26–467.09; p_{Bonf} < 0.05).

Injuries

A total of 149 TLI were recorded during the six seasons, with averages of 24.7 ± 7.6 TLI and 6.0 ± 1.9 MI per season. An incidence of 37 TLI in the 2012–13 season stands out as the highest value, with a maximum of 9 MI, in contrast to the 2011–12 season with 17 TLI, only 3 were MI. In terms of mesocycles, the third produced the highest number of injuries (58), followed by the second (24), fourth (14), fifth (13), seventh (11), first (10), and sixth (6).

No significant differences were observed in the number of injuries according to the training group, so they should not be determined by this factor. Differences did emerge between seasons (H = 36.21; df = 5; p < 0.001) and mesocycles (H = 65.01; df = 6; p < 0.001). The *post hoc* test highlighted differences between the 2012–13 with the rest of the seasons (z: –4.57 to 4.13; w_i: 315.62–385.65; w_j: 315.62–432.3; p_{Bonf} < 0.01) (see **Figure 5**). Regarding the mesocycles, the same test showed differences between the third and the other six (z: −6.4 to 6.05; w_i: 322.86–439.54; w_j: 322.58–434.54; $p_{Bonf} < 0.001$).

Team Performance Outcomes

A total of 425 games were played, of which 342 were won (80.5%) and 83 lost (19.5%), with an average of 57.0 ± 4.3 games won (GW) per season, reaching a peak of 63 in the 2013–14 season, and 13.8 ± 4.6 games lost (GL) per season, the highest value was 21 in 2012–13. In all, 16 competitive objectives were attained, an average of 2.7 ± 0.9 per season, outstanding among which were the four performance outcomes in 2009–10 (Super Cup, King's Cup, Final Four qualification, and Euroleague Championship). Three were achieved during the 2010–11 and 2011–12 seasons, and two in the other seasons.

Relationships Among Variables

The correlation analysis using Pearson's rho test showed very significant (nearly perfect) relationships between MI and tpV (r: 0.94; $p < 0.01$) (see **Figure 5**) and significant (very large) relationships between F and GL per season (r: 0.85; $p < 0.05$) and also between MI and GL per season (r: −0.81; $p < 0.05$).

A multiple linear regression analysis was used to select the most promising independent variables (strength and injury rate parameters) to determine performance outcomes. The procedure revealed that F, tpV, and MI parameters together accounted for 92% of the variation of performance outcomes over the six seasons ($r = 0.98$, $r^2 = 0.97$, adjusted $r^2 = 0.92$, $p < 0.01$).

DISCUSSION

The present longitudinal study aimed to analyze potential associations among three strength training programs, team performance, and injury rates during six seasons in a top basketball professional team that included thirty-six male players. Among others, the most critical findings in this specific context are that strength variables and injury rate are independent of the training program. Finally, strength variables such as F, tpV, and MI could be associated with team performance outcomes. However, the team periodization might be designed and interpreted according to the individual players' needs, competitive schedule, and team goals of each different season.

The competition calendar determines team periodization (Ireland et al., 2019), with a very high traveling frequency required to compete in elite professional sport (Calleja-Gonzalez et al., 2020). In this scenario, the design of both strength programs and their workload should be adapted to each player's individual needs and characteristics (Rogalski et al., 2013). Concretely, during the six seasons analyzed, the players studied were distributed in three types of strength programs precisely based on their individual profiles (Gabbett et al., 2014). No differences emerged among the recorded variables, either of strength or susceptibility to injury, allowing to assess this distribution positively and design tailored to each player (Bogdanis et al., 2007). For this purpose, it is necessary to monitor, as far as possible, and in a specific and non-invasive manner (Bangsbo et al., 2006), all the available performance, physical fitness, and health parameters from a holistic approach (Nagorsky and Wiemeyer, 2021). Using a comprehensive framework for sports training with a performance model integrating insights from game research and sport science (Calleja-González et al., 2018) the aim is to be fully available for competitive play (Gabbett et al., 2018b). Monitoring of load management allows to adapt individual programs (Fernández et al., 2021), to competition demands, but involving players and staff in common team objectives (Thorpe et al., 2017) and combine competition demands and each member of staff (Gabbett et al., 2018a).

Overall, all the strength variables analyzed behaved independently of each other. Periodization was different every season, given that although the coach and staff were the same, the entire roster was not. In turn, the programming and load design were adapted to the determinants of a highly competitive context: changing squad, with some older players; more games for a new Euroleague schedule from the 2011–2012 season; and an increasing pressure to maintain the team performance outcomes success. The data can be well-contextualized in the team's current competitive situation, allowing each season and programming unit to be interpreted independently. Periodization will depend on multiple factors (Aoki et al., 2017), and each season must be analyzed and all the contents tailored to specific needs (Stone and Steingard, 1993).

From the 2011–12 season onward, the number of games in European competition increased, and this meant going from having between 12 and 14 weeks with a single game to at most 4. At that point, conditioning had to be oriented more to recovery than to accumulation (Fox et al., 2018) managing strength work now focused on intensity rather than volume (Naclerio et al., 2013b). Up till then, the first day of the week in the gym was performed with general or directed contents, and second for more specific ones. But from then on, the second weekly session was predominantly for recovery (Calleja-González et al., 2016), so the first had to include more specific contents during the period of competition (Fox et al., 2020), with the aim to perform higher P, V, and pV values (Santos and Janeira, 2012). The fact is that the new calendar entailed a reduction in the accumulation period, additionally to the constraint of competing for the first competitive goal at the end of the preseason (Doeven et al., 2020). In this sense, the F levels could not be adopted as before, representing a physical limitation (Šarabon et al., 2020). Greater specificity may conditionally be assumed (Fernandes-da-Silva et al., 2016), but it can be related to other issues such as performance (Gabbett et al., 2018a) and susceptibility to injury (Hulin et al., 2016). Each phase of the season presents different demands (Ferioli et al., 2018): the first phase of three mesocycles was oriented toward F work, with the subsequent management of P and qualitative and specific issues at the end of the season (Ferioli et al., 2021). This could be related to susceptibility to injury and observed during the third mesocycle (accumulating as many as 37 injuries), a period that coincides with an overload of competition and training, as well as periods of acute overload (spikes) (Hulin et al., 2014) at a conditional level. Correct data interpretation would lead to moderate this workload in this mesocycle to aid recovery (Terrados et al., 2019). For this purpose, the preceding mesocycles are essential in the appropriate management of chronic workload (Gabbett, 2016), and monitoring weekly changes during the in-season phase should help to adjust acute workload that may predispose players to unwanted spikes (Paulauskas et al., 2019).

In a previous study with this sample (Caparrós et al., 2016), TLI was not related to the competitive outcome. However, in this case, the correlation analysis, now including conditional factors, does identify clear relationships between MI and F and GL in the season ($p < 0.05$)—which in turn are related to the achievement of championships as team performance outcomes ($p < 0.05$). The fact is that during the first three seasons, the development of F in the first mesocycles made it possible to take on conditional levels that enabled players to reach a competitive fitness state (Speranza et al., 2015) and with the squad members available in all competitions. Nevertheless, during the last three seasons (from 2011 to 2012), the exercises' orientation was more specific on a more congested calendar. Subsequently, these are associated with greater susceptibility to injury in this specific context, especially muscle injury, which would be closely related to lower F values (Malone et al., 2019) or worse recovery, reflected in variables of a qualitative nature that deteriorate, such as pV (Serpiello et al., 2011). These factors are associated with shorter preseasons (Killen et al., 2010) and a fuller competitive calendar, noting two different trends: first, there is the highest injury incidence during the third mesocycle. Players could have reached this point in a competitive state of fitness but with less capacity for recovery from these exertions at this point of the season (Killen et al., 2010). And second, lower injury rates are on seasons with best tpV values. Load management must balance recovery strategies and optimal strength training, avoiding low chronic workloads (Malone et al., 2019) too early in the season.

It is essential to note the association among F, tpV, and MI (R^2 = 0.96), but it needs to be put into context. The proposed model establishes that in this specific context, the three variables determine performance outcomes. The optimal chronic strength values (Caparrós et al., 2014) and the specific details of the proposal need to be determined for each player (Ferioli et al., 2021). The tpV value and its possible relationship to muscle recovery (Serpiello et al., 2011) and better states of fitness (Fernandes-da-Silva et al., 2016) must be adequately monitored throughout the in-season (Gabbett, 2016; Paulauskas et al., 2019). These two factors, in turn, could determine muscle injury. Injuries may continue not to impede competing in championships. However, correct management and monitoring of variables such as F and tpV, and consequently a reduction in muscle injuries (Rodas et al., 2019), will make it possible to have a roster in its full potential to achieve the maximum number of competitive goals, as happened in the seasons from 2009–10 to 2011–12.

The present study presents limitations inherent in a sporting and competitive context, despite the wealth of data related to the study period, players in the sample, and team performance outcomes. First, and from a global vision, the possibility of comparing this longitudinal study with others would allow us to determine the applicability of the results. Second, and for this specific case, having different tests does not allow us to obtain consistent results, but that was not the intention in this research. Each workgroup and player must be assessed independently to adopt the same objectives simultaneously as a team. In this connection, given these specific sporting processes, not all the players were monitored using all the tests; in some cases, they were injured. Third, and related to the number of tests, a gradual decrease occurred as the seasons passed. Nevertheless, primarily, the reduction in the quality of monitoring must be assessed and, once again, interpreted: the increase in the number of games reduced the number of sessions that included exercises for recording data. And especially in the last two seasons, although competitive objectives were undertaken, the number of games lost was higher, and consequently, competitive pressure did not make it easy for the staff to manage data collection. Neither the seasons' routine nor adverse competitive situations should give rise to a lack of rigor in any detail of the training process. These are precisely the situations in which greater importance should be given to monitoring (Burgess, 2017), to optimize the players' performance as much as possible, monitoring the attainment of the objectives of periodization, and not overlooking risk factors (Gabbett et al., 2018a). However, the strength of this study is a six-season follow-up of top Euroleague players, to date not described, in the daily reality of the sports competition.

To conclude, in this specific context, strength variables and injury rate data show no association with a single type of strength training program in this cohort of high-performance basketball players. F, tpV, and MI showed association with team performance outcomes.

PRACTICAL APPLICATIONS

Performance (both team and individual) data and strength variables should be integrated in the workload monitoring process, with the aim to optimize training, individual availability for competition, and team performance outcomes. This process is longitudinal, and it is the staff's responsibility to involve the players in it to understand their importance for improving their performance and health. Sports organizations and coaches should assess these data using this perspective. In turn, S&C and Sports Science professionals have more tools and experience available to manage this process in an ethical and minimally invasive manner, providing the rest of the staff and the players with concise and reliable information.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Universitat de Vic-Universitat Central de Catalunya Research Ethics Committee. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

TC and GR conceived and designed the research, analyzed and interpreted the data, drafted the article, and approved the final version submitted for publication. JP and EB analyzed and interpreted the data, and drafted the article. JP, EB, XB, and JC-G critically reviewed the article and approved the final version submitted for publication. All authors contributed to the article and approved the submitted version.

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Simplifying External Load Data in NCAA Division-I Men's Basketball Competitions: A Principal Component Analysis

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The primary purpose was to simplify external load data obtained during Division-I (DI) basketball competitions via principal component analysis (PCA). A secondary purpose was to determine if the PCA results were sensitive to load demands of different positional groups (POS). Data comprised 229 observations obtained from 10 men's basketball athletes participating in NCAA DI competitions. Each athlete donned an inertial measurement unit that was affixed to the same location on their shorts prior to competition. The PCA revealed two factors that possessed eigenvalues >1.0 and explained 81.42% of the total variance. The first factor comprised total decelerations (totDEC, 0.94), average speed (avgSPD, 0.90), total accelerations (totACC, 0.85), total mechanical load (totMECH, 0.84), and total jump load (totJUMP, 0.78). Maximum speed (maxSPD, 0.94) was the lone contributor to the second factor. Based on the PCA, external load variables were included in a multinomial logistic regression that predicted POS (Overall model, $p < 0.0001$; $AUC_{centers} = 0.93$, $AUC_{guards} = 0.88$, $AUC_{forwards} = 0.80$), but only maxSPD, totDEC, totJUMP, and totMECH were significant contributors to the model's success ($p < 0.0001$ for each). Even with the high significance, the model still had some issues differentiating between guards and forwards, as in-game demands often overlap between the two positions. Nevertheless, the PCA was effective at simplifying a large external load dataset collected on NCAA DI men's basketball athletes. These data revealed that maxSPD, totDEC, totJUMP, and totMECH were the most sensitive to positional differences during competitions. To best characterize competition demands, such variables may be used to individualize training and recovery regimens most effectively.

Keywords: sport science, wearables, inertial measurement unit (IMU), collegiate athletics, athlete monitoring

INTRODUCTION

Sport science applications in collegiate basketball synergize sport coach knowledge and data-driven scientific strategies to individualize player training and recovery regimens. The goal is to facilitate beneficial physiological adaptations to enhance in-game performances. The data most commonly collected for the aforementioned purposes include, but are not limited to, external player loads via player trackers [e.g., radio frequency identification (RFID), inertial measurement units (IMU)], internal player loads *via* wearables [e.g., heart rate monitors via electrocardiography (ECG) straps], internal player loads via subjective ratings of perceived exertion, subjective wellness, sleep monitoring via wearables or self-report, neuromuscular performance (e.g., force plate testing), as well as basketball-specific performance (e.g., shooting percentages, efficiency ratings) and tactical schemes (e.g., drill and play-call selections) (Fox et al., 2017; Edwards et al., 2018; Svilar and Jukić, 2018). From these data, daily individual player preparedness reports are generated and disseminated to the coaching staff via the performance and sports medicine personnel (i.e., sport scientist, strength and conditioning coach, nutritionist, athletic trainer, physical therapist, team physician). More specifically, these analyses often comprise comparisons within each athlete's objective and subjective external and internal training and recovery statuses, as well as group comparisons between positions (POS; e.g., guards, forwards, centers), player statuses (e.g., starters, reserves), and/or competition outcomes (e.g., Wins and Losses) (Parmar et al., 2018; Svilar et al., 2018; Svilar and Jukić, 2018; Bunker and Thabtah, 2019; Rojas-Valverde et al., 2019; Russell et al., 2020). When these data are valid and reliable, they may be automated and actioned to closely monitor physiological and psychological demands during training and competitions with a high degree of individualization. By identifying strengths and weaknesses of individual athletes and the team, the quantification of training and competition demands provide enhanced contextual feedback on athlete performance and recovery that subsequently enables improved individualized programming efforts. Pertaining to applied performance and sport scientists, data-driven performance monitoring is helpful for purposeful organizing (and individualizing) within their athlete monitoring framework.

