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Does the Intent Match the Output: Aligning Development Goals With Training Load in Youth Basketball

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ABSTRACT

This study investigated the alignment between external training load metrics and coach-prescribed development goals in an elite youth basketball setting. External training load data from training drills were collected over two years from 25 elite male youth basketball players in a full-time residential academy. At the start of each term, coaches developed and assigned individual developmental goals (IDGs) for each player. Using inductive thematic analysis, these IDGs were retrospectively grouped into four overarching development goal categories (defensive, offensive, skill, and physical) and 16 specific goal types (e.g., cutting, shooting, and load tolerance). Separately, external load metrics were recorded during all on-court training sessions using Catapult Vector S7 devices. To align IDGs with external load metrics, two multinomial logistic regression models were developed to classify (1) development goal category and (2) specific goal type (SGT) using per-minute external load metrics. Both models achieved 66% classification accuracy (Kappa = 0.60). Key predictors, such as high-intensity deceleration counts, vertical PlayerLoad, and high-speed running distances, were retained in both models following stepwise selection. Model performance was strong, with large reductions in AIC (ΔAIC = 1224.1 and 2540.7, respectively), demonstrating that coach-assigned IDGs were associated with distinct external load profiles. Additionally, accumulated training time differed significantly across specific goal types, reflecting systematic variation in emphasis across the season. These findings demonstrate that external training load metrics reflect the structure of coach-assigned development goals, offering a data-driven framework to evaluate alignment between training design and physical demands in youth basketball.

1 | Introduction

In basketball, player development is a complex multidimensional process requiring the coordinated advancement of technical skills, tactical understanding, and physical capacities (Ziv and Lidor 2009). Within high-performance (McKay et al. 2022) youth academies, basketball coaches frequently tailor individual development plans that guide the selection of drills, session structures, and seasonal training blocks (Leite and Sampaio 2012) aiming to develop the physical requirements of elite cohorts (Bartlett and Murray 2025). These coaching plans emphasize specific goals, including improving defensive footwork, enhancing offensive decision-making, refining ball-handling, or building physical endurance. Despite this individualized and goal-driven approach to training design, performance support practices often operate in parallel, monitoring physical output

Highlights

- In high-performance youth basketball, external training load metrics moderately distinguish coach-prescribed development goals, indicating measurable alignment between coaching intent and physical outputs.
- High-intensity decelerations, vertical PlayerLoad, and high-speed running distances most clearly differentiate between goals.
- Defensive and physical drills displayed distinct physical profiles, whereas skill and offensive focused drills showed limited classification accuracy.
- In practice planning, these profiles support integrating load monitoring with individualized development goals to verify drill fidelity and adjust session design.

through wearable technology without explicit consideration of coaching intent of the specific drills (Leite and Sampaio 2012; Fox et al. 2017).

This disconnect between coach-led design and physical output monitoring presents a significant challenge in basketball and sport more broadly. Although external training load metrics provide valuable insights into the physical demands of basketball, they are frequently reported in isolation, without alignment to the technical or tactical objectives they are intended to support (Portes et al. 2019; Svilar and Jukić 2018). Consequently, coaches often receive limited feedback on whether their chosen drills are eliciting the desired physical responses, whereas performance support staff may lack sufficient sport-specific context to interpret whether elevated or reduced training loads are appropriate. This may be particularly evident in basketball environments where drill-level intentions are not routinely shared or tagged (Fox et al. 2017; Lever et al. 2025). As a result, physical and technical aspects of training are often evaluated separately rather than in an integrated manner to evaluate whether the physical outputs of training align with intended purposes. Understanding this alignment has implications for coaching efficiency, managing exercise prescription, and targeted load as well as individualized development programming.

Previous research has advanced understanding of the physical demands of basketball across contexts such as competition (García et al. 2020), training camps (Arede et al. 2021), and longitudinal exposure (Lever et al. 2024a, 2024b). However, few studies have examined how physical demands vary as a function of specific developmental goals, despite the increasing emphasis on individualized planning within youth sport development models (Leite and Sampaio 2012; Pichardo et al. 2018). Verifying whether training elicits the intended physical responses is critical to ensuring delivery of a targeted developmental stimulus. For instance, drills designed to improve cutting or reactive defense are likely produce to different external loads than those focused on decision-making in half-court offense or low-intensity technical repetition. Coaches frequently manipulate space (court size), speed (intensity of play), and player numbers (e.g., small-sided vs. full-team drills) to control the physical and tactical demands imposed on athletes (Conte et al. 2017; Vazquez-Guerrero et al. 2020). Yet despite these distinctions, limited evidence links quantifiable physical outputs to coach-assigned development goals, particularly within structured academy environments. Within these training-specific approaches, a large proportion of training is often classified as "Situational" or "Live Play" (Russell, McLean, Stolp, et al. 2021), comprising small-sided games or open format segments that may lack specific tagging to individualized goals despite their developmental relevance. Therefore, the challenge is twofold; first, to classify and structure the diverse training drills used in elite basketball based on their intended purpose and second, to determine whether external load metrics meaningfully reflect these goals. Initial evidence suggests that basketball coaches value load monitoring practices but remain skeptical of its relevance to technical training outcomes (Lever et al. 2025). Without demonstrating that physical output maps onto developmental aims, load data may continue to be perceived as an adjacent rather than integrated part of training design.

