Comparison of Physical Activity Level, Body Composition, Strength, and Flexibility of Teen Basketball Players and Adolescents Non-Practitioners of Sport: An Observational Study with Machine Learning Analysis

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ABSTRACT

Background: Increasing youths' physical activity is mandatory to reduce the risk of non-communicable diseases (NCCDs). Basketball is a team sport that is potentially positive in increasing teenagers' physical performance, health indicators, and well-being. **Objective:** The objective was to compare the physical activity level (PAL), body composition, strength, and flexibility of teen male basketball players (BG) ($n = 15$) and adolescent non-practitioners of sport (NS: $n = 14$). **Methodology:** All participants were healthy and free from any health disability from a Brazilian high school. A linear regression machine learning algorithm was applied to predict the adolescent´s physical components. In a quasi-experimental analysis, data were extracted by PAL, body fat percentage (BF%), handgrip strength (HG), back extensor muscle's' strength (BMS), lower limb power (LLP), and lower limb flexibility (LLF). Parametric (independent T-test) and non-parametric (Mann-Whitney U test) were employed to compare the variable's average and chi-square was applied to compare categorical data. **Results:** BG presented an upper number of adolescents classified with high PAL than the NS group ($p = 0.0002$, large ES, $V = 0.73$) and a lower number of adolescents classified with low PAL than the NS group ($p = 0.0002$, $V = 0.73$), less BF% ($p = 0.02$, $r = 0.85$), greater values of HGS ($p = 0.005$, $r = 0.34$), greater values of BMSLS ($p = 0.005$, $r = 0.33$), greater values of LLP ($p = 0.007$, $r = 0.30$), and greater values for LLF ($p = 0.02$, $r = 0.17$). Therefore, there was a positive effect of high PAL compared with low PAL in HG, ($p = 0.005$, $r = 0.24$) and also for high PAL in LLF, (High PAL: ($p = 0.006$, $r = 0.23$). Regarding machine learning analysis, the four models (linear regression, Ridge regression, random forest regression, and Bayesian regression) expressed good generalization performance, with a coefficient of determination (R^2) ranging from 0.77 to 0.88, root mean square error (RMSE) from 1.01 to 3.92, with an average mean difference of four points between the predicted and real values. The worst model was random forest regression $R^2 = 0.77$, RMSE = 3.92, and the best model was Bayesian regression ($R^2 = 0.88$, RMSE = 1.01). **Conclusion:** The BG group presented better results than the NS group for PAL, BF%, HG, BMS, LLP, and LLF. Body fat percentage precisely predicted the player's' vertical jump (VJ). In addition to the physical superiority of the BG, this study revealed the importance of managing body composition for both health and performance improvements.

Key words: Teenagers, Athletic, Sports Performance, Physical Activity Level

INTRODUCTION

Physical inactivity is a worrying factor in health, quality of life (QoL), and physical development in youth (Chaput et al., 2020). The reduced time spent practicing physical exercise (PE) leads to a decrease in physical activity level and increases the risk of (NCCDs), such as obesity, which in turn leads to metabolic deregulation, dyslipidemias, diabetes, heart disease, and cancer emergence, and its complications for health worsen QoL and early mortality in consequence of the combination of all these negative factors (Chang et al., 2020; Elagizi et al., 2020; Hannan et al., 2021; Li & Moosbrugger, 2021).

Therefore, it is known that adolescence is a time of life when physical inactivity and sedentary behavior have become so common nowadays, and it has been influenced by unhealthy behaviors like increased time using technology (e.g. smartphones and computers) also accompanied by bad eating habits (Shen et al., 2021; Woessner et al., 2021).

Most precisely, recent data from the World Health Organization (WHO) shows that around 81% of adolescents globally are not sufficiently physically active, and there is a variation in this prevalence across different countries, genders, and regions (Guthold, 2020). For this purpose, in 2018, the WHO launched the WHO's Global Action Plan on Physical Activity 2018–2030, in which the WHO members of the states agreed to make interventions to decrease 15% physical inactivity and improve the health and QoL of adolescents globally by 2030 (WHO, 2018). As body fat increases, systemic inflammation increases in parallel, contributing to a smaller immunologic response (Maligianni et al., 2021). On the other hand, the increase in physical capacities through the increase in physical activity level leads to the control of obesity and helps prevent the emergence and evolution of NCCDs (Ramírez-Vélez et al., 2016). Moreover, sports practice is an inexpensive and effective way to decrease physical inactivity and improve the overall health of adolescents (Li & Moosbrugger, 2021).

Basketball is a team sport with high-intensity demands during a training sessions or a matches characterized by sprints, jumps, and anaerobic/aerobic resistance (Castillo et al., 2021). Also, due to the high-intensity action profile during a training session or match, basketball practice can stimulate different physical capacities, such as muscle strength and power, mobility and flexibility, and endurance, that improve not only sports performance but also body composition and body system functioning, thus being positive for improving QoL and decreasing the risk of NCCDs (DiFiori et al., 2018; Liu & Kan, 2021). Therefore, basketball has a lot of physical plasticity in its skills, attracting teenagers' attention to start practicing this modality (DiFiori et al., 2018). Furthermore, comparing the physical capacities of adolescents who practice basketball and those who do not practice sports in a country like Brazil, where soccer practice and scientific investigation keep growing, gains importance and helps delineate interventions to build new evidence about the diversification of sports and new possibilities to improve the health of this population (Schmitz et al., 2009).