However, despite rigorous pursuit by practitioners and researchers, the identification of key metrics for athlete monitoring purposes continues to be a difficult problem. The expansion of wearables in the sport industry inherently inflates the number of monitoring variables, with data now being systematically sampled at high rates at the individual athlete level from technologies such as RFID, IMU, ECG, global positioning systems (GPS), local positioning systems, accelerometers, or some combination of multiple sensors (Taylor et al., 2012). Consequently, these automated collections create large individual athlete data sets, often making it even more challenging to identify the most appropriate monitoring variables within a given team. Additionally, as new technologies are developed and commercialized, end users are left with limited understanding regarding the metrics reported until further scientific investigations are executed.

One statistical approach that assists in simplifying datasets in team-sports and other high-performance environments (e.g., tactical) is a principal component analysis (PCA), which is an effective strategy for making athlete monitoring datasets more actionable for practitioners (O'Donoghue, 2008; Federolf et al., 2014; Laffaye et al., 2014; Stein et al., 2017; Parmar et al., 2018; Svilar et al., 2018; Rojas-Valverde et al., 2019, 2020; Merrigan et al., 2021; Terner and Franks, 2021). In general, a PCA reduces the number of dimensions in a relatively large dataset by identifying variables that possess low degrees of multicollinearity and are the most responsible for fluctuations in overall variance (typically at least 70–80% of the total variance explained) (Rojas-Valverde et al., 2020). Previous research in professional 1st Spanish Division basketball athletes deployed a series of PCA's for Guards, Forwards, and Centers and determined that the training load demands differed across POS (Svilar et al., 2018). For example, high intensity and total counts of accelerations explained reasonable amounts of variance in Centers but not Guards and Forwards, whereas high intensity and total counts of decelerations appeared to be more relevant. Although that study demonstrated clear differences in external load demands during training itself for basketball position groups, the analysis did not contain competition data, which is imperative for the sake of training specificity. Still, those findings suggest that player monitoring tactics (i.e., selection of metrics for monitoring and reporting) likely vary based on the different POS at the elite level of basketball. Similarly, PCAs were utilized in college and professional rugby, American football, basketball, baseball, volleyball, and soccer (Parmar et al., 2018; Casamichana, 2019), with recent proposals and systematic reviews asserting a need for more PCAs in sport settings (Stein et al., 2017; Rojas-Valverde et al., 2019, 2020). Provided the situational specificity of individualized athlete monitoring, continual research incorporating PCAs into other team-sport applications, such as collegiate athletics, is certainly warranted. To practically apply PCA results in these types of settings, one might consider how well (or not) the variables contained within the reduced dimensions predict various sport-specific contexts of interest, such as position group assignment, home and away competitions, opponent difficulty (e.g., Power 5 conference opponent or not), regular and postseason competitions, and/or player statuses (e.g., starter or reserve) (Fowler et al., 2017; Staunton et al., 2018; Fox et al., 2019, 2021). Depending on the intended outcome from analysis, in these instances a multinomial logistic regression may be preferred in lieu of alternative methods (e.g., discriminant analysis) because the focal point may be the predictor variables themselves and the prevention of overfitting such that analytical insights were more applicable to outside applications (e.g., other teams, researchers) (Luo et al., 2011). Moreover, a sport scientist might be interested in determining which external and/or internal load metrics are the most sensitive to group classification (i.e., how did the predictor variables change between POS groups) rather than solely being interested in the prediction outcome itself (i.e., which POS group did the model assign an athlete to). Indeed, the latter likely justifies the utilization of discriminant analysis, such as an instance in which a coach is trying to decide which POS group a new athlete might be most suitable for during training. However, when the primary question pertains to how the load demands vary between POS group (or home/away, Power 5/not, starter/non-starter), logistic regression may be more suitable.

Therefore, the primary purpose of this study was to utilize PCA to simplify external loadmetrics from IMU data that were collected during competitions across a single season of NCAA Division-I (DI) men's basketball in a Power-5 conference team.

The secondary purpose was to examine whether there were discernible player POS differences in the most pertinent metrics identified in the PCA.

METHODS

All athletes signed the institutionally approved informed consent document. All procedures were approved by West Virginia University's Institutional Review Board (#2102249143).

Subjects

Ten NCAA DI men's basketball athletes (Mean ± SD; $n = 10$; height: 196.09 ± 8.01 cm; weight: 96.95 ± 11.14 kg) were included in the present study. The athletes were partitioned into three POS groups as these were dictated by the sport coaching staff at the start of the season based on team playing style (Guards: $n = 4$; height = 188.60 ± 4.34 cm; weight = 85.98 ± 3.24 kg; Forwards: $n = 3$; height = 192.27 ± 5.87 cm; weight = 94.72 ± 4.78 kg; Centers: $n = 4$; height = 204.89 ± 3.88 cm; weight = 113.80 ± 3.33 kg). These positions also align with previous research in basketball athletes (Svilar et al., 2018).

Experimental Design

To examine the external load demands that are characteristic for NCAA DI men's basketball competitions, a retrospective study design was utilized following a single competitive season. Prior to competitions, the IMUs were positioned in a holster that was stitched into the uniform shorts and located near the posterior superior iliac spine on the right side for each athlete. These holsters were constructed in collaboration between the sensor manufacturers and team equipment managers to ensure unnecessary movement of the sensors was negligible and positioning was consistent throughout the season. Data were obtained from a wearable IMU sensor and then compiled into a central database after each competition. Following the season conclusion, data were de-identified, exported, and analyzed for the purposes of identifying KPIs specific to basketball competitions.

Protocol

External load data from wearable IMU sensors (KINEXON Precision Technologies, version 1.0, Munich, Germany) were collected, at 20 Hz, from each athlete during 27 competitions interspersed throughout the 2020-2021 NCAA Men's Basketball season. A previous study examining the validity of this system reported an average total typical error of estimates to be 2.5% (± 1.5%) when five adult male team sport amateur athletes performed a variety of movements comprising walking, jogging, and sprinting of different distances, as well as changes of direction and jumping (Alt et al., 2020). All system installations and calibrations were performed by the same technician prior to the season starting. Competitions comprised 24 regular season games, one game from the conference tournament, and two games from the NCAA tournament. A total of 221 observations of players in each game were recorded, which were further broken down into 64, 75, and 82 cases for Centers, Forwards, and Guards, respectively.

Session recordings occurred throughout each game-day and were initiated and ceased at the same time for each athlete. Individual phase recordings were time stamped and segmented into Shoot around, Warm-Up, 1st Half, Half-Time, and 2nd Half phases. However, for the sake of this study, the dataset that was analyzed only included external load data obtained during the active competition minutes (i.e., during the 1st Half and 2nd Half). The 1st Half recording was initiated immediately prior to the referee throwing up the ball to signify the "tip-off" and concluded upon the sound of the buzzer when the game clock reached zero. A separate half-time phase was generated to account for the time spent in the locker room to partition the data from the 1st and 2nd Halves. The 2nd Half session began as soon as a team took possession and the game clock started counting down. Similar to the 1st Half, this phase concluded when the buzzer sounded, and the game clock reached zero. Any overtime periods were excluded from analysis as the scope of this study was to merely examine typical competitions. The variables of interest encapsulated summated mechanical loads (totMECH; a.u.), jump loads (totJUMP; J), accelerations (totACC; count), and decelerations (totDEC; count) from the 1st and 2nd Half, as well as the average speed (avgSPD; mph) and maximum speed (maxSPD; mph) from the entire game. Mechanical loads were calculated utilizing a proprietary equation that placed acceleration and deceleration events into multiple, weighted intensity bins that were collectively summated into a single value (i.e., totMECH) for a given phase (e.g., halves). The totACC and totDEC were identified using a threshold of 1.5 m/s^2 and a minimum duration 0.5 s as dictated by the proprietary software. The total jump loads (totJUMP) were calculated by multiplying the player's body mass by the gravity constant (9.8 m/s), and the jump height in meters for each jump event. Then, all jump loads were summated to provide the totJUMP, as a volume-load metric describing the cumulative intensity and volume of jumps for the session. For a movement to be considered a jump, an athlete had to elevate for a minimum airtime of 0.3 s.

Statistical Analysis

Data were collected, stored, and exported from Kinexon before being imported and prepared for analysis in R Version 4.0.3 (Team, 2019). The Kinexon companion software exports a total of 109 external load variables, which are left for practitioners to determine which are the most useful. These variables comprise event counts (e.g., number of accelerations, decelerations, jumps, sprints), intensity bandings (e.g., acceleration zones 1–4), and durations (e.g., time spent in speed zones) of both two-dimensional (2D) and three-dimensional (3D) movements. Since many of these variables are redundant and utilized as contextual information (e.g., durations and distances covered over certain speed zones, counted numbers of accelerations/decelerations in different intensity zones) to help characterize primary summary variables (e.g., mechanical load, jump load, total counts), most of them were omitted from analysis to prevent high degrees of multicollinearity and improve overall sampling adequacy.

To ensure data adequacy for factor analysis, a measure of sampling adequacy (MSA) was derived for the entire data set *via* the Kaiser-Meyer-Olkin measure (KMO). The overall MSA was meritorious at 0.81; thus, providing sufficient confidence to conduct the PCA (Kaiser, 1960; Kaiser and Little, 1974). Bartlett's Test of Sphericity was also conducted and confirmed that the correlation and identity matrices were divergent (i.e., the variables included were correlated enough to provide practical value without redundancy in the data), further supplying confidence that dimension reduction was suitable ($p < 0.0001$). A PCA on correlations was calculated to identify the principal components accounting for the most relevant variance, which was dictated by those possessing eigenvalues > 1.0. From there, a variable loading matrix with a *VariMax* rotation was generated to identify variables in the principal components with an individual loading value ≥ 0.70. Next, a multinominal logistic regression was constructed using athlete POS (Guards, Forwards, Centers) as the response variable, and the most relevant PCA variables as predictors. This helped to better understand POS differences (i.e., which position was higher or lower with respect to each predictor) with the variables identified in the PCA as having a loading ≥ 0.70. With this regression, an odds ratio (OR) was calculated for each predictor with respect to a Guards to Forwards comparison, as well as a Guards to Centers comparison. The areas under the receiver operating characteristics (ROC) curves were also reported. These ROC curves were meant to depict the probability that the external load variables could correctly assign athletes to the correct POS group. Lastly, one-way analysis of variance (ANOVA) tests were conducted for those variables that significantly increased the odds of accurately assigning an athlete to their correct POS group in the regression. Following significant univariate effects, Tukey's HSD *post-hoc* analysis was carried out to ascertain differences between individual POS groups. Cohen's *d* was used to calculate effect size with thresholds as follows: trivial: 0.0–0.19; small: 0.20–0.49; moderate: 0.50–0.79; large: ≥ 0.80 (Cohen, 1988). All alpha levels were set at $p < 0.05$ and statistical analysis was conducted in JMP Pro Version 16 (Jones and Sall, 2011).

RESULTS

Simplifying External Load Data

The first (eigenvalue = 3.80; % variance = 63.45%) and second (PC2; eigenvalue = 1.07; % variance = 17.85%) factors explained 81.30% of the total variance in athletes' external loads during basketball competitions. The third factor only possessed an eigenvalue of 0.43 and thus was omitted from further analysis, according to Kaiser criterion.

A loading matrix for the first two factors was created to only report instances where the loading magnitude was ≥ 0.70. Additionally, summary plots for the individual observations

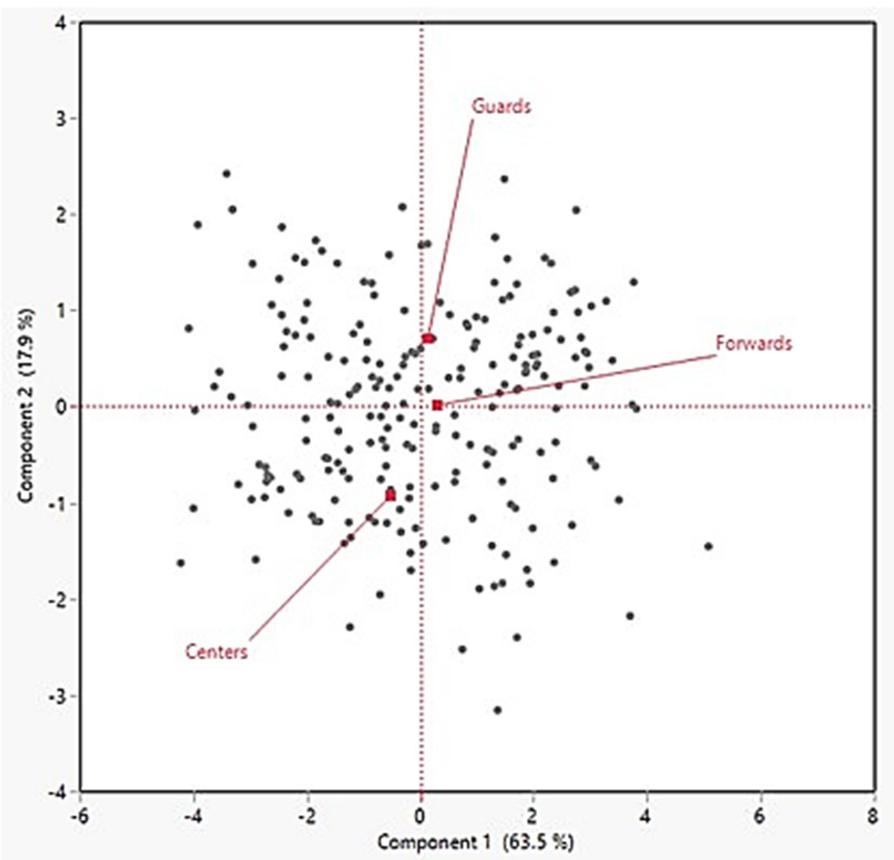

FIGURE 1 | Individual observations derived from the principal component analysis and supplemented with the player position variable.