To address this gap, this study examined whether coach-prescribed development goals aligned with the physical demands of the drills used to achieve them. Through thematic analysis and classification modeling, we evaluated whether per-minute external load metrics could accurately differentiate drills based on their technical, tactical, or physical focus. By testing this alignment, the study offers a novel, data-driven approach to integrating performance support and coaching practice, providing a framework for selecting drills that elicit appropriate stimuli and interpreting physical load data through the lens of development goals, advancing an integrated model of training planning in youth basketball.

2 | Materials and Methods

2.1 | Participants

Data were collected from 25 highly trained male youth basketball players (age = 17.1 ± 1 year, height = 201.4 ± 9.6 cm, and mass = 89.5 ± 13.0 kg) enrolled in a full-time academy program in Australia over two training years (24 months). The academy provides a full-time residential basketball development program alongside athletes' academic commitments. Upon completing the program, these players are typically recruited to Division 1 National Collegiate Athletic Association (NCAA) schools or professional teams (e.g., Australia's National Basketball League or NBA G-League).

2.2 | Study Overview

This study adopted a multimethod design (Tenenbaum and Driscoll 2005) to report basketball drills according to coach-prescribed developmental goals and evaluate how external load metrics align with specific coaching objectives. To do so, individualized development goals (IDGs) were prescribed at the beginning of each training block based on the player's technical, tactical and physical developmental needs. Separately, external training load data were collected during on-court coach-led training sessions throughout the 2021 and 2022 training seasons (Figure 1). A typical training week within the structured

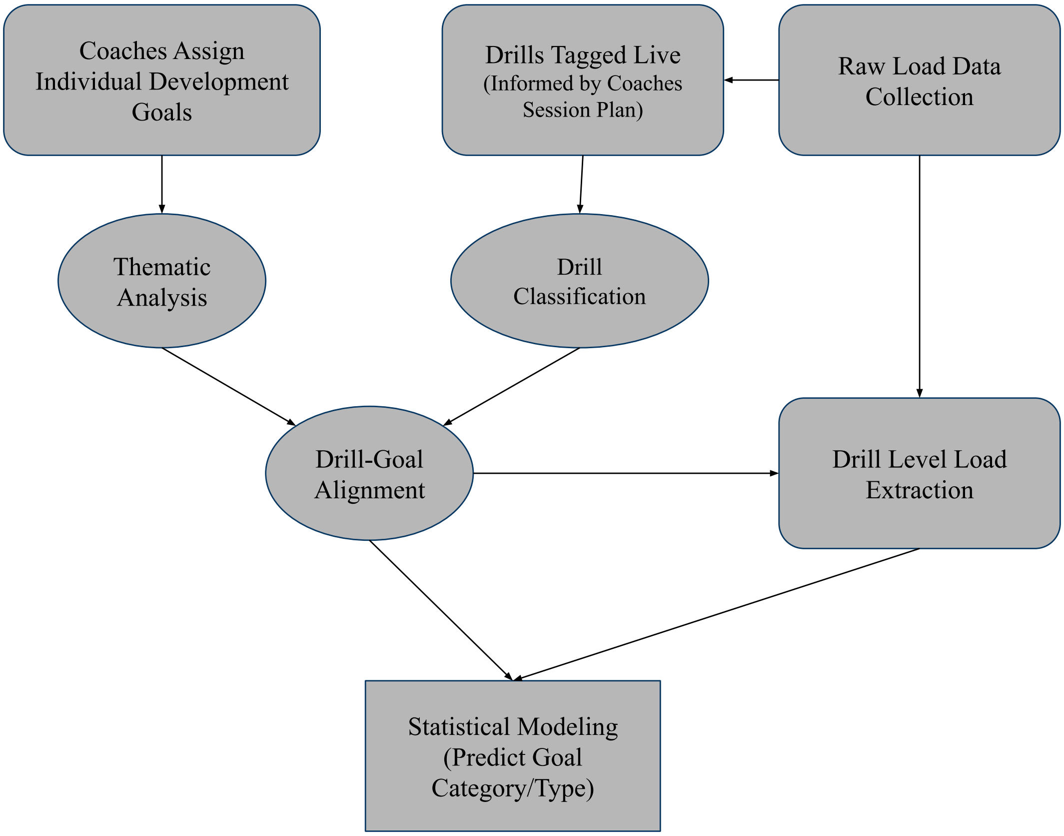

FIGURE 1 | Diagrammatic representation of the study design.

training environment of the youth basketball academy involved 12–16 coach-led hours on-court, 4–5 h of strength and conditioning, and 1–2 h of injury prevention each week, along with structured recovery sessions 2–3 times per week (Lever et al. 2024a, 2024b). On-court sessions include shooting, team or individual practice, volume shooting (standardized drills to track shooting performance), and scrimmages. In addition, athletes are encouraged to engage in self-led skills training (e.g., shooting and ball handling) daily. Data were collected with permission from relevant governing bodies. Ethical approval was granted by the Institutional Human Research Ethics Committee (Blinded).

2.3 | Procedures

2.3.1 | Individual Development Goals

Individual development goals were prescribed by coaching staff (basketball coaching experience = 21 ± 13 years and range: 4–30 years). Each coach was certified by the World Association of Basketball Coaches (WABC) with varying years of experience at youth, collegiate, professional, and international levels of basketball.

IDGs were developed at the beginning of each training term (approximately every 8 weeks), where coaching staff had a formal meeting to assess the current status progress to date and future direction of each athlete. This process allowed the tailoring of technical, tactical, and physical development goals geared toward the long-term development of each athlete. In addition to athlete-specific needs, coaches' broader developmental philosophy and term-based training priorities informed the selection and emphasis of goals.