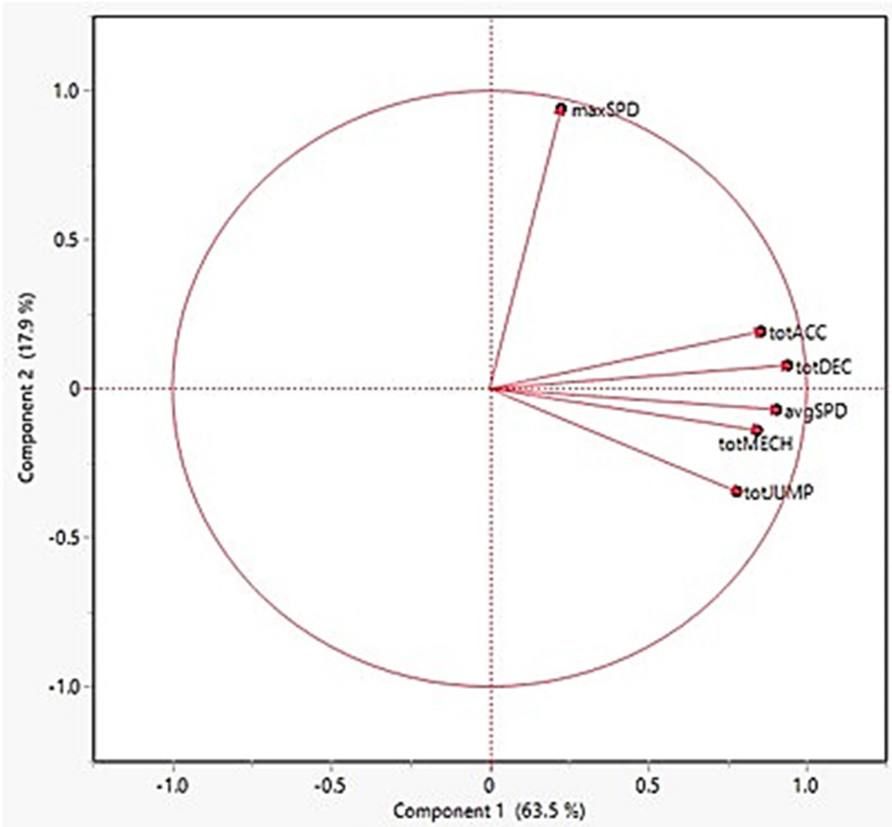

FIGURE 2 | Loading plot for principal components 1 and 2. Total mechanical load, totMECH; jump load, totJUMP; accelerations, totACC; decelerations, totDEC; average speed, avgSPD; maximum speed, maxSPD.

(supplemented by POS) and rotated loading factors are found in **Figures 1**, **2**, respectively. In **Figure 1**, the three POS groups (Guards, Forwards, Centers) appear to distance themselves from each other, implying that there are distinct differences in the external load demands among them. In the first factor, the main contributors included five of the six external load variables with the following relative loadings: totDEC, 0.94; avgSPD, 0.91; totACC, 0.86; totMECH, 0.84; totJUMP, 0.78. However, maxSPD was the sole main contributor, with a relative loading of 0.94, in the second factor thereby suggesting maxSPD possesses a low correlation with the PC1 variables. The loading plot further illustrates this as the five variables in PC1 are relatively "clustered" together whereas the loading arrow for maxSPD clearly distinguishes itself from the rest.

Predicting Player Positions Based on External Load

The overall model was significant at assigning athletes to POS ($p < 0.0001$; AICc = 322.15; BIC = 367.69), with maxSPD, totJUMP, totDEC, and totMECH each contributing to the model's successful POS assignment ($p < 0.0001$; **Table 1**). The confusion matrix (**Table 2**) details that Centers, Guards, and Forwards were correctly assigned in 82.8, 70.7, and 54.7% of model iterations, respectively. The greatest predictive error appeared when Forwards were labeled as Guards, which occurred nearly one-third of the time. The differences in prediction accuracy for each POS was further confirmed by ROC curves, which revealed the greatest area under the curve for Centers (0.93), followed by Guards (0.88) then Forwards (0.80) (**Figure 3**).

Differences in External Load KPI's for Player Positions

Descriptive statistics of each external load variable, separated by POS, are displayed in **Table 3**. There were significant differences among POS for maxSPD [$F_{(2, 218)} = 66.06$, $p < 0.0001$], totDEC [$F_{(2, 218)} = 11.52$, $p < 0.0001$], and totJUMP [$F_{(2, 218)} = 5.28$, $p < 0.01$], but not totMECH (**Figure 4**).

Guards possessed significantly higher maximum speeds than Forwards and Centers ($p < 0.0001$) and Forwards were significantly faster than Centers ($p < 0.0001$). All three of these comparisons also reported large effect sizes (≥ 0.90). Forwards ($p < 0.0001$) and Guards ($p < 0.01$) performed significantly more totDEC compared to Centers, although Forwards and Guards did not differ in the totDEC performed. The observed effect size comparing Forwards to Centers was large with a near medium effect size for Guards and Centers and a small effect size for Forwards and Guards. With respect to totJUMP, Centers produced significantly greater total jump loads (measured in

TABLE 1 | Summary parameter estimates from a multinomial logistic regression on external load variables.

Term	Estimate ± SE	Exp(β)	Exp(β) $CI_{95\%}$	ChiSquare	*p*-value
			Guards to Centers		
Intercept	29.28 ± 4.43			43.71	<0.0001*
totJUMP	0.00033 ± 0.000071	1.00033	(1.000191, 1.000469)	21.67	<0.0001*
totMECH	−0.00069 ± 0.00062	0.99931	(0.998097, 1.000525)	1.23	0.27
totDEC	−0.013 ± 0.0067	0.98708	(0.974206, 1.000132)	3.99	<0.05*
totACC	0.0028 ± 0.0045	1.00280	(0.993998, 1.011688)	0.37	0.54
avgSPD	−1.24 ± 2.44	0.28938	(0.002424, 34.549739)	0.26	0.61
maxSPD	−4.23 ± 0.69	0.01455	(0.003764, 0.056270)	37.34	<0.0001*
			Guards to Forwards		
Intercept	16.56 ± 3.43			23.34	<0.0001*
totJUMP	0.0000016 ± 0.000051	1.00000	(0.999902, 1.000102)	0.00	0.98
totMECH	−0.0026 ± 0.00065	0.99740	(0.996133, 0.998675)	15.56	<0.0001*
totDEC	0.020 ± 0.0049	1.02020	(1.010450, 1.030047)	16.48	<0.0001*
totACC	−0.0044 ± 0.0033	0.99561	(0.989191, 1.002070)	1.74	0.19
avgSPD	0.72 ± 2.04	2.05443	(0.037689, 111.988927)	0.12	0.73
maxSPD	−2.64 ± 0.52	0.07136	(0.025753, 0.197740)	25.44	<0.0001*

SE, standard error; Exp(β), exponentiation of the β coefficient; Exp(β)$CI_{95\%}$, 95% confidence intervals; total mechanical load, totMECH; jump load, totJUMP; accelerations, totACC; decelerations, totDEC; average speed, avgSPD; maximum speed, maxSPD.

*The estimates are the log odds of moving from baseline (Guards) to either Centers or Forwards. Ex. For every increase in totJUMP the odds of being predicted as a Center increase since the estimate is positive. However, every unit increase in totDEC and maxSPD lead to a lower likelihood of being predicted as Centers from Guards. *Denotes statistical significance at $p < 0.05$.*

TABLE 2 | A confusion matrix from a multinomial logistic regression on external load variables.

	Actual N	Predicted count		
Position		**Centers**	**Forwards**	**Guards**
Centers	64	53	9	2
Forwards	75	13	41	21
Guards	82	3	21	58

arbitrary units) than Guards ($p < 0.01$; near medium effect size) but there were no differences between Centers and Forwards or Forwards and Guards (small effect sizes). A summary table of the results from the *post-hoc* analysis is presented in **Table 4**.

DISCUSSION

The specific aims of the present study were initially to utilize PCA to simplify external load in collegiate basketball athletes. From there, the objective was to utilize the PCA results to ascertain whether key external load metrics were sensitive to varying POS demands during competition. By reducing the number of dimensions in large datasets, as often experienced in high performance environments, staff can focus on a small collection of variables for individualized daily athlete monitoring. Undoubtedly, this is a preferred framework in comparison to sifting through hundreds of variables after each session, as the latter is far too cumbersome when trying to make routine, data-driven decisions and/or automate portions of the daily monitoring analysis (Rojas-Valverde et al., 2020). Subsequently, performance staff and sport coaches are better able to adjust training designs and game strategies for desirable performance

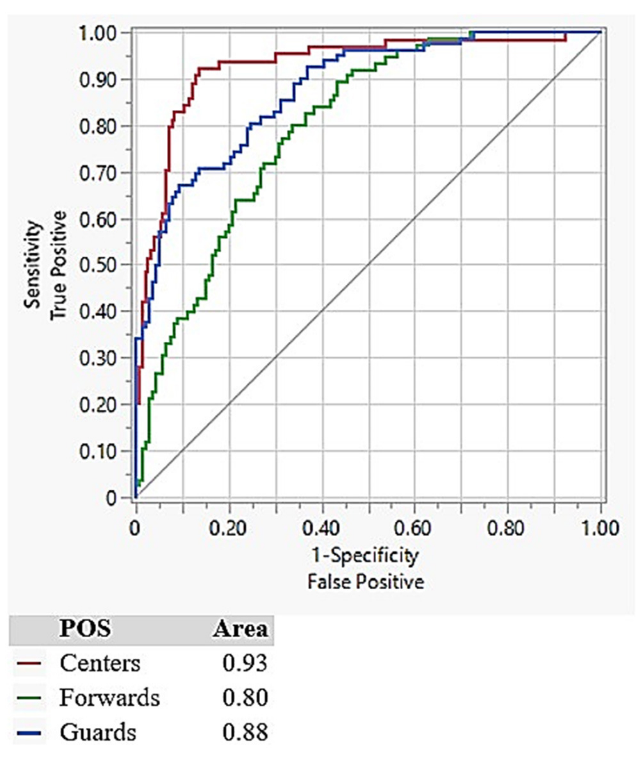

FIGURE 3 | Receiver operating characteristic curves for each of the athlete position groups.

TABLE 3 | Primary external load variables for Centers (n = 64), Forwards (n = 75), Guards (n = 85).

Variable	POS	Mean ± SD	SE Mean	$CI_{95\%}$
maxSPD (m/s)	Centers	6.23 ± 0.33	0.04	(6.14, 6.31)
	Forwards	6.63 ± 0.52	0.06	(6.51, 6.75)
	Guards	7.04 ± 0.39	1.04	(6.95, 7.12)
totJUMP (J)	Centers	14009.34 ± 6017.65	752.21	(12506.17, 15512.50)
	Forwards	11960.21 ± 4324.49	499.35	(10965.24, 12955.19)
	Guards	10753.27 ± 7249.65	800.59	(9160.34, 12346.19)
totDEC (count)	Centers	307.95 ± 87.27	10.91	(286.15, 329.75)
	Forwards	397.04 ± 106.45	12.29	(372.55, 421.53)
	Guards	362.32 ± 126.38	13.96	(334.55, 390.09)
totMECH (au)	Centers	1853.31 ± 814.06	101.76	(1649.97, 2056.66)
	Forwards	1907.11 ± 480.79	55.52	(1796.49, 2017.73)
	Guards	2034.63 ± 848.26	93.67	(1848.29, 2221.06)

POS, position; SD, standard deviation; SE Mean, standard error mean; $CI_{95\%}$, 95% confidence intervals; totJUMP, total jump load; totDEC, decelerations; maxSPD, maximum speed.