2.4 | Thematic Analysis

An inductive thematic analysis was conducted on the IDG data at the conclusion of data collection, following Braun and Clarke's six-stage process (Braun and Clarke 2006). The authors first familiarized themselves with the data by reading and noting preliminary ideas. Initial codes were then generated across the entire data set, which were iteratively refined into higher-order and subthemes. These themes were reviewed and defined in alignment with the study's objectives.

A secondary reflexive process was undertaken to categorize external training load data based on the thematic structure of the development goals. The appended drill tags, recorded contemporaneously by the researcher using OpenField based on session plans, were systematically reviewed and aligned with the IDG themes established through prior inductive thematic analysis of coach-assigned goals. This ensured consistency between drill classification and the IDG objectives set by coaches. Drills were then categorized according to the dominant subtheme they addressed, allowing for a structured mapping of external training load data to specific developmental objectives. In cases where a drill aligned with multiple themes, its classification was determined based on the primary focus outlined in the session plan.

These themes were organized into two hierarchical levels: (1) Development goal categories (n = 4; physical, skill, offensive, and defense) representing broad domains of focus and (2) specific goal types (n = 16; (e.g., cutting, shooting, and load tolerance.), which were nested within these categories to capture more detailed technical or tactical intentions (Figure 2). This hierarchical structure was used in subsequent analyses to evaluate alignment between physical output and coaching intent.

2.5 | External Training Load

External training load data were collected from all coach-led on-court sessions using Local Positioning System (LPS) devices (Catapult Vector S7, Catapult Sports, Melbourne, Australia), in accordance with the NBA/NBPA wearables safety guidelines (Basketball Association 2017). Each athlete wore the same device in a fitted vest positioned between the scapulae to minimize interdevice variability (McLean et al. 2018). Players were classified as backcourt (n = 7) or frontcourt (n = 18) based on established positional groupings (Russell, McLean, Impellizzeri, et al. 2021). Training load was organized by academic term blocks (T1–T4), each spanning 8–11 weeks, with breaks between terms and longer gaps across years.

LPS units sampled position at 10 Hz and included a triaxial accelerometer, gyroscope, and magnetometer (100 Hz). These systems are validated for indoor basketball and commonly used in team sport load monitoring. Training sessions were live-coded by the researcher using the Catapults proprietary software (Openfield Console, v3.7, Catapult Sports, Melbourne, Australia), based on coaching plans and standardized drill tags describing the context and purpose of each drill. Openfield includes tagging options that allow users to attach metadata to each activity segment. These tags provide customizable drill-level contextual and subjective information, thereby enhancing the richness and interpretability of the training dataset. Data collection began at the start of each drill and excluded rest periods or coach instruction. Following each session, data were cleaned to isolate drill-specific activity and exported to CSV files for analysis. A complete list of reported external load metrics is shown in Table 1. All selected variables were validated for use by the National Basketball Players Association (NBPA) (Basketball Association 2017). To enable alignment with individual development goals, only drills with clearly tagged objectives were retained for goal classification. Drills without identifiable developmental focus (e.g., some 'Situational' segments) were coded separately.

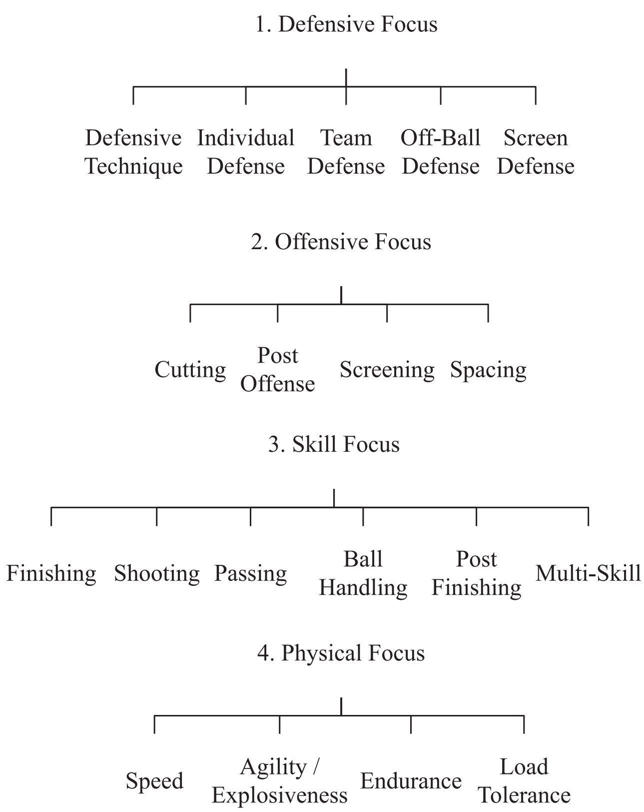

FIGURE 2 | Hierarchical structure of development goal categories and specific goal types identified across the academy training dataset.

2.6 | Data Analysis

All analyses were conducted using *R* Studio (Version 4.2, *R* Core Team). To contextualize how coach-prescribed IDGs were distributed over time, we calculated the frequency and relative proportion of drills assigned to each development goal category and specific goal type across academic terms. Drill counts were grouped by player, term, and IDG, and proportions were calculated accordingly.

To examine whether physical output could distinguish between development goal themes, we fitted two multinomial logistic regression models. These models used per-minute external load variables, averaged at the drill level, as predictors. The outcome variables were (1) development goal category (4 levels) and (2) specific goal type (16 levels) based on the primary coaching objective associated with each drill. In total, 192 drill-level observations were included, each representing a single instance of a coach-led drill tagged to a specific goal.