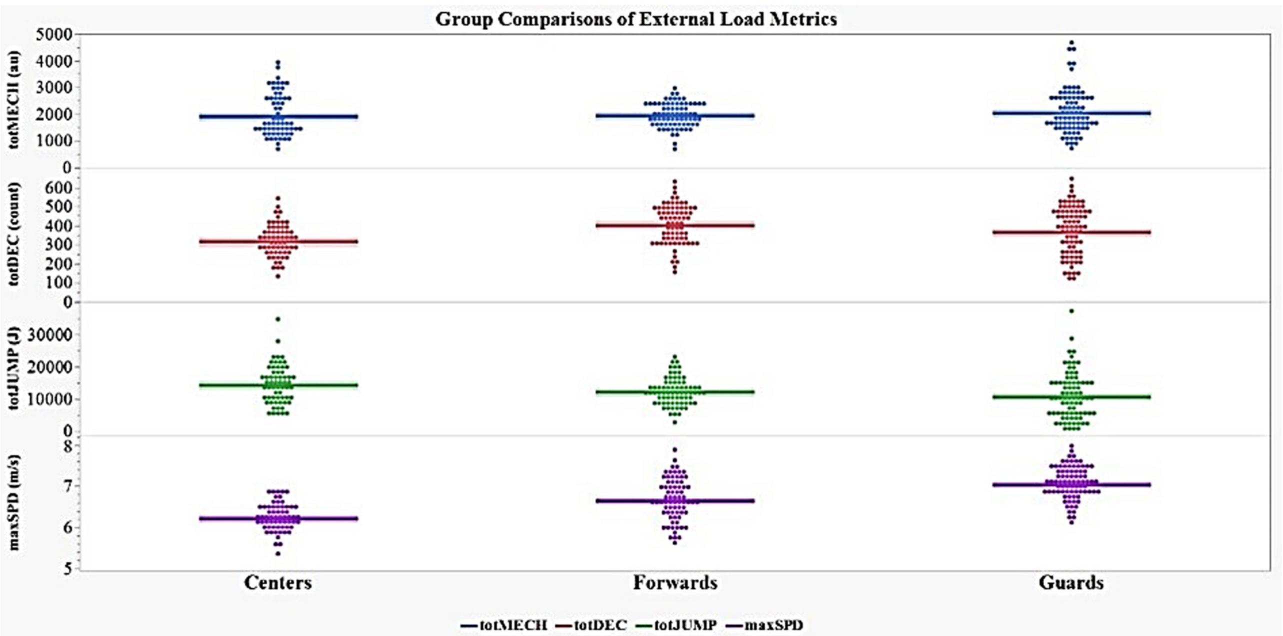

FIGURE 4 | Group comparisons of external load variables by player position. maxSPD, maximum speed; totDEC, total decelerations; totJUMP, total jump load.

enhancements that are based on quantitative insights. The present study utilized PCA to reduce the dimensions of external load data collected during collegiate basketball competitions, which simplified the dataset to two factors that helped differentiate player POS. In sport, coaches and practitioners often apply the approach of training specificity to their programming, with the primary goal being to sufficiently prepare athletes for the physical and psychological demands of competition (Schelling and Torres-Ronda, 2016). As such, for training to be as specific as possible, one must first consider the demands for which they are preparing for, which is obtained through analyses of different competition scenarios (i.e., competition levels, across seasons, sports, genders). Then, coaches and practitioners may work backwards as they begin to develop micro-, meso-, and macro-cycle periodization plans based upon competition demands to subsequently augment recovery and performance while mitigating injury and burnout risk (Schelling and Torres-Ronda, 2016; Cunanan et al., 2018; Stone et al., 2021). The PCA (and follow-up analyses) contained herein follows this train-of-thought as discernible differences between POS in basketball athletes were recognized using only a few of the most pertinent variables that were sensitive to variations in competition demands.

The totDEC possessed the largest loading in the first factor, which is similar to previous findings from PCA on international professional-level basketball athletes' external load data (Svilar et al., 2018). Although the aforementioned study conducted separate PCAs for each POS group and only focused on the

TABLE 4 | Tukey's HSD *post-hoc* ordered differences pairwise comparisons for the external load demands of different player positions.

Variable	Group 1	Group 2	Difference ± SE	$CI_{95\%}$	*p*-value	Cohen's d
maxSPD	Guards	Centers	0.81 ± 0.07	(0.65, 0.98)*	<0.0001*	2.22
	Guards	Forwards	0.41 ± 0.07	(0.25, 0.57)*	<0.0001*	0.90
	Forwards	Centers	0.40 ± 0.07	(0.23, 0.57)*	<0.0001*	0.90
totDEC	Forwards	Centers	89.09 ± 18.63	(45.13, 133.04)*	<0.0001*	0.91
	Guards	Centers	54.36 ± 18.26	(11.28, 97.45)*	<0.01*	0.49
	Forwards	Guards	34.72 ± 17.49	(−6.55, 75.99)	0.12	0.30
totJUMP	Centers	Guards	3256.07 ± 1005.49	(883.21, 5628.93)*	<0.01*	0.48
	Centers	Forwards	2049.12 ± 1025.86	(-371.79, 4470.04)	0.12	0.40
	Forwards	Guards	1206.95 ± 963.19	(−1066.08, 3479.97)	0.42	0.20

**Denotes statistical significance at $p < 0.01$; POS, position; SD, standard deviation; SE Mean, standard error mean; $CI_{95\%}$, 95% confidence intervals; totJUMP, total jump load; totDEC, decelerations; maxSPD, maximum speed.*

load demands of in-season training, not competitions, total decelerations were revealed as one of the most important metrics for each POS. These similarities in findings likely suggest that a large amount of braking motor actions occur in response to the majority of movements performed during basketball. Examples include high-intensity bursts of acceleration and changes of direction, as well as rapidly altering pacing strategies, such as when a ball handler is attempting to deceive and surpass a defender (Schelling and Torres-Ronda, 2016). The high volume of decelerations may become difficult to manage as high volumes of these eccentric actions typically elicit skeletal muscle damage (Howatson and Milak, 2009). Resultantly, neuromuscular functioning may be impaired (if not properly managed), so close monitoring of daily fluctuations in such movements is crucial to ensuring desirable training adaptations are achieved rather than overtraining. Based on the repeated bout effect, athletes may better prepare for these volumes of decelerations during basketball competition by slowly progressing training strategies that optimize eccentric loading (i.e., greater eccentric velocities and power with lower exercise induced muscle damage) (Merrigan and Jones, 2021), as well as the elastic properties that maximize the utilization of the stretch-shortening (Gual et al., 2016; Schelling and Torres-Ronda, 2016).

Of course, a comprehensive training regimen for basketball athletes extends well-beyond the sole purpose of enhancing declarative ability. High performance in basketball necessitates high capacities of executive function and psychomotor performance, muscular strength and endurance, range of motion, and, more specifically, sprinting, changing of directions, pace (i.e., accelerating and decelerating), and jumping (Schelling and Torres-Ronda, 2016). According to our findings and others, these demands likely differ per player POS (due to the individual roles/responsibilities of each athlete and POS group), thereby suggesting that training programs should be tailored to each POS and individualized to each athlete (Svilar et al., 2018). For example, Guards performed over 50 more decelerations on average during competition and reached significantly faster maximal speeds in comparison to Centers, while Centers generated significantly higher jump loads than Guards (over 3,000 J; **Table 4**). Centers are mainly tasked with playing around the rim on offense and defense (i.e., close-range shooting, rebounding, rim protecting) whereas Guards play around the perimeter (i.e., mid- and long-range shooting, on-ball defending). Therefore, it is conceivable that Centers, who are inherently larger bodied individuals than Guards, are doing more straight line running from rim-to-rim with a large proportion of their actions ending with a high-intensity jump; while Guards are more likely to engage in much more accelerations and decelerations as they navigate a larger area of the court at much faster speeds. Meanwhile, forwards are not as easy to dissociate, as they typically perform hybrid roles between Guards and Centers. Often, these athletes are similar in stature to Centers but similar in playing style to Guards. Indeed, the present multinomial logistic regression predicted player POS using the PCA variables with remarkable success, except for assigning Forwards to the correct group. More specifically, Forwards were wrongfully labeled as Guards more than 25% of the time and as Centers nearly 20% of the time (**Table 4**). Moreover, other factors beyond just POS influence training and competition demands and were omitted from the present study for sake of brevity, such as travel and home vs. away vs. neutral site competitions, the quality of an opponent, and player statuses/roles (Fowler et al., 2017; Staunton et al., 2018; Fox et al., 2019, 2021). Future investigations and practitioners aiming to implement similar analysis strategies into their practices should consider these factors (and more) as they begin structuring to their athlete monitoring framework.

In attempt to improve the sample size, an entire season of data were examined in the PCA to increase intraindividual variations in external loads. To further remedy this concern, future research should consider longitudinal studies that venture beyond a single season. This will provide a greater understanding of the external load demands during competition, particularly as it relates to seasonal changes (or perhaps a lack thereof). Moreover, to improve interindividual variance (between player variance), collaborative efforts are encouraged that will allow further investigation into differences across positions, competitive playing levels, and coaching styles. These types of efforts will assist in remedying much of the challenge in sport science, basketball particularly in this case, in which sample sizing might be inherently limited. In the present study, one limitation was the partitioning of players into three POS groups as the sample sizes for each group were then significantly reduced. Consequently, any subsequent predictions based on statistical modeling will only be that much more accurate as the sampling sizes increase. Additionally, the inclusion of an internal load measure (or multiple) overlayed with external load will greatly contribute to this body of knowledge (i.e., load demands during basketball competition and training).

PRACTICAL APPLICATIONS

Training programs for basketball athletes, especially at the micro- and meso-cycle level of periodization, should consider the varying external load demands during competition on individual athletes because it is likely that the demands differ based on player roles (e.g., POS). Resultantly, the accumulated fatigue from competition demands may differ across POS and warrant individualized recovery and training load modifications throughout the season. Meanwhile, the preparation for the season may also be dependent upon the player roles to ensure each athlete is physiologically equipped to endure the high volumes of decelerations and explosive vertical jumping capabilities, as well as maximal speeds of NCAA DI basketball competitions. These data provide a detailed framework that may help coaches better understand the demands of a collegiate basketball season (e.g., positional differences, physiological demands throughout a season, etc.) and, for those with access to player tracking technology, presents a useful strategy for handling player tracking data.

CONCLUSIONS

The PCA was effective at (1) reducing the number of dimensions in a large, longitudinal, team-sport dataset and (2) identifying external load variables that are sensitive to differences in POS demands during basketball competition. A culmination of summated decelerations, accelerations, jumping and mechanical loads, as well as average and maximal speeds possessed large loadings in the first two components of the PCA (≥ 70). Further analysis revealed that totDEC, totMECH, totJUMP, and maxSPD were the most sensitive to differences in POS external load demands during competition. Therefore, it is recommended to focus on these variables to characterize competition demands, especially for POS groups in DI Power 5 basketball athletes.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by West Virginia University Institutional Review Board. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

JS, JM, JR, RB, GC, WH, HS, SG, and JH: conceptualization, writing—original draft, writing—review, and editing. JS and JR: data curation and formal analysis. SG and JH: funding acquisition. JS, JM, JR, RB, GC, SG, and JH: investigation. JS, JR, RB, GC, WH, SG, and JH: methodology. JS, SG, and JH: project administration and resources. JS, RB, and GC: software. JS, RB, SG, and JH: supervision. JS and RB: validation. JS, JM, JR, and JH: visualization. All authors contributed to the article and approved the submitted version.

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Performance Differences in Male Youth Basketball Players According to Selection Status and Playing Position: An Evaluation of the Basketball Learning and Performance Assessment Instrument

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The Basketball Learning and Performance Assessment Instrument (BALPAI) has been initially developed and evaluated to assess the performance of students or youth basketball players on the entry level. As it is currently the only observational instrument that allows an overall assessment of players' in-game performance, it might represent a valuable tool for talent identification and development purposes. To investigate this potential field of application, this study aimed to evaluate the BALPAI regarding reliability and diagnostic validity when assessing youth basketball players within a competitive setting. The study sample comprised $N = 54$ male youth players ($M_{age} = 14.36 \pm 0.33$ years) of five regional selection teams (Point Guards, PG: $n = 19$; Shooting Guards and Small Forwards, SG/SF: $n = 21$; and Power Forwards and Centers, PF/C: $n = 14$) that competed at the annual U15 national selection tournament of the German Basketball Federation ($n = 24$ selected; $n = 30$ non-selected). A total of 1997 ball-bound actions from five games were evaluated with BALPAI. The inter-rater reliability was assessed for technical execution, decision making, and final efficacy. The diagnostic validity of the instrument was examined via mean group comparisons of the players' offensive game involvement and performance regarding both selection-dependent and position-dependent differences. The inter-rater reliability was confirmed for all performance-related components ($\kappa_{adj} \geq 0.51$) while diagnostic validity was established only for specific the BALPAI variables. The selection-dependent analysis demonstrated higher offensive game involvement of selected players in all categories ($p < 0.05$, $0.27 \leq \Phi \leq 0.40$) as well as better performance in shooting and receiving ($p < 0.05$, $0.23 \leq \Phi \leq 0.24$). Within the positional groups, the strongest effects were demonstrated among PG ($p < 0.05$, $0.46 \leq \Phi \leq 0.60$). The position-dependent analysis revealed that PG are more involved in total ball-bound actions ($p < 0.05$; $0.34 \leq \Phi \leq 0.53$), passing ($p < 0.001$; $0.55 \leq \Phi \leq 0.67$), and dribbling ($p < 0.05$, $0.45 \leq \Phi \leq 0.69$) compared to players in other positions. Further differences between players according to selection status and playing position were not detected. The results of this evaluation indicate that the instrument, in its current form, is not yet applicable in competitive youth basketball. The findings highlight the importance of optimizing BALPAI for reliable and valid performance assessments in this context. Future studies should investigate the application of stricter and position-specific criteria to use the observational tool for talent identification and development purposes.

Keywords: team sports, talent identification and development, tactical skills, technical skills, diagnostic validity, reliability, systematic game observation

INTRODUCTION

The search for valid performance indicators in team sports such as basketball has been a focus of research and practice (Sampaio et al., 2013; Ibáñez and Feu, 2021). Multiple factors influence a player's performance such as anthropometric, physiological, psychological, or sociological aspects as well as technical and tactical skills (Rogers et al., 2021). However, players differ regarding these factors, as players are assigned with different in-game tasks in their respective playing positions, which will be illustrated in the following by their main tasks in offense (Trninić and Dizdar, 2000; Trninić et al., 2000). In general, basketball players are categorized into five playing positions (i.e., Point Guard, Shooting Guard, Small Forward, Power Forward, and Center). *Point Guards* direct their teams' offenses by creating and utilizing advantages through their outstanding passing and dribbling skills. *Shooting Guards* and *Small Forwards* are usually the best scorers on a team and, thus, require variable finishing skills. Additionally, Small Forwards are also capable of scoring inside and creating second-chance opportunities. *Power Forwards* and *Centers* help other players to get open by screening for them and they rebound offensively. Players in both positions operate around the basket, although Power Forwards are also capable of attacking from distance. Because of these different in-game responsibilities players' anthropometry and physiology also vary between playing positions (Stojanović et al., 2018; Russell et al., 2021). For example, Centers are taller and heavier than Forwards or Guards enabling them to sustain contact while attacking close to the basket (e.g., Cormery et al., 2008). Although the traditional classification has been challenged as the game has evolved through rule changes and alternative classifications have been proposed (e.g., Bianchi et al., 2017; Rangel et al., 2019), it still serves as a reference point for the identification and development of youth basketball players (de la Rubia Riaza et al., 2020).