Outcome variables were treated as unordered factors, with "situational play" set as the reference level. To evaluate model performance and avoid overfitting, we used a stratified training/testing split approach. Datasets were randomly split into training (70%) and testing (30%) subsets using stratified sampling to preserve class balance across outcome levels. Full models were fit using the *multinom* function from the ***nnet*** package. Multinomial logistic regression was selected due to the categorical nonordinal nature of the outcome variables (development goal category and specific Goal Type), enabling classification across multiple nominal classes. Stepwise model selection was performed using the Akaike information criterion (AIC)-based *stepAIC* function from the ***MASS*** package to identify the most parsimonious predictor and interpretable subset of predictors. Variance inflation factors (VIF) were examined to assess multicollinearity; predictor(s) with VIF > 5 were flagged for concern and removed prior to model interpretation. Model fit was evaluated using changes in AIC, and classification performance was assessed through classification accuracy and Cohen's Kappa on the held-out test set. Accuracy

TABLE 1 | External load Parameters (all per minute) obtained from the catatapult ClearSky LPS.

Parameter	Units of measure	Definition
PlayerLoad (PL) and derivatives (1D and 2D)	AU	Pl: The sum of accelerations across all axes of the triaxial accelerometer. 1D: Accumulated acceleration in a single movement plane—vertical (jumping/landing), lateral (side-to-side), or sagittal (forward/backward). 2D: Accumulated acceleration in two movement planes—typically lateral and sagittal.
PlayerLoad accumulated in bands	AU	The sum of accelerations across all axes of the triaxial accelerometer within the specified band. Band 1: 0–1 AU Band 2: 1–2 AU Band 3: 2–3 AU Band 4: 3–4 AU Band 5: 4–5 AU Band 6: > 5 AU
Distance	Meters	The total distance covered.
Deceleration efforts (bands 1–3)	Count	The total number of deceleration efforts counted in the specified band. Band 1: −2 to −3 m/s Band 2: −3 to −4 m/s Band 3: <-4 m/s
Distance covered in velocity thresholds (bands 1–6)	Meters	The total distance covered in the specified band. Band 1: 0–1 m/s Band 2: 1–3 m/s Band 3: 3–4.5 m/s Band 4: 4.5–6 m/s Band 5: 6–7 m/s Band 6: > 7 m/s
Jumps (low, medium, and high)	Count	Vertical jumping actions detected via the inertial sensor and categorized based on magnitude. High: > 40 cm Medium: 20–40 cm Low: < 20 cm

confidence intervals were estimated using binomial proportions. In parallel, Two-way ANOVAs were conducted to examine differences in the percentage of training time spent across development goal categories and specific goal types as a function of Term. Post hoc comparisons were performed using Tukey's HSD where appropriate. Odds ratios (ORs) with 95% confidence intervals were reported for all predictors, though *p*-values were interpreted cautiously due to the exploratory classification focus of the models.

3 | Results

Thematic analysis of the dataset yielded 20 subthemes grouped within four overarching development goal categories: (1) defensive-focus, (2) offensive-focus, (3) skill-focus, and (4) physical-focus (Figure 2). Supporting Information S1: Table S1 provides descriptive statistics of external training load metrics by goal category and types.

3.1 | Time Allocation Across Goal Categories and Goal Types

At the category level, a significant main effect of development goal category was observed ($F(4, 415) = 1279.0$ and $p < 0.001$), indicating significant difference in the total time accumulated across training categories. Situational play accounted for the greatest proportion of total training time (~50%) (Figure 3A). All structured training categories received significantly less total time than situational play ($p < 0.01$). There was no main effect of term ($p = 0.90$), and the development goal category × term interaction was not significant ($p > 0.05$).

At the specific goal type level, a significant main effect of specific goal type ($F(15, 1082) = 1787.75$ and $p < 0.001$) confirmed substantial variation in how training time was distributed across specific development goal types (Figure 3B). Situational play accounted for the largest proportion of training time ($p < 0.001$) (Figure 4). Although the main effect of term was not significant ($p = 0.37$), a significant specific goal type × term