Talent identification in basketball is a complex process considering the multidimensional nature of this team sport. Coaches or scouts are usually assigned with the challenging task to identify talented players at an early stage of their athletic development and to decide on their inclusion in the respective talent development system (Johnston and Baker, 2020). To support these stakeholders in making such important decisions, it is common to assess the current performance of potential recruits by using specific testing procedures. Therefore, typically, the players' physical and physiological skills are assessed through objective tests (Johnston et al., 2018; for a review of validated basketball-specific physical field tests see Gál-Pottyondy et al., 2021). In contrast, technical and tactical in-game performance is difficult to capture through such tests (Koopmann et al., 2020) and is thus mainly evaluated based on the "coach's eye"—an intuitive, subjective, experience-based, and holistic evaluation (Lath et al., 2021). For example, the National Basketball Association (NBA) employs these approaches at the annual draft combine to support the teams evaluating prospective players (Teramoto et al., 2018; Cui et al., 2019; García-Rubio et al., 2020). The combine consists of a series of measurements of anthropometric and physiological parameters as well as an assessment of the players' shooting skills. In addition, scrimmages are organized where the coaches subjectively evaluate the players regarding their technical and tactical skills. To date, little has been published about this common way of players' in-game evaluation and the possibilities to support such practice with objective data (Roberts et al., 2019; Höner et al., 2021). Complementary data collection could help to standardize this process by confirming coaches' subjective impressions or, conversely, to improve the accuracy of talent identification systems by contradicting them (Baghurst et al., 2021; Johnston et al., 2021).

For match analysis in basketball, four methods of game observation are distinguished—*subjective impression analysis*, *scouting*, *qualitative game observation*, and *systematic game observation* (König and Heckel, 2021). Among these, systematic game observation is the only method that acquires quantitative data applying specific criteria, while the others rely mainly on qualitative data. At every basketball game on international level, systematic game observation is used to gather game-related statistics (e.g., points, assists, and turnovers) which are therefore conveniently utilized to inform selection decisions (Butterworth et al., 2013). Extensive research on such data revealed performance indicators that discriminate between basketball teams (e.g., Lorenzo et al., 2010; García et al., 2014). For example, differences between winning and losing teams can be identified based on field goals and defensive rebounds (García et al., 2013). Further, differences between senior players depending on their playing position were demonstrated in such performance data, although they have been studied less frequently (Sampaio et al., 2006; Choi et al., 2015; Escudero-Tena et al., 2021).

Game-related statistics are also recorded in elite youth basketball and recent studies analyzed the data for position-dependent differences. García-Rubio et al. (2019) examined performance differences of Point Guards, Shooting Guards, and Centers competing in the Adidas Next Generation Tournament (ANGT, U18). The results show that Point Guards recorded more assists than both Shooting Guards and Centers. However, Shooting Guards registered more rebounds than Point Guards and more 3-point shot attempts than Centers. Centers had more 2-point shot attempts, rebounds, and blocks than Point Guards, whereas they were not better than Shooting Guards in any of the categories examined. Kokanauskas et al. (2021) identified multiple position-dependent differences in the game-related statistics of the U16, U18, and U20 European youth championships held in 2016/17, 2017/18, and 2018/19. For example, Point Guards were found to have more minutes, assists, turnovers, and steals compared to other playing positions. Further, such performance data have been shown to predict future success of youth basketball players in adulthood (Berri et al., 2011; Rösch et al., 2021), whereas selection-dependent differences in game-related statistics remain to be analyzed in basketball-related research. However, within such data, only the efficacy of a play action (i.e., action specific to the game of basketball) is considered, while other performance-related components like decision making or technical execution are excluded. For example, a youth player's shooting performance is thereby only evaluated by made or missed baskets, disregarding that he might also make good shooting decisions and execute them well technically. Thus, these components (i.e., decision making and technical execution) provide valuable information for selection decisions or the development of individual training recommendations. Moreover, they could contribute to an even more reliable prediction of future success (Schorer et al., 2020).

Instead of solely recording the output of play actions (i.e., game-related statistics) during systematic game observations, observational tools may be used that focus on the process of executing play actions while considering these components. The Game Performance Assessment Instrument (GPAI; Oslin et al., 1998) and the Team Sport Assessment Procedure (TSAP; Gréhaigne et al., 1997) are the most commonly used instruments for the assessment of tactical game performance in all team sports (Arias and Castejón, 2012; Barquero-Ruiz et al., 2020). Based on these instruments, specific tools have been developed for various team sports. For basketball, the Basketball Offensive Game Performance Instrument (BOGPI; Chen et al., 2013) was developed to evaluate the offensive game performance competency of preservice teachers in basketball. It assesses a player's offensive game performance while dribbling, passing, and shooting with respect to technical skill execution, decision making, and support. However, the BOGPI is not validated for youth basketball and only assesses few offensive actions using a binary rating scale without evaluating the efficacy of a play action. The Individual Technical-Tactical Basketball Performance Assessment Instrument (IAD-BB; Folle et al., 2014) analyzes offensive and defensive actions of players in formative developmental stages regarding adaptation, decision making, and efficacy. Hatem et al. (2020) employed this instrument in Brazilian youth basketball and were able to identify position-dependent differences between Guards, Forwards, and Centers in the ball-bound actions of shooting, dribbling, and receiving. However, the IAD-BB does not consider the technical execution of a play action and is currently only available in Portuguese. The Basketball Learning and Performance Assessment Instrument (BALPAI; Ibanez et al., 2019) is the latest observational tool and has been initially developed and evaluated to assess the performance of students or youth basketball players on the entry level in small-sided basketball games (i.e., 3 vs. 3). It allows the assessment of players' participation in offensive and defensive play actions, as well as an analysis of their respective performance in these actions according to decision making, technical execution, and final efficacy. The instrument has been utilized to demonstrate the progress of students in basketball lessons applying different teaching methodologies in primary education in Spain (González-Espinosa et al., 2017, 2019) and an adapted version of the BALPAI was successfully employed in soccer lessons (García-Ceberino et al., 2020). The BALPAI advances with respect to the differentiated evaluation of play actions (e.g., shooting or passing) on a three-point scale according to specific criteria. As it is currently the only observational instrument that allows an overall assessment of players' in-game performance, it might represent a valuable tool for talent identification and development purposes in competitive youth basketball. However, it is unknown so far whether the instrument can be applied in such a context as it was not designed and validated for this purpose.

The aim of the present study was to evaluate the BALPAI when applied to youth basketball players within a competitive national selection tournament. This was pursued by two objectives: *First*, the inter-rater reliability was assessed for all performance-related components of the instrument. *Second*, the diagnostic validity of the observational tool was examined via selection-dependent and position-dependent differences in BALPAI variables. In talent identification research, it is common to examine differences in performance variables between more and less skilled athletes, assuming that usually higher performing athletes are selected for talent development purposes (Johnston et al., 2018). Thus, it was expected that selected players perform better than non-selected players regarding the investigated BALPAI variables. More specifically, in a first step, diagnostic validity was evaluated with respect to selection-dependent differences by testing the following hypotheses:

> *H1a*: Selected players outperform non-selected players with respect to offensive game involvement and performance in shooting, passing, dribbling, receiving, and total ball-bound actions.
>
> *H1b*: *Within* each positional group, selected players outperform non-selected players regarding offensive game involvement and performance in shooting, passing, dribbling, receiving, and total ball-bound actions.

Moreover, the playing positions differ regarding their specific requirements (Trninić and Dizdar, 2000; Trninić et al., 2000). Based on these requirements, it was expected that players in certain playing positions would perform better than those in other positions regarding specific BALPAI variables. Thus, in a second step, the diagnostic validity was examined by analyzing position-dependent differences. For this purpose, the following hypotheses were derived from the positional requirements:

> *H2a*: Point Guards are more involved in passing, dribbling, and total ball-bound actions than both Shooting Guards and Small Forwards as well as Power Forwards and Centers.
> *H2b*: Point Guards perform better in passing and dribbling actions than both Shooting Guards and Small Forwards as well as Power Forwards and Centers.
> *H2c*: Shooting Guards and Small Forwards demonstrate higher offensive game involvement and performance in shooting actions compared to Point Guards as well as Power Forwards and Centers.

Additionally, based on the evaluation of the BALPAI in terms of reliability and diagnostic validity, implications for the optimization of the observational instrument were derived.

MATERIALS AND METHODS

Sample

The present study was conducted at the annual U15 national selection tournament of the German Basketball Federation (Deutscher Basketball Bund, DBB). This event represents the first stage of talent selection at the national level in Germany and involved eight regional selection teams with a total of 96 players. Each team played three games in this tournament. In all games, the official rules of the International Basketball Federation (FIBA) were applied with exception of a shorter total playing time (i.e., two 15-min halftimes). The coaches of the youth national teams observed these games and selected 40 players for further talent development purposes.

Five regional selection teams were chosen for this study according to the final standings of the tournament with two higher-ranked teams, two lower-ranked teams, and one team in between being considered. Thus, a balanced choice was maintained regarding the performance level of the teams. The investigated players were members of these regional selection teams and they also competed in the highest German U16 league (Jugend Basketball Bundesliga, JBBL).

Out of 96 male youth basketball players involved in the tournament, $N = 54$ players ($M_{age} = 14.36 \pm 0.33$ years) comprise the sample of the present study. From these players, $n = 24$ ($M_{age} = 14.26 \pm 0.39$) were selected by the federation while $n = 30$ ($M_{age} = 14.43 \pm 0.26$) were not. The proportion of selected players in the sample (44.44%) was comparable to that in the tournament (41.67%). No significant difference in chronological age was detected when comparing selected and non-selected players, $t(52) = 1.92$, $p = 0.06$. Consequently, influences related to chronological age (e.g., relative age effect; de la Rubia Riaza et al., 2020) were not further considered in this study. The number of players at each playing position both in total and separated by their selection status is displayed in **Table 1**.

TABLE 1 | Total number of players at each playing position separated by selection status.

Playing position	Total ($N = 54$)	Selected ($n = 24$)	Non-selected ($n = 30$)
		n	
Point Guard	19	9	10
Shooting Guard	10	5	5
Small Forward	11	4	7
Power Forward	11	4	7
Center	3	2	1

For analyses purposes, players were assigned to three positional groups (PG: $n = 19$; SG/SF: $n = 21$; and PF/C: $n = 14$) based on the similarity of their in-game responsibilities (Trninić and Dizdar, 2000; Trninić et al., 2000).

Procedures

One out of three games from each of the sampled teams was randomly selected for analysis in this study. Overall, a total of 1997 ball-bound actions from five games were evaluated with the BALPAI. All games were retrospectively analyzed by one coder. To evaluate the coding procedure (Objective 1), a subset of one game with a total of 498 ball-bound actions (24.94% of all actions) was additionally rated by a second independent coder. The first coder who rated all games was 28 years old, a licensed basketball coach and an experienced basketball player for 8 years. The second coder was 25 years old, completed a basic and major subject in basketball during his studies and played recreational basketball. In line with notational analyses in other team sports (e.g., Muñoz et al., 2018), both coders were trained in the use of the instrument: Initially, they were provided with general information about the study's objectives and design. Subsequently, the coders were trained with video samples and exemplary ratings after they had been familiarized with the rating system and the assessment criteria. Afterward, both coders had to rate 15 min of a competitive basketball game that did not involve any of the players examined in the present study. Finally, the researchers and coders met to discuss questions and specific game situations where the coders disagreed with each other or rated comparable scenes differently themselves.

The games were filmed by the German Basketball Federation (Deutscher Basketball Bund, DBB) and publicly shared through an online platform (see **Supplementary Table 2**). The videos and team rosters were additionally provided to the researchers by the DBB. The selection status of the players (selected or non-selected), as well as the playing positions determined by the respective clubs (Point Guard, PG; Shooting Guard, SG; Small Forward, SF; Power Forward, PF; and Center, C), was obtained through an online search (Deutscher Basketball Bund, 2020; NBBL gGmbH, 2020). All data processed in this study were publicly available. The analyses were based solely on secondary data, and the aggregated values did not allow conclusions to be drawn about individuals. The university's ethics department and the DBB approved the implementation of this study.

Measures

The games were analyzed using the Basketball Learning and Performance Assessment Instrument (Ibanez et al., 2019). It is designed to assess both offensive and defensive play actions, but it also allows to focus only on certain items (Ibanez et al., 2019, p. 7). Thus, only ball-bound actions in offense performed in the frontcourt were considered in this study (i.e., shooting, dribbling, passing, and receiving). For these actions, both the performance of the players and their participation were assessed. Performance was evaluated with respect to three components (i.e., decision making, technical execution, and final efficacy). Within these components, each play action was rated according to its adequacy (i.e., adequate = 3 points, neutral = 2 points, and inadequate = 1 point). The ratings were conducted according to the instrument's assessment criteria, which are exemplified by the evaluation of a player's decision making in shooting (see Annex 1; Ibanez et al., 2019). Making a shot was rated (a) adequate when there was no clear defensive pressure and when the condition to shoot was more favorable than that of the teammates, (b) neutral when there was clear defensive pressure or there was a teammate in a more favorable condition to shoot, and (c) inadequate when there was clear defensive pressure and there was a teammate in a more favorable condition to shoot. Based on the specific ratings for each play action, three performance indices were computed with respect to the performance-related components (PI_{DM}, PI_{TE}, and PI_{FE}) and additionally compiled in a Total Performance Index (PI):

$$\textbf{Performance Index for Decision – Making}\left(PI_{DM}\right) = \frac{\text{Sum of points for decision-making}}{\text{Total ball-bound actions performed by a player in offense}}$$

$$\textbf{Performance Index for Technical Execution}\left(PI_{TE}\right) = \frac{\text{Sum of points for technical execution}}{\text{Total ball-bound actions performed by a player in offense}}$$

$$\textbf{Performance Index for Final Efficacy}\left(PI_{FE}\right) = \frac{\text{Sum of points for final efficacy}}{\text{Total ball-bound actions performed by a player in offense}}$$

$$\textbf{Total Performance Index}\left(PI\right) = \frac{PI_{DM} + PI_{TE} + PI_{FE}}{3}$$

Moreover, a score for match participation is usually calculated that reflects the involvement of a player in both offensive and defensive actions (Ibanez et al., 2019). Considering that only offensive actions were evaluated in this study, Offensive Game Involvement (OGI) was used as an alternative score. Due to differences in playing style, the sampled teams varied regarding the total number of ball-bound actions (see **Supplementary Table 1**). Therefore, to compare the involvement of the players in the game regardless of their teams' playing style, the data for each player were normalized with respect to the total ball-bound actions of each team:

$$\textbf{Offensive Game Involvement}\left(OGI, \%\right) = \frac{\text{Total ball-bound actions performed by a player in offense}}{\text{Total ball-bound actions performed by his team in offense}} \times 100$$

The performance scores (i.e., PI, PI_{DM}, PI_{TE}, and PI_{FE}), as well as the game involvement (i.e., OGI), were computed and analyzed for all ball-bound actions accumulated, but also with respect to each category (i.e., shooting, dribbling, passing, and receiving).

Statistical Analysis

The data were analyzed using IBM SPSS Version 27.0 (IBM Corporation, Armonk, NY, United States). Additionally, a web-based PABAK-OS calculator was utilized for the reliability analyses (Vannest et al., 2016). The alpha level for significance was set at $p < 0.05$.

With respect to the first objective, the inter-rater reliability was assessed using Cohen's weighted kappa κ_w (Cohen, 1968). However, imbalances were detected in the marginal distributions of the observed ratings that could lead to possible prevalence problems (Hallgren, 2012). Therefore, the prevalence-adjusted bias-adjusted kappa κ_{adj} (Byrt et al., 1993) adapted for ordinal scaled data (PABAK-OS) was additionally computed. Besides, the total percentages of agreement were reported. All kappa values were interpreted according to Landis and Koch (1977).

Regarding the second objective, the investigation of the distributional properties revealed that the distributions of the data deviated from the assumption of a normal distribution, with the exception of only four variables. Considering these assumptions and the small sample sizes of the respective groups, non-parametric analyses were conducted to examine the diagnostic validity of the BALPAI. As it was hypothesized that selected players are better than non-selected players with respect to the BALPAI variables, one-tailed Mann–Whitney *U*-tests were performed to examine selection-dependent differences overall (H1a) and within the positional groups (H2b). Kruskal–Wallis tests with *post-hoc* pairwise comparisons (Bonferroni adjusted Mann–Whitney *U*-tests) were conducted to identify position-dependent differences. To evaluate the diagnostic validity of the BALPAI, one-tailed *post-hoc* tests were conducted for those group comparisons where hypotheses about position-dependent differences in offensive game involvement and performance could be derived in advance (H2a–H2c). However, for several comparisons, no hypotheses could be established based on the respective positional requirements. Although not used for diagnostic validation, two-tailed *post-hoc* tests were performed for these comparisons to provide a comprehensive analysis of position-dependent differences. Additionally, effect sizes ω and Φ were calculated and classified according to Cohen (1992).

RESULTS

Reliability (Objective 1)

With respect to the first objective, Cohen's weighted kappa indicated moderate agreement between the raters for decision making ($\kappa_w = 0.48$), fair agreement for technical execution ($\kappa_w = 0.39$), and almost perfect agreement for final efficacy ($\kappa_w = 0.81$). However, according to PABAK-OS, the inter-rater reliability for decision making ($\kappa_{adj} = 0.51$) was found to be moderate, while those for technical execution ($\kappa_{adj} = 0.86$) and final efficacy ($\kappa_{adj} = 0.87$) were almost perfect. The total percentages of agreement were 67.47% for decision making, 90.36% for technical execution, and 91.37% for final efficacy.

Diagnostic Validity (Objective 2)

Selection-Dependent Differences

Table 2 displays the descriptive statistics and effect sizes for the BALPAI variables separated by selection status and playing position.

With respect to selection-dependent differences (H1a), Mann–Whitney *U*-tests demonstrated higher offensive game involvement in all categories for selected players compared to non-selected players ($192.50 \le U \le 244.50$, $p < 0.05$). Hereby, medium effect sizes were found in all categories ($0.34 \le \Phi \le 0.40$) except for involvement in passing, where a small effect size was detected ($\Phi = 0.27$). Moreover, selected players showed a better shooting performance ($U = 246.00$, $p < 0.05$) and outperformed non-selected players in receiving and specifically in decision making regarding this action ($260.00 \le U \le 262.50$, $p < 0.05$). Small effect sizes were revealed for all these performance-related differences ($0.23 \le \Phi \le 0.24$). No performance advantages were detected for selected players in passing ($U \le 346.00$, $p \ge 0.08$), dribbling ($U \le 318.00$, $p \ge 0.07$), or total ball-bound actions ($U \le 336.50$, $p \ge 0.09$).

The results of the Mann–Whitney *U*-tests within the three positional groups (H1b) revealed that selected PG were significantly more involved in shooting ($U = 11.00$, $p < 0.01$), dribbling ($U = 18.50$, $p < 0.05$), and total ball-bound actions ($U = 18.00$, $p < 0.05$). Thereby, strong effect sizes were found in all categories ($0.50 \le \Phi \le 0.60$). Further, selected PG demonstrated a better shooting performance as well as a better decision making and final efficacy regarding this action ($19.50 \le U \ge 20.50$, $p < 0.05$) than non-selected players on this position. Medium effect sizes were found for all these performance-related differences ($0.46 \le \Phi \le 0.48$). Selected SG/SF were significantly more involved in passing ($U = 30.50$, $p < 0.05$) and receiving ($U = 27.50$, $p < 0.05$). Medium effect sizes were demonstrated for the differences in both categories ($0.36 \le \Phi \le 0.41$). Moreover, performance-related differences were found for dribbling ($U = 24.50$, $p < 0.05$) and overall game performance ($U = 21.00$, $p < 0.05$). Specifically, selected players showed a better decision making in passing ($U = 30.50$, $p < 0.05$), receiving ($U = 27.50$, $p < 0.05$), and total ball-bound actions ($U = 27.00$, $p < 0.05$) than non-selected players on these positions. Further, they demonstrated a better final dribbling efficacy ($U = 30.50$, $p < 0.05$). A strong effect size was revealed for the difference in overall game performance ($\Phi = 0.51$), while medium effect sizes were found for the other performance-related differences among players on these positions ($0.37 \le \Phi \le 0.46$). Selected PF/C displayed a higher involvement in dribbling actions with a medium effect size ($U = 11.00$, $p < 0.05$, $\Phi = 0.45$). No further expected differences between players within the respective positional groups were identified.

Position-Dependent Differences

Table 3 displays the descriptive statistics and multiple group comparisons for the BALPAI variables separated by playing position.

With respect to position-dependent differences, Kruskal–Wallis tests revealed significant differences between positional groups regarding the involvement in passing [$H(2) = 19.36$, $p < 0.001$], dribbling [$H(2) = 18.83$, $p < 0.001$], and total ball-bound actions [$H(2) = 10.36$, $p < 0.01$]. Hereby, strong effect sizes were demonstrated for the involvement in passing and dribbling ($0.59 \le \omega \le 0.60$), while a medium effect size was found for the involvement in total ball-bound actions ($\omega = 0.44$). The *post-hoc* analyses revealed that PG are significantly more involved in passing (all $p < 0.001$), dribbling (PG vs. SG/SF: $p < 0.05$; PG vs. PF/C: $p < 0.001$), and total ball-bound actions (all $p < 0.05$) compared to players in other positions (H2a). Thereby, the comparison of PG and SG/SF revealed a strong effect size for involvement in passing ($\Phi = 0.55$) as well as a medium effect size for involvement in dribbling ($\Phi = 0.45$) and total ball-bound actions ($\Phi = 0.34$). Strong effect sizes were found for these variables comparing PG and PF/C ($0.53 \le \Phi \le 0.69$).

However, Kruskal–Wallis tests identified no significant differences between positional groups for involvement in shooting [$H(2) = 0.18$, $p = 0.91$]. Moreover, no performance-related differences were found in passing [$H(2) \le 4.55$, $p \ge 0.80$], dribbling [$H(2) \le 2.51$, $p \ge 0.29$], or shooting [$H(2) \le 5.62$, $p \ge 0.06$]. Consequently, the *post-hoc* analyses did not confirm the expected performance advantages for PG in passing (PG vs. SG/SF: $p \ge 0.31$; PG vs. PF/C: $p \ge 0.18$) and dribbling (PG vs. SG/SF: $p \ge 0.58$; PG vs. PF/C: $p \ge 0.23$) when compared to SG/SF and PF/C (H2b). Likewise, no higher offensive game involvement in shooting was found for SG/SF (H2c; SG/SF vs. PG: $p = 0.29$; SG/SF vs. PF/C: $p = 0.96$). Moreover, no performance advantages regarding this action were found for SG/SF in comparison with PG ($p \ge 0.10$) or PF/C ($p \ge 0.25$), except for SG/SF outperforming PG in decision making with a medium effect size ($\Phi = 0.35$, $p < 0.05$).

DISCUSSION

The present study aimed to evaluate the applicability of the BALPAI in competitive youth basketball. It examines a highly selective sample within an ecologically valid setting and is among the first to analyze process-oriented performance data of competitive youth basketball players. The use of such data for talent identification purposes has only been sporadically studied across team sports (Schorer et al., 2020). Therefore, this study contributes to a research gap by evaluating a promising observational tool regarding the investigated objectives. The inter-rater reliability for all performance-related components was confirmed (Objective 1), whereas diagnostic validity was established only for specific

TABLE 2 | Descriptive statistics and effect sizes for BALPAI variables separated by selection status and playing position.

BALPAI variables	Total			PG			SG/SF			PF/C		
	Selected ($n = 24$)	Non-selected ($n = 30$)		Selected ($n = 9$)	Non-selected ($n = 10$)		Selected[a] ($n = 9$)	Non-selected ($n = 12$)		Selected ($n = 6$)	Non-selected ($n = 8$)	
	$M \pm SD$		Φ	$M \pm SD$		Φ	$M \pm SD$		Φ	$M \pm SD$		Φ
All actions												
OGI (%)	10.64 ± 5.04	6.90 ± 3.63	0.37**	13.77 ± 4.83	8.96 ± 4.00	0.51*	9.70 ± 4.44	6.45 ± 3.15	0.33	7.37 ± 3.96	5.00 ± 2.81	0.24
PI (pts)	2.70 ± 0.09	2.67 ± 0.11	0.12	2.71 ± 0.08	2.73 ± 0.11	0.21	2.74 ± 0.07	2.66 ± 0.08	0.51*	2.62 ± 0.07	2.61 ± 0.12	0.09
PI_{DM}	2.55 ± 0.16	2.46 ± 0.22	0.19	2.58 ± 0.11	2.57 ± 0.20	0.15	2.61 ± 0.15	2.46 ± 0.20	0.42*	2.41 ± 0.15	2.33 ± 0.21	0.28
PI_{TE}	2.90 ± 0.09	2.89 ± 0.10	0.06	2.92 ± 0.05	2.92 ± 0.07	0.09	2.92 ± 0.05	2.87 ± 0.10	0.22	2.83 ± 0.15	2.86 ± 0.11	0.07
PI_{FE}	2.66 ± 0.12	2.66 ± 0.12	0.09	2.64 ± 0.13	2.68 ± 0.12	0.07	2.71 ± 0.12	2.66 ± 0.09	0.11	2.62 ± 0.07	2.64 ± 0.17	0.17
Shooting												
OGI (%)	11.69 ± 7.44	6.09 ± 4.55	0.40**	13.94 ± 8.38	5.02 ± 5.21	0.60**	10.87 ± 7.95	7.24 ± 4.82	0.25	9.54 ± 5.02	5.69 ± 3.24	0.35
PI (pts)	2.47 ± 0.23	2.36 ± 0.29	0.24*	2.44 ± 0.25	2.22 ± 0.28	0.48*	2.55 ± 0.14	2.44 ± 0.22	0.28	2.40 ± 0.31	2.40 ± 0.35	0.07
PI_{DM}	2.23 ± 0.33	2.05 ± 0.48	0.19	2.16 ± 0.41	1.83 ± 0.38	0.47*	2.36 ± 0.28	2.22 ± 0.53	0.08	2.16 ± 0.26	2.08 ± 0.47	0.00
PI_{TE}	2.86 ± 0.21	2.88 ± 0.23	0.11	2.85 ± 0.23	2.95 ± 0.11	0.27	2.94 ± 0.08	2.81 ± 0.29	0.23	2.77 ± 0.28	2.88 ± 0.23	0.33
PI_{FE}	2.31 ± 0.31	2.14 ± 0.56	0.19	2.31 ± 0.20	1.87 ± 0.69	0.46*	2.35 ± 0.36	2.28 ± 0.27	0.04	2.25 ± 0.41	2.25 ± 0.64	0.03
Passing												
OGI (%)	10.17 ± 5.56	7.33 ± 4.47	0.27*	14.06 ± 4.18	11.06 ± 4.86	0.35	9.09 ± 5.19	6.07 ± 2.61	0.36*	5.95 ± 4.54	4.58 ± 3.23	0.17
PI (pts)	2.79 ± 0.14	2.80 ± 0.17	0.13	2.82 ± 0.08	2.83 ± 0.13	0.25	2.84 ± 0.11	2.74 ± 0.19	0.31	2.66 ± 0.17	2.85 ± 0.18	0.54
PI_{DM}	2.85 ± 0.21	2.79 ± 0.21	0.20	2.89 ± 0.09	2.83 ± 0.15	0.19	2.90 ± 0.12	2.80 ± 0.15	0.37*	2.72 ± 0.38	2.73 ± 0.34	0.02
PI_{TE}	2.87 ± 0.14	2.83 ± 0.23	0.03	2.88 ± 0.12	2.89 ± 0.14	0.06	2.88 ± 0.12	2.72 ± 0.27	0.30	2.83 ± 0.21	2.94 ± 0.18	0.46
PI_{FE}	2.65 ± 0.26	2.78 ± 0.25	0.30	2.70 ± 0.18	2.79 ± 0.12	0.28	2.75 ± 0.27	2.70 ± 0.33	0.02	2.43 ± 0.24	2.88 ± 0.22	0.71
Dribbling												
OGI (%)	11.01 ± 6.65	6.65 ± 4.40	0.36**	16.22 ± 5.96	10.11 ± 4.70	0.50*	9.17 ± 5.66	6.09 ± 2.84	0.33	5.97 ± 3.18	3.15 ± 2.76	0.45*
PI (pts)	2.76 ± 0.12	2.70 ± 0.24	0.10	2.74 ± 0.11	2.74 ± 0.21	0.09	2.80 ± 0.08	2.71 ± 0.18	0.46*	2.74 ± 0.18	2.65 ± 0.36	0.07
PI_{DM}	2.77 ± 0.16	2.74 ± 0.36	0.13	2.75 ± 0.12	2.76 ± 0.37	0.33	2.80 ± 0.10	2.71 ± 0.35	0.02	2.76 ± 0.29	2.75 ± 0.39	0.06
PI_{TE}	2.91 ± 0.12	2.90 ± 0.20	0.11	2.94 ± 0.06	2.97 ± 0.11	0.18	2.96 ± 0.05	2.90 ± 0.15	0.18	2.79 ± 0.18	2.82 ± 0.31	0.29
PI_{FE}	2.61 ± 0.22	2.48 ± 0.41	0.20	2.53 ± 0.20	2.51 ± 0.26	0.15	2.65 ± 0.15	2.52 ± 0.26	0.37*	2.66 ± 0.34	2.37 ± 0.69	0.24
Receiving												
OGI (%)	10.30 ± 4.48	7.12 ± 3.82	0.34**	11.17 ± 4.18	7.78 ± 3.89	0.36	10.53 ± 4.56	6.64 ± 4.18	0.41*	8.66 ± 5.12	6.70 ± 3.53	0.09
PI (pts)	2.70 ± 0.13	2.63 ± 0.17	0.23*	2.72 ± 0.09	2.64 ± 0.16	0.32	2.73 ± 0.12	2.65 ± 0.19	0.24	2.63 ± 0.17	2.59 ± 0.17	0.09
PI_{DM}	2.24 ± 0.24	2.10 ± 0.29	0.24*	2.24 ± 0.19	2.15 ± 0.16	0.20	2.32 ± 0.24	2.09 ± 0.39	0.41*	2.12 ± 0.31	2.07 ± 0.26	0.05
PI_{TE}	2.94 ± 0.11	2.91 ± 0.16	0.05	2.98 ± 0.07	2.89 ± 0.21	0.30	2.94 ± 0.08	2.97 ± 0.08	0.27	2.88 ± 0.17	2.86 ± 0.16	0.09
PI_{FE}	2.92 ± 0.10	2.87 ± 0.19	0.06	2.95 ± 0.07	2.87 ± 0.22	0.11	2.93 ± 0.11	2.90 ± 0.20	0.01	2.88 ± 0.13	2.84 ± 0.17	0.11