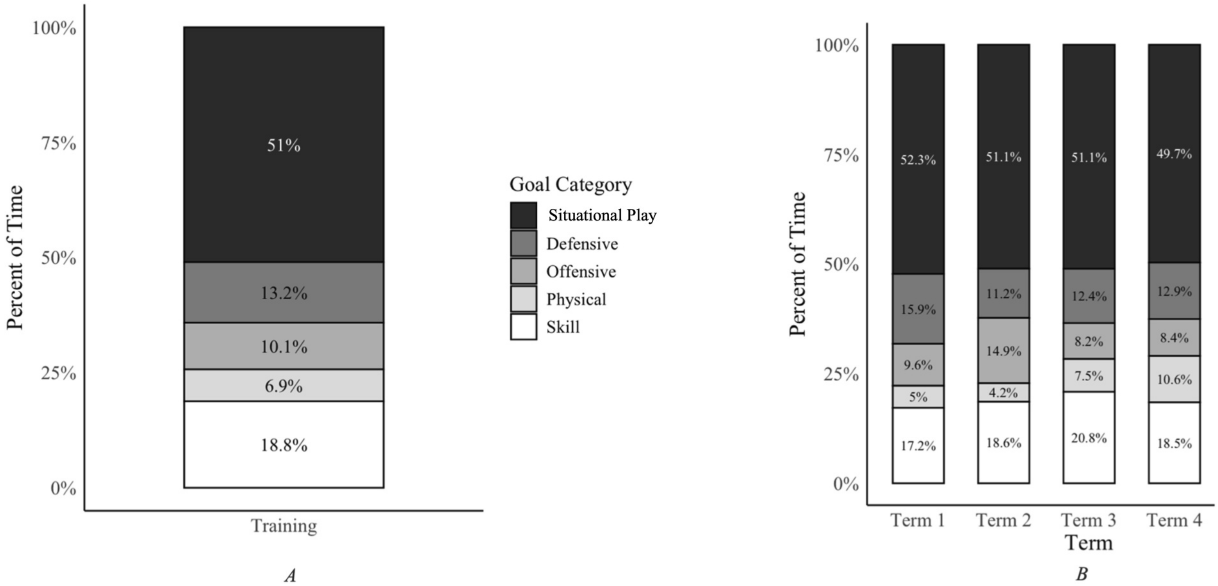

FIGURE 3 | Distribution of total training time across development goal categories and specific goal types.

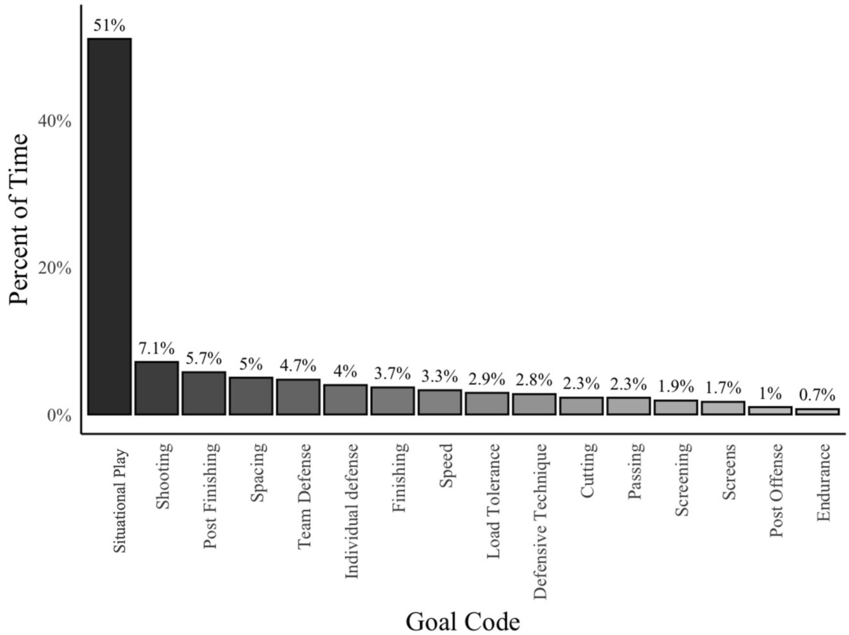

FIGURE 4 | Interaction between term and specific goal type showing seasonal variation in training priorities.

interaction ($F(42, 1082) = 3.32$ and $p < 0.001$) revealed differing training priorities across the season.

3.2 | Classifying Developmental Goals From Physical Output

Stepwise multinomial logistic regression was used to examine whether per-minute physical output metrics could classify coach-prescribed IDGs (Table 2). The development goal category model (Table 3) demonstrated substantial improvement in model fit following stepwise selection (AIC reduced from 3917.7 to 2693.6 and $\Delta AIC = 1224.1$). Classification accuracy on the test set was 66.0% (95% CI: 61.9%–69.9%), with a Cohen's Kappa of 0.60, indicating substantial agreement between classified and actual categories. Class-level sensitivity ranged from 35.0% (cutting) to 87.5% (endurance). Positive classification values were also high for some classes, including 100% for endurance and 96.9% for shooting. Although no single predictor reached statistical significance ($p < 0.05$), several interpretable metrics, including velocity bands, deceleration counts, and PlayerLoad intensity bands, aligned meaningfully with development goal categories.

The specific goal type model (Table 4) also improved substantially with stepwise selection (AIC reduced from 5444.9 to 2904.2), yielding comparable classification accuracy (66.1%) and Kappa (0.60). Predictor sets varied across goal types, reflecting distinct physical output profiles. For example, cutting drills

TABLE 2 | Multinomial logistic regression model performance for goal category and goal type classification.

Model	Full model AIC	Stepwise model AIC	Accuracy	Kappa	Residual deviance
Goal category	3917.70	2693.60	0.66	0.60	1959.38
Goal type	5444.90	2904.20	0.66	0.60	2153.57

TABLE 3 | Top three significant ($p < 0.05$) predictors for goal category.

Category	Predictor	OR	Standard error	Z-Statistic	p	OR confidence interval - lower	OR confidence interval - upper
Defensive	Deceleration band 3	195,754.4	3.42	3.56	0.00	239.69	159,870,607.75
	Deceleration band 2	22.7	1.10	2.84	0.00	2.64	195.54
	Deceleration band 1	13.2	0.56	4.59	0.00	4.38	39.55
Offensive	Deceleration band 3	9275.4	3.14	2.91	0.00	19.63	4,383,280.74
	Velocity band 6 distance	15.0	1.12	2.41	0.02	1.65	135.56
	Deceleration band 1	6.1	0.54	3.35	0.00	2.12	17.80
Physical	Deceleration band 3	25,796.5	3.48	2.92	0.00	28.26	23,546,030.55
	Velocity band 6 distance	53.6	1.14	3.48	0.00	5.70	503.52
	PlayerLoad 1D vertical	52.1	0.80	4.97	0.00	10.96	247.41
Skill	Deceleration band 1	22.5	0.54	5.81	0.00	7.87	64.32
	High jump count	8.5	0.30	7.08	0.00	4.70	15.40
	Medium jump count	6.0	0.21	8.55	0.00	4.00	9.10

Note: Odds ratios (OR): > 1 indicate greater odds of a drill being classified into the given development goal category based on the predictor; OR < 1 indicates lower odds[31]. Standard error: standard error of the log odds coefficient; reflects estimation uncertainty. Z-statistic: test statistic for whether the log odds coefficient differs from zero.

were associated with higher PlayerLoad 1D Vertical per minute (OR = 3.82) and lower low intensity jump count per minute (OR = 0.37). Load tolerance drills were characterized by elevated values across multiple physical output metrics, including a markedly higher PlayerLoad 1D Vertical per minute (OR = 424), indicating substantially greater vertical load.

4 | Discussion

This study sought to determine whether external training load metrics could distinguish between coach-prescribed development goals in a high-performance youth basketball setting. The findings showed that per-minute load variables, especially deceleration, vertical PlayerLoad, and velocity band distances, aligned with specific development goal categories and specific drill types. Notably, both models showed strong performance, with classification accuracy of 66% and substantial agreement (Kappa = 0.60), indicating that drills prescribed for different development goals tend to elicit distinct physical output profiles. Although this does not confirm alignment with coaching intent, it suggests that goal-oriented drill design may result in identifiable external load patterns related to movement demands and intensity characteristics.

Physical output metrics successfully differentiated development goal categories in this study, with defensive and physical drills showing consistently higher mechanical load and intensity values compared to skill-based or offensive drills. These results align with established assumptions in coaching and performance support that defensive and physical drills impose greater mechanical demands (Fox et al. 2017; Conte et al. 2017; Schelling and Torres-Ronda 2016), whereas the demands of skill-based and tactical drills vary depending on structure (Ibanez et al. 2020). Deceleration bands emerged as the most consistent predictors across categories and types, underscoring their relevance to basketball's repeated high-intensity movement profile (Klusemann et al. 2012). For example, defensive drills were almost perfectly separated by Deceleration Band 3 (OR ≈ 195,000), indicating that high-intensity deceleration actions were a defining feature. Physical drills were best classified by a combination of high PlayerLoad 1D Vertical (OR = 52.08) and Velocity Band 6 Distance (OR = 53.58), reflecting a combination of explosive and sustained locomotor output. These findings align with previous research showing that external load profiles differ based on drill type, with variations in intensity, locomotor output, and mechanical load across formats such as small-sided games, technical drills, and full-court scrimmages (Svilar and Jukić 2018; Russell, McLean, Stolp, et al. 2021). However, this study extends that work by demonstrating that load profiles are not just a function of drill design but can be associated with coach-assigned development goals, offering a potential framework for aligning physical performance monitoring with individualized training objectives in elite youth sport.

The classification accuracy of specific goal type classification further highlights the feasibility of distinguishing not just broad training themes but also specific technical or tactical foci based on physical demands. For instance, cutting drills were identified

TABLE 4 | Top 3 significant ($p < 0.05$) predictors for goal type.

Type	Predictor	OR	Standard error	Z-Statistic	p	Confidence interval - lower	Confidence interval - upper
Cutting	Deceleration band 2	33.08	1.29	2.71	0.01	2.64	413.90
	Deceleration band 1	26.22	0.87	3.74	0.00	4.72	145.50
	Velocity band 5 distance	2.80	0.33	3.08	0.00	1.45	5.40
Defensive technique	Deceleration band 1	196.99	0.85	6.20	0.00	37.11	1045.62
	PlayerLoad band 2	4.34	0.60	2.45	0.01	1.34	14.05
	Medium jump count	< 0.01	0.97	−5.66	0.00	0.00	0.03
Endurance	Deceleration band 2	21.85	1.32	2.33	0.02	1.63	292.89
	Velocity band 6 distance	11.83	1.14	2.17	0.03	1.27	110.13
	Velocity band 5 distance	3.55	0.34	3.70	0.00	1.81	6.95
Finishing	Hight jump count	100.94	0.65	7.08	0.00	28.12	362.35
	Medium jump count	9.69	0.39	5.88	0.00	4.54	20.66
	Velocity band 5 distance	4.77	0.39	4.00	0.00	2.22	10.26
Individual defense	PlayerLoad band 3	41.87	0.74	5.07	0.00	9.88	177.43
	Deceleration band 1	16.53	0.91	3.09	0.00	2.78	98.17
	Velocity band 5 distance	0.13	0.97	−2.12	0.03	0.02	0.85
Load tolerance	PlayerLoad 1D vertical	423.76	1.40	4.34	0.00	27.51	6526.86
	Velocity band 6 distance	11.99	1.15	2.17	0.03	1.27	113.12
	Velocity band 5 distance	3.32	0.40	3.02	0.00	1.52	7.24
Passing	Deceleration band 1	352.02	0.75	7.85	0.00	81.36	1523.02
	PlayerLoad 1D vertical	7.52	0.75	2.71	0.01	1.74	32.44
	Velocity band 5 distance	2.42	0.38	2.35	0.02	1.16	5.06
Post finishing	Deceleration band 1	39.95	1.52	2.43	0.02	2.04	783.03
	Hight jump count	32.29	0.57	6.12	0.00	10.61	98.25
	Velocity band 5 distance	3.96	0.51	2.72	0.01	1.47	10.67
Post offense	Deceleration band 1	94.92	1.13	4.03	0.00	10.35	870.57
	PlayerLoad band 3	8.83	0.98	2.23	0.03	1.30	60.01
	PlayerLoad band 3	5.79	0.70	2.52	0.01	1.48	22.63
Screening	Deceleration band 1	120.24	0.86	5.56	0.00	22.21	651.08
	Deceleration band 2	26.05	1.55	2.11	0.03	1.26	538.92
	High jump count	0.02	0.88	−4.50	0.00	0.00	0.11
Screens	Deceleration band 1	1020.35	1.11	6.26	0.00	116.49	8937.07
	Deceleration band 2	259.36	1.91	2.91	0.00	6.14	10,952.46
	Low jump count	4.35	0.58	2.51	0.01	1.38	13.68
Shooting	Medium jump count	10.04	0.48	4.78	0.00	3.90	25.84
	PlayerLoad band 3	0.00	2.92	−2.04	0.04	0.00	0.79
	Hight jump count	0.01	2.03	−2.44	0.01	0.00	0.38
Spacing	Deceleration band 2	42.97	1.49	2.53	0.01	2.33	792.98
	Deceleration band 1	33.99	0.96	3.66	0.00	5.13	225.06
	PlayerLoad 1D vertical	13.62	1.05	2.48	0.01	1.72	107.68
Speed	Deceleration band 1	24.75	0.90	3.58	0.00	4.27	143.42
	Deceleration band 2	14.04	1.31	2.02	0.04	1.08	183.23
	Velocity band 6 distance	12.59	1.13	2.25	0.02	1.39	114.21