OGI, Offensive Game Involvement; PI, Total Performance Index; PI_{DM}, Performance Index for Decision Making; PI_{TE}, Performance Index for Technical Execution; PI_{FE}, Performance Index for Final Efficacy; PG, Point Guard; SG/SF, Shooting Guard and Small Forward; and PF/C, Power Forward and Center.

[a]One player did not take any shot. Thus, PI, PI_{DM}, PI_{TE}, and PI_{FE} were not calculated and the sample size was reduced to $n = 8$ for these performance indicators.

$^*p < 0.05$; $^{**}p < 0.01$.

TABLE 3 | Descriptive statistics and multiple group comparisons for BALPAI variables separated by playing position.

BALPAI variables	Descriptive statistics				Kruskal–Wallis Test		*Post-hoc* analyses[a]		
	Total ($N=54$)	PG ($n=19$)	SG/SF[b] ($n=21$)	PF/C ($n=14$)			PG vs. SG/SF	PG vs. PF/C	SG/SF vs. PF/C
	$M \pm$ SD				H(2)	ω	Φ		
All actions									
OGI (%)	8.56 ± 4.66	11.23 ± 4.95	7.84 ± 4.01	6.02 ± 3.43	10.36**	0.44	**0.34***	**0.53***	0.23
PI (pts)	2.68 ± 0.10	2.72 ± 0.10	2.70 ± 0.09	2.61 ± 0.10	9.32**	0.42	0.19	0.48*	0.40
PI_{DM}	2.50 ± 0.20	2.58 ± 0.16	2.52 ± 0.19	2.36 ± 0.18	9.02*	0.41	0.19	0.49*	0.37
PI_{TE}	2.89 ± 0.09	2.92 ± 0.06	2.89 ± 0.09	2.84 ± 0.12	3.75	0.26	0.18	0.31	0.19
PI_{FE}	2.66 ± 0.19	2.66 ± 0.13	2.68 ± 0.10	2.63 ± 0.14	0.23	0.06	0.01	0.04	0.10
Shooting									
OGI (%)	8.58 ± 6.58	9.25 ± 8.11	8.80 ± 6.44	7.34 ± 4.38	0.18	0.06	**0.03**	0.03	**0.08**
PI (pts)	2.40 ± 0.27	2.32 ± 0.28	2.48 ± 0.20	2.40 ± 0.32	3.30	0.25	**0.29**	0.18	**0.08**
PI_{DM}	2.13 ± 0.43	1.99 ± 0.42	2.28 ± 0.44	2.11 ± 0.38	5.62	0.32	**0.35***	0.20	**0.24**
PI_{TE}	2.87 ± 0.22	2.90 ± 0.18	2.86 ± 0.24	2.84 ± 0.25	0.84	0.12	**0.12**	0.14	**0.03**
PI_{FE}	2.21 ± 0.47	2.08 ± 0.56	2.31 ± 0.30	2.25 ± 0.53	1.76	0.18	**0.20**	0.17	**0.01**
Passing									
OGI (%)	8.59 ± 5.14	12.48 ± 4.68	7.36 ± 4.11	5.16 ± 3.75	19.36***	0.60	**0.55*****	**0.67*****	0.25
PI (pts)	2.79 ± 0.15	2.83 ± 0.10	2.78 ± 0.17	2.77 ± 0.19	0.45	0.09	**0.09**	**0.10**	0.01
PI_{DM}	2.82 ± 0.21	2.85 ± 0.13	2.84 ± 0.14	2.73 ± 0.34	0.40	0.09	**0.05**	**0.10**	0.08
PI_{TE}	2.85 ± 0.19	2.88 ± 0.13	2.79 ± 0.23	2.89 ± 0.19	4.55	0.29	**0.20**	**0.27**	0.31
PI_{FE}	2.72 ± 0.26	2.74 ± 0.16	2.72 ± 0.30	2.69 ± 0.32	0.12	0.05	**0.06**	**0.00**	0.03
Dribbling									
OGI (%)	8.59 ± 5.88	13.00 ± 6.05	7.41 ± 4.44	4.36 ± 3.17	18.83***	0.59	**0.45***	**0.69*****	0.37
PI (pts)	2.73 ± 0.20	2.74 ± 0.17	2.75 ± 0.15	2.69 ± 0.29	0.11	0.04	**0.03**	**0.04**	0.05
PI_{DM}	2.75 ± 0.29	2.75 ± 0.27	2.75 ± 0.27	2.75 ± 0.34	0.50	0.10	**0.06**	**0.09**	0.10
PI_{TE}	2.91 ± 0.16	2.95 ± 0.09	2.93 ± 0.12	2.81 ± 0.25	2.51	0.22	**0.05**	**0.25**	0.23
PI_{FE}	2.53 ± 0.34	2.52 ± 0.23	2.58 ± 0.23	2.49 ± 0.57	0.64	0.11	**0.14**	**0.07**	0.00
Receiving									
OGI (%)	8.53 ± 4.39	9.38 ± 4.29	8.31 ± 4.67	7.71 ± 4.19	1.40	0.16	0.13	0.20	0.05
PI (pts)	2.66 ± 0.15	2.68 ± 0.14	2.69 ± 0.16	2.60 ± 0.16	2.96	0.23	0.01	0.26	0.26
PI_{DM}	2.16 ± 0.28	2.19 ± 0.17	2.19 ± 0.35	2.09 ± 0.27	2.36	0.21	0.04	0.26	0.20
PI_{TE}	2.92 ± 0.14	2.93 ± 0.16	2.96 ± 0.08	2.86 ± 0.16	4.84	0.30	0.01	0.32	0.33
PI_{FE}	2.90 ± 0.16	2.90 ± 0.17	2.92 ± 0.16	2.86 ± 0.15	2.64	0.22	0.09	0.20	0.26

OGI, Offensive Game Involvement; PI, Total Performance Index; PI_{DM}, Performance Index for Decision Making; PI_{TE}, Performance Index for Technical Execution; PI_{FE}, Performance Index for Final Efficacy; PG, Point Guard; SG/SF, Shooting Guard and Small Forward; and PF/C, Power Forward and Center.

[a]*Group comparisons referring to the diagnostic validation of the BALPAI (Objective 2; H2a–H2c) were performed utilizing one-tailed post-hoc tests. In these cases, effect sizes were printed in bold. For the remaining comparisons, two-tailed post-hoc tests were performed to provide a comprehensive analysis of position-dependent differences.*

[b]*One player did not take any shot. Thus, PI, PI_{DM}, PI_{TE}, and PI_{FE} were not calculated and the sample size was reduced to $n=20$ for these performance indicators.*

$^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

BALPAI variables (Objective 2). The selection-dependent analysis revealed that selected players were more involved in ball-bound actions and performed better than non-selected players in shooting and receiving. Within the positional groups, the strongest effects were found among PG. The position-dependent analysis showed higher offensive game involvement of PG in total ball-bound actions, passing and dribbling compared to players in other positions. Further differences between players according to selection status and playing position were not detected.

Reliability (Objective 1)

The first objective of this study was to evaluate the inter-rater reliability to ensure that differences in BALPAI variables reflect actual differences in players' performance and not random measurement errors (Schweizer et al., 2020). During the reliability analyses, a prevalence problem was detected with respect to technical execution (see **Table 3**). Due to the high performance level of the players, many actions were rated with the highest possible score (i.e., three points). This resulted in imbalanced marginal distributions of the observed ratings and unrepresentatively low values of Cohen's weighted kappa (Hallgren, 2012). Therefore, PABAK-OS and the total percentages of agreement were additionally reported. Considering all coefficients, the analyses revealed satisfactory results, indicating almost perfect agreement between the raters for technical execution and final efficacy as well as moderate agreement with respect to decision making. In the original study designing and validating the BALPAI, almost perfect agreement between raters was found regarding all three components assessing the performance of fifth-grade students (Ibanez et al., 2019). However, in the present study, elite youth basketball players competing in the national selection tournament of the German Basketball Federation were assessed. In this context, it should be acknowledged that the estimates of inter-rater reliability might be substantially reduced when a rating system is applied to a new population due to restrictions of range of talent (Hallgren, 2012; Ackerman, 2014). Further, it should be noted that the applied criteria were designed for small-sided basketball games (i.e., 3 against 3). However, tactical decisions within regular basketball games (i.e., 5 against 5) are more complex due to the increased number of players. For example, in the format 3 against 3, a player in possession of the ball has only two options to pass the ball to an open teammate (i.e., two other players on his team). However, in a regular 5 against 5, the players' options are doubled. Thus, discrepancies may have occurred in the evaluation of players' decision making when applying the criteria in the present study.

Diagnostic Validity (Objective 2)

Selection-Dependent Differences

Regarding the second objective, the diagnostic validity of the BALPAI was initially evaluated by analyzing selection-dependent differences in the assessed data. It was hypothesized that selected players would outperform non-selected players with respect to offensive game involvement and performance.

The results confirm higher *offensive game involvement* for selected players in all categories supporting the diagnostic validity of the BALPAI (H1a). Previously, selection-dependent differences in youth basketball players have mainly been investigated with respect to physical performance parameters (e.g., anthropometry, Torres-Unda et al., 2013). Thus, the comparison of the results with those of other studies is difficult. However, the findings of the current study with respect to offensive game involvement correspond with those found in other youth team sports. For example, Saward et al. (2019) reported that male youth soccer players retained by an academy in England performed more dribbles in matches between Premier League Academies compared to those released. Further, Schorer et al. (2020) found that the reached league level in adulthood of female youth handball players in Germany is determined by the number of actions taken but not the quality of those actions. The findings of these studies suggest that youth players in these team sports who are more involved in the respective game have higher chances for short-term (e.g., selection) and long-term success (e.g., performance level in adulthood). This is also indicated by the results of the present study with respect to short-term success.

Performance-related differences in the current study were only detected in shooting and receiving. Therefore, diagnostic validity was not established for most of the BALPAI variables in this context. Guimarães et al. (2019) found better shooting, passing, and dribbling skills in male youth players selected for an elite regional team in Portugal compared to their non-selected counterparts. With respect to shooting, the results of the present study confirm the findings of Guimarães et al. (2019). However, technical skills were assessed through basketball-specific tests in this study. Given the simplified conditions in such tests (e.g., no defending players), it may have been possible to discriminate between players in more categories than in the present study, in which players' performance was assessed in a real basketball game. Further, the analysis of the game-related statistics from international tournaments of youth and senior national teams demonstrated that players on winning teams performed better in shooting than those on losing teams (Csataljay et al., 2009; Lorenzo et al., 2010; Milanovic et al., 2016; Leicht et al., 2017). Studies on national team programs demonstrated that at least 70% of youth basketball players selected for such programs were retained from one year to the next (Kalén et al., 2021). Moreover, players that were members of a senior national team in Europe played three international youth championships on average in their careers (Kalén et al., 2017). In this context, the importance of shooting skills is further emphasized for players who aim to get selected for such programs and want to contribute to youth and senior national teams' success. However, no comparable studies were found on performance in receiving. Previous research reported that the performance in skills prior to shooting (e.g., receiving the ball) may affect shooting effectiveness (Okazaki et al., 2015). Therefore, selected players who perform better in receiving may also be better in shooting.