(Continues)

TABLE 4 | (Continued)

Type	Predictor	OR	Standard error	Z-Statistic	*p*	Confidence interval - lower	Confidence interval - upper
Team defense	Deceleration band 2	1233.94	1.67	4.26	0.00	46.76	32,561.66
	Deceleration band 1	130.22	1.10	4.43	0.00	15.12	1121.82
	PlayerLoad 1D vertical	16.05	0.90	3.08	0.00	2.75	93.68

Note: Odds ratios (OR): > 1 indicate greater odds of a drill being classified into the given development goal category based on the predictor; OR < 1 indicates lower odds [31]. Standard Error: standard error of the log odds coefficient; reflects estimation uncertainty. Z-Statistic: test statistic for whether the log odds coefficient differs from zero.

by elevated Deceleration Band 1 (−2 − −3 m/s and OR = 26.22) and Band 2 (−3 − −4 m/s and OR = 33.08), whereas load tolerance drills showed high values in PlayerLoad 1D Vertical (OR = 423.76). Endurance drills were distinguished by higher distances covered in Velocity Band 6 (≥ 6.0 m/s and OR = 11.83) and Band 5 (5.0–5.99 m/s and OR = 3.55), consistent with drills involving sustained high-speed running or repeated movement across large areas of the court (Vazquez-Guerrero et al. 2020). These velocity profiles suggest that endurance drills likely included more continuous transitions between offensive and defensive roles or covered greater spatial zones compared to other goal types. This aligns with previous research showing that drill design variables, such as court size, player number, and task constraints, significantly influence external load characteristics (Conte et al. 2017; Schelling and Torres-Ronda 2016; Klusemann et al. 2012). Future studies could more systematically evaluate how spatial constraints and tactical context influence the physical demands of endurance-focused drills in basketball. Similarly, finishing drills were characterized by increased high-intensity jump counts (OR = 100.94), aligning with the vertical demands of rebounding or contested scoring (Ben Abdelkrim et al. 2010). This level of specificity supports the utility of external metrics not just in global workload monitoring, but in verifying drill integrity relative to its developmental aim.

Interestingly, although the classification models demonstrate alignment between physical outputs and coach-prescribed IDGs at the drill level, discrepancies were observed when examining how time was distributed across these development goal categories. Our results suggest that coaches consistently prescribed development goals with a balanced and stable distribution across terms, reflecting intentional and structured planning. However, actual implementation, measured as time spent in goal-specific drills, revealed greater variability and divergence from intended proportions. This mismatch suggests that despite clear coaching intentions, practical constraints, such as athlete readiness, changing training priorities, or situational adjustments, significantly influence how training time is ultimately allocated (Lever et al. 2025). Consequently, even with strong alignment in drill design, actual practice implementation may vary, underscoring the complexity of aligning planned training intent with real-world training delivery (Edwards et al. 2018). This highlights the importance of continually integrating coaching intentions with training load monitoring to optimize developmental outcomes. Now that specific metrics have been identified as differentiators between development goals, live monitoring can enhance this integration by providing real-time feedback on whether drills are eliciting the intended stimulus, allowing for immediate data-informed adjustments to training.

Time allocation analyses revealed that situational play accounted for the largest share of total training time across the season, comprising over 50% of all recorded minutes. However, each structured development goal category, such as skill, physical, offensive, and defensive, received significantly different amounts of time (all $p < 0.001$), indicating clear differentiation in how structured drills were emphasized. Skill-based drills were prioritized most within this group, receiving significantly more time than physical and offensive drills. This aligns with findings in highly trained youth basketball showing an increase in technical and tactical drill volume during later-season periods. Although there was no main effect of Term on overall training time, a significant development goal category × term interaction ($p < 0.001$) indicated meaningful shifts in training priorities across the season. These changes may reflect strategic periodization, in which early-term emphasis on physical development gives way to more skill-based training as athletes progress toward competition. This approach aligns with contemporary models of skill training periodization, which advocate for structured progression of skill complexity and contextual interference to optimize learning and performance in youth athletes (Otte et al. 2019). At the specific goal type level, similar patterns were observed: large between-type differences in time allocation and a significant specific goal type × term interaction suggested evolving developmental emphasis. Notably, post finishing and shooting drills received increased time in later terms, whereas certain defensive drills declined, reflecting seasonally adjusted development priorities.

A noteworthy finding was that over 50% of total training time was spent in sessions categorized as 'situational play.' However, this label likely reflects the use of unspecified or open-format drills, such as small-sided games or situational play, designed to test the integration of skills developed through goal-based training, rather than a lack of structure per se (Perdima et al. 2024). These segments may serve important pedagogical purposes by facilitating decision-making, contextual learning, player autonomy, and the application of newly acquired skills in dynamic game-like environments (Bennett et al. 2018). Nonetheless, the generic tagging of situational play limits the ability to attribute specific physical demands or developmental aims, posing challenges for monitoring alignment with individual development plans. Although this study shows that drills with clearly defined goals can be differentiated based on training load output, open-format or generically tagged segments remain difficult to interpret. Integrating clearer tagging or metadata around drill intent during these periods would improve interpretability and support more targeted load tracking.

Although prior studies have called for alignment in coaching intent and load monitoring output (Fox et al. 2017; Edwards et al. 2018), they have lacked the individualized, goal-driven structure and modeling approach applied here. As such, this study offers a model for other academy and high-performance settings seeking to integrate performance data with player development planning. Although our study offers novel insights, several limitations warrant consideration. First, only on-court coach-led sessions were monitored; off-court activities, such as strength training, recovery, and injury prevention, which likely supported physical development, were not captured. Drill classification was based on primary intent and may not fully reflect the multidimensional nature of some activities; for instance, defensive drills typically require competing against an offense and, in turn, offensive drills oftentimes require playing against defense. As the study was conducted within a single elite youth academy, generalizability may be limited. Additionally, the observational design precludes causal inference between development goals and physical outputs. Skill progression was not assessed, so it remains unclear whether drill demands translated into improved performance. Similarly, contextual data, such as competition schedules, that can influence training plans were not able to be accounted for. Finally, short self-led sessions before or after training were not recorded, which may have contributed minor additional volume not reflected in the dataset. Despite these limitations, the study provides a practical data-driven approach to aligning training intent with physical demand in highly-trained youth basketball.

These findings support several strategies to improve alignment between training design and physical performance monitoring in elite basketball. Coaches may use expected load profiles to evaluate whether drills are eliciting the intended physical demands, allowing them to refine session content to better match development goals. For instance, if a cutting drill is expected to yield high deceleration loads, observed deviations may signal poor drill fidelity or reduced engagement. This approach also addresses coaching priorities identified in existing literature (Lever et al. 2025), where lateral movement was frequently cited as a key performance determinant, especially for defensive effectiveness. Furthermore, this model may help coaches organize and structure their practices to maximize the desired effectiveness/outcome of the drill. Specifically, deviations indicative of fatigue or reduced engagement could be identified, allowing sessions to be restructured to achieve the desired outcomes.

These findings support integrating drill selection within a broader physical periodization framework. The distinct load profiles identified across development goal categories highlight how drill design can be strategically scheduled to align technical and physical training aims. Coaches can use expected drill-level load profiles to both verify whether drills elicit their intended demands and to guide when specific skills should be emphasized given athletes' current physical readiness. For example, higher-load drills (e.g., deceleration-dominant defensive work) may be best programmed during phases targeting adaptation, whereas lower-load technique-focused drills are appropriate during recovery or deload microcycles. Such alignment promotes balanced technical progression and physical development across the training cycle, supporting existing models of load management and skill periodization in team sport settings (Edwards et al. 2018; Otte et al. 2019).

Our results confirm that defensive drills were uniquely classified by high-intensity deceleration, aligning with coach emphasis on lateral quickness and change of direction. This suggests an opportunity to use movement-based metrics, such as deceleration load or PlayerLoad 1D (lateral), to quantify traits coaches already value but currently assess subjectively. Moreover, several metrics were consistently associated with multiple development goal categories, including PlayerLoad per minute and Velocity Band 5–6 distances. These may serve as a core set of monitoring variables, with additional context-specific metrics (e.g., deceleration load for defense and vertical load for load tolerance) layered in based on session intent. Future monitoring systems or dashboards could adopt this tiered structure; tracking universal load markers whilst emphasizing metrics specific to the developmental goal of each drill. Finally, this integration supports improved periodization by enabling staff to identify high- and low-load sessions across a term. Linking drill types to expected outputs also facilitates clearer communication between coaching and performance staff, particularly if embedded within educational tools or real-time dashboards. Such practices answer recent calls to contextualize training load data within technical-tactical aims and development priorities rather than treating it as standalone information.

5 | Conclusion

External training load metrics collected via wearable technology can reflect coach-prescribed IDGs in youth basketball. Through thematic analysis and classification modeling, this study demonstrated that distinct load profiles align with different technical, tactical, and physical drill intentions. These findings support a more integrated approach to training design and monitoring, promoting shared understanding between coaching and performance staff. Future research should explore how these relationships vary across levels of competition and athlete maturity and whether ongoing feedback based on goal alignment leads to improved developmental outcomes and performance over time.

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The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon request. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Table S1: Descriptives (mean ± SD) of external training load metrics by goal category and goal type.