However, the diagnostic validity was not established regarding performance-related differences in passing, dribbling, or total ball-bound actions. The reason for that might be that the evaluation criteria have been developed for students or youth basketball players on the entry level (Ibanez et al., 2019). In the given competitive context, these criteria were applied to elite youth basketball players. Therefore, also the performance of non-selected players has been rated quite high. For example, this is particularly evident in the ratings for technical execution of total ball-bound actions performed by non-selected players ($PI_{TE} = 2.89 \pm 0.10$; see **Table 2**). A ceiling effect was detected in this performance-related variable, as the non-selected players averaged almost the highest possible rating (i.e., three points). Moreover, the youth national team coaches may have followed a different selection pattern. Thus, players may have been selected who did not perform well in the examined games or even in the tournament, but who the coaches expect to perform best in the long term (Trunić and Mladenović, 2014; Buekers et al., 2015). This could have affected the mean performance indicators compared in this study.

To the best of our knowledge, there are no comparable studies investigating performance differences between selected and non-selected players within different playing positions in youth basketball. However, one goal of talent identification decisions is to identify developing athletes with the potential to become successful performers in adulthood (Till and Baker, 2020). In team sports such as basketball, the individual performance of the players is linked to the respective team's success. Thus, studies are referred that analyzed within-position differences in the performance of high performing senior players of winning and losing teams. Hence, the game-related statistics of successful senior basketball players were compared to see if they are already reflected in the performance data of selected youth basketball players in the same playing positions. Further, the results are discussed according to the positional requirements.

Selected PG were more involved in shooting, dribbling, and total ball-bound actions (H1b). Further, they outperformed non-selected players on this position with respect to shooting. The central role of the point guard in a basketball teams' attack has been confirmed for youth and senior basketball by in-depth analyses of passing sequences (Clemente et al., 2015; Korte and Lames, 2018). The results of the present study reflect this centrality as selected players are more involved in their teams' offensive game play. Further, previous research in senior basketball found that PG from winning teams score more points with higher efficiency from all distances than those from losing teams (Choi et al., 2015; Escudero-Tena et al., 2021). However, PG are usually less responsible for scoring points but more for directing the offense by dribbling the ball and passing it to their teammates (Trninić and Dizdar, 2000; Trninić et al., 2000). In this context, the results indicate that also in elite youth basketball, the PG has to take responsibility for scoring besides organizing the game (Bianchi et al., 2017).

Selected SG/SF were more involved in passing and receiving while they outperformed non-selected players on these positions with respect to dribbling and overall game performance. It is also noticeable that selected SG/SF made better decisions in total ball-bound actions, passing, and receiving. These findings are also consistent with those found in the analyses of position-dependent differences in players' game-related statistics on winning and losing teams. Escudero-Tena et al. (2021) found more assists in both SG and SF while Choi et al. (2015) emphasized that both Guards and Forwards contributed positively to victory by providing more assists and fewer turnovers. While more assists can be associated with the higher number of passes and better decision making executing these actions, fewer turnovers can be linked to both better passing decisions and better dribbling performances. However, both studies also reiterated the importance of scoring for players in these playing positions. In contrast, the findings of the present study suggest that selected SG/SF are not primarily expected to score points to get selected. The descriptive statistics even show a tendency for PG being slightly more involved in shooting actions while SG/SF being only the second option in this regard (see **Table 3**). Instead, they have to separate themselves from non-selected players by their versatility, making smart decisions with the ball and involving their teammates. Rangel et al. (2019) highlighted the high degree of versatility among players in these positions, which is generally shown by players accomplishing multiple tactical demands.

Selected PF/C only displayed a higher involvement in dribbling actions. However, players in these positions are generally assigned to help other players to get open (e.g., by screening for them) instead of creating by themselves (Trninić and Dizdar, 2000; Trninić et al., 2000). Therefore, the results suggest that the youth national team coaches were looking for players in these positions who are capable to create (e.g., their own shot) off the dribble. This conclusion is also supported by the findings of the position-dependent analysis in this study, which revealed that PF/C have fewer ball-bound actions than players on other positions (see **Table 3**). Thus, when they got the ball, they should use this chance to create off the dribble in order to get selected. However, research has reported that players on winning teams in these positions deliver more assists (Choi et al., 2015; Escudero-Tena et al., 2021). This could not be confirmed assessing players' performance with the BALPAI. In contrast, the descriptive statistics of the present study suggest that non-selected PF/C outperformed selected players in passing (see **Table 2**). In this context, it should be noted that Power Forwards are the positional group that has shown the fastest growth in versatility in the last decade (Rangel et al., 2019). Accordingly, this suggested contradictory performance-related differences may be due to the grouping of the two playing positions (i.e., Power Forward and Center) within this study.

Additionally, compared to SG/SF and PF/C, stronger effects in the expected direction were demonstrated within the group of PG ($0.46 \leq \Phi \leq 0.60$, see **Table 2**). Therefore, these results indicate that selected PG can be identified more clearly than players in other positions based on the performance data assessed with the BALPAI.

Position-Dependent Differences

With respect to position-dependent differences, it was hypothesized that PG would be more involved in total ball-bound actions, passing, and dribbling than both SG/SF and PF/C (H2a). Further, it was expected that PG would perform better in passing and dribbling actions than players in the other positional groups (H2b). Moreover, it was assumed that SG/SF demonstrate higher involvement and performance in shooting actions compared to both PG and PF/C (H2c). The results indicate diagnostic validity regarding *offensive game involvement* as PG were more involved in passing, dribbling, and total ball-bound actions than SG/SF and PF/C (H2a). These findings are in line with former research of position-dependent differences in activity demands demonstrating that Guards are more involved in movements with the ball, especially in passing and dribbling (Abdelkrim et al., 2007; Scanlan et al., 2011, 2012; Delextrat et al., 2015; Ferioli et al., 2020a). Further, the results match with those of Ortega et al. (2006), who found that PG made more passes compared to other playing positions in Spanish youth basketball. However, SG/SF were surprisingly not showing higher offensive game involvement with respect to shooting (H2c). It has been reported by research that SG and SF attempt more shots from 3-point range while PF and C take more shots from 2-point range (Sampaio et al., 2006; García-Rubio et al., 2019; Escudero-Tena et al., 2021; Kokanauskas et al., 2021). As BALPAI does not differentiate between shooting ranges, this study thus might not have been able to distinguish between SG/SF and other playing positions with respect to their involvement in shooting actions.

Advantages in *performance* for PG in passing and dribbling compared to the other positional groups were not detected in this study (H2b). Also, SG/SF did not outperform PG or PF/C as far as shooting is concerned (H2c). With respect to passing, this is confirmed by Hatem et al. (2020) who also did not find advantages for Guards with respect to passing. However, previous research analyzing position-dependent differences in game-related statistics have reported advantages for point guards in assists (Sampaio et al., 2006; García-Rubio et al., 2019; Escudero-Tena et al., 2021; Kokanauskas et al., 2021). In contrast to the results of the present study, Hatem et al. (2020) were able to demonstrate a higher proportion of appropriate dribbling actions for Guards. Surprisingly, they also detected a better performance in shooting for Centers. This can be explained by Centers taking a high number of shots close to the basket which are usually executed with high efficiency (e.g., dunks, Kokanauskas et al., 2021). As the observational instrument utilized in that study (i.e., IAD-BB; Folle et al., 2014) does not account for shooting ranges either, centers advanced in this category.

The limited sensitivity to differentiate performance in the present study may be explained by the criteria that has been developed for students or youth basketball players on the entry level (Ibanez et al., 2019). Moreover, the instrument evaluates all players according to the same criteria, regardless of their playing position. However, players have different responsibilities in their respective playing position which requires a more differentiated analysis (Trninić and Dizdar, 2000; Trninić et al., 2000). Therefore, also players aside from the PG who are less skilled with respect to certain ball-bound actions (e.g., passing or dribbling) were able to score high. Further, differences between players in the same playing position should be considered. Although they have to fulfill the same tasks in certain areas, they may have different strengths. In the process of building a team (e.g., youth national team), coaches consider that players complement each other in terms of the various tasks on the basketball court (Pérez-Toledano et al., 2019). As the selection tournament under investigation represented the first stage of selection on national level in Germany, different types of players may have been selected for the same playing positions for further talent development purposes. For example, besides very strong PG "on the ball" (e.g., strong passers and dribblers), also players who rather have outstanding defensive qualities may have been selected. However, as only ball-bound actions in offense were evaluated in the present study, this diversity could not be displayed and players' performance was not discriminated as expected. In addition, the focus in younger age groups is more on general and less on position-specific skill development (DiFiori et al., 2018; Arede et al., 2019a; Koopmann et al., 2020). Youth basketball players start to specialize in one position at the age of 16 years (Dezman et al., 2001). Assuming that the respective coaches of the investigated players implemented these guidelines and emphasized general skills development throughout their promotion, the players did not have a fixed playing position yet when the study was conducted. Rather, the players may have been used in different playing positions during the selection tournament. This may have affected the differentiation between the playing positions in this study.

The additional comparisons, not utilized for diagnostic validation, revealed that PG outperformed PF/C overall and especially regarding decision making with medium effect sizes (all $p < 0.05$, $0.48 \leq \Phi \leq 0.49$; see **Table 3**). Performance-related differences may have been identified in these variables because only ball-bound actions were evaluated in this study and PG have more "on-ball tasks" (e.g., passing the ball) than players on the other positions. These findings correspond to the differences in the requirement profiles that are more pronounced between PG and PF/C than among PG and SG/SF (Trninić and Dizdar, 2000; Trninić et al., 2000). This is also indicated by the results of the position-dependent analyses (H2a) demonstrating that the differences between PG and PF/C were more pronounced as reflected in the stronger effect sizes found for the involvement in passing, dribbling, and total ball-bound actions (PG vs. PF/C: $0.53 \leq \Phi \leq 0.69$; PG vs. SG/SF: $0.34 \leq \Phi \leq 0.55$). Further, this is also evident when comparing these playing positions with respect to game-related statistics (Escudero-Tena et al., 2021; Kokanauskas et al., 2021) and physical and physiological demands (Stojanović et al., 2018).

Limitations and Implications for Optimization

Based on the evaluation of the BALPAI, several limitations need to be addressed in order to derive implications for the optimization of the observational instrument.

First, within the present study, only ball-bound actions in offense were considered. Thus, players with more tasks in defense or "off the ball" in offense were possibly disadvantaged by being evaluated according to factors that are not the primary determinants of performance in their respective playing positions. Therefore, the results indicate that only focusing on certain items of the BALPAI in offense when analyzing competitive youth basketball players in different playing positions is not recommended. Rather, the criteria should be weighted with respect to the position-specific requirements in both offense and defense as proposed by Trninić and Dizdar (2000). A system of weighted criteria per position adapted to the BALPAI can contribute to a higher diagnostic validity of the BALPAI when applied in a competitive setting.

Second, all players were rated according to the same criteria, which were not adjusted to the performance level or playing position. This may have led to the fact that performance-related differences could barely be detected. Considering sharper and position-specific criteria in future studies could improve the sensitivity of the instrument. For example, a player receives the highest possible rating (i.e., three points) for decision making in a passing action when delivering the ball to a teammate without high defensive pressure and when not having the opportunity to shoot or advance to the basket (see Annex 1; Ibanez et al., 2019). However, when evaluating elite youth basketball players in this context, the criterion should also address whether the pass was the best option if more teammates were available to receive this pass. An adjustment of the rating in this case (i.e., three points if it was the best option, otherwise only two points if the other criteria were met) could contribute to a clearer discrimination between different performance levels (e.g., between selected and non-selected players).

Third, as players of different teams were analyzed and compared within this study, the data regarding their game involvement were normalized according to the total number of actions of their respective teams. However, players receive different playing times within their teams, which is determined by the coaching staff based on their performance. The data of this study were not normalized for individual playing time as a selection tournament was analyzed. Here, the main focus was not on winning, but on the presentation of all players, so that equal playing times were assumed. However, the normalization for playing time should be considered when applying the instrument to other competitive settings in future studies (e.g., Ferioli et al., 2020b).

Fourth, the impact of intra-individual factors such as the biological maturity status of the players were not considered within the evaluation of players' performance in this study. However, it has been shown in youth basketball that players' performance and selection procedures are affected by maturation processes (e.g., Arede et al., 2019b, 2021). In the present study, these processes may have influenced players' performance, the selection procedures, as well as the ratings performed with the BALPAI, all of which should be addressed in future studies. Furthermore, players' performance is dynamically influenced by the other players on the court (Rico-González et al., 2020). Therefore, future studies should account for the influence of, for example, teammates (e.g., Piette et al., 2011) or defenders (e.g., shooting, Gorman and Maloney, 2016; dribbling and passing, Vencúrik et al., 2021). Besides, other contextual factors such as the remaining game time or the current score when a play action takes place should be considered. These variables potentially cause increased pressure on players and may affect their performance (Christmann et al., 2018).

CONCLUSION

In conclusion, the results of this evaluation confirm the inter-rater reliability while establishing diagnostic validity only for specific variables. Thus, the findings indicate that the instrument, in its current form, is not yet applicable to competitive youth basketball players. This highlights the importance of optimizing the BALPAI for reliable and valid performance assessments of competitive youth basketball players. Future studies should investigate the application of stricter and position-specific criteria to utilize the instrument for talent identification and development purposes.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethics Committee of the Faculty of Economics and Social Sciences at the University of Tübingen. Written informed consent for participation was not provided by the participants' legal guardians/next of kin because all data processed in this study were publicly available. Further, the implementation of the study was approved by the German Basketball Federation (Deutscher Basketball Bund, DBB).

AUTHOR CONTRIBUTIONS

DR, MS, DL, and OH: conceptualization. DR and MS: data curation, investigation, and validation. DR: formal analysis, resources, and writing—original draft. DR, DL, and OH: methodology and project administration. DL and OH: supervision. DR and DL: visualization. DR, MS, DL, SI, and OH: writing—review and editing. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.859897/full#supplementary-material

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