However, to our knowledge, there is a lack of studies comparing the physical capacities of teen basketball players and non-sport practitioners in a scholarly environment, thus seeking to understand how beneficial sports practice can be for the health of adolescents. Furthermore, the employment of advanced data analysis techniques are very appreciated in health and sports science. In this context, artificial intelligence (AI) is a powerful tool to forecast conditions and events in diverse areas of humanity (Xu et al., 2021). Especially in health sciences, these techniques help professionals predict and anticipate conditions, thus becoming more efficient for prevention and targeting interventional strategies (Habehh & Gohel, 2021).

Therefore, this study aims to compare the physical activity level, body fat percentage, handgrip strength, lower limb power, and lower limb flexibility of teen basketball players and adolescent non-practitioners of sports. A linear regression machine learning algorithm was also applied to predict the adolescent's' physical components.

MATERIAL AND METHODS

Study Design

This was a quasi-experimental study in which 29 male adolescents, mean age 16 ± 0.6 years, students of high school at the Instituto Federal do Sudeste de Minas Gerais, Campus Rio Pomba, were divided into two groups per convenience: the basketball group (BG: $n = 15$), and the non-sport practitioner's group (NS: $n = 14$). All participants were healthy and free from any health-disabling condition. The statistical power was calculated in Rstudio (Field et al., 2012), and the minimal statical effect to reach significance in a 95% confidence interval ($p < 0.05$) and a large Cohen's effect size ($r \geq 0.50$) was set in 0.80 (high statistical power) (Cohen, 2013). The BG had been participating in basketball training three times a week, with a duration of 50 minutes in each session, for a total of two continuous years, except for the two-month vacation period, while the NS group did not participate in any teen sport or other types of sports during the same two years of high school.

The data collection happened in the Laboratory of Sports Sciences of the Education Department of the Federal Institute of Southeast of Minas Gerais (Campus Rio Pomba, Brazil). All valuators were previously trained and capacitated by the researcher for all testing procedures done in this study.

Inclusion and Exclusion Criteria

The inclusion criteria for the BG were: (i) have medical health consent to practice sports during the period of the study, relating no historical of any pathological or disabling condition (the same for CG); (ii) in the BG, have at least 75% participation in training sessions during the two years in which the team was trained; (iii) accept to participate in the study, signing the informed consent form.

For the NS group, it was: they did not participate in any continuous sports practice during the same time of the study they accepted to participate in the study and signed the informed consent form.

The exclusion criteria for the BG were as follows: they have not reached the minimal training frequency on bas-

ketball sessions determined in the study and they have not signed the informed consent form.

For the NS group, it was: did not sign the informed consent form; have participated in some team sports for at least 4 four months across the study. The volunteers gave their consent to participate in the study.

The sample and collection eligibility processes are described in the flowchart in Figure 1 below.

Data Collection

The project evaluators were trained so that they could apply the instruments used in the research. The following data were extracted: PAL, BF%, HG, BMS, LLP, and LLF.

Physical activity levels

The PALs were collected using the International Physical Activity Questionnaire (IPAQ), a short version validated for use with Brazilian adolescents (Guedes et al., 2005). The PAL was divided into three categories, as follows:

High: those who perform vigorous-intensity activity for at least three days, reaching a minimum total physical activity of at least 1500 METs/minutes/week, or; those who perform seven or more sessions per week of any combination of these activities, accumulating a minimum of 3000 METs/minutes/week;

Moderate: those who perform three or more days of vigorous activity of at least 20 minutes a day or; those who perform at least five days or more of moderate-intensity activity or walking for at least 30 minutes a day or; those who perform five or more sessions per week of any combination of walking, moderate or vigorous intensity activities, accumulating a minimum of 600 METs/minutes/week;

Low: those not classified in either of the two categories above.

Body fat percentage

The BF% was verified following the body fat percentage method validated by Slaughter et al. (1988), following the

next equation to measure the body fat percentage of boys aged 8–18 years:

$$BF\% = 0.735 \,(td + cd) + 1$$

Where BF% is the body fat percentage, td is the triceps diameter, and cd is the calf diameter.

The triceps skinfold was measured using a clinic radiometer CESCORF®, with an accuracy of 0.001 mm. The measures were employed vertically on the posterior medial point of the arm, between the acromial process and inferior margin of the ulna olecranon, and the calf skinfold was measured diagonally, approximately 45°, 2 cm below the medial point of the leg, in the region of the medial calf. The measurements were performed twice; if there was a deviation larger than 0.05 meters, the third measurement was performed, and the median was taken as the final result.

Handgrip strength

The HS was analyzed using a hydraulic Jamar® handgrip dynamometer, adopting the kilograms-force with a range from 0 to 90 kg-f and precision of 1 kg-f with the voluntary sited in a chair and supporting the arm on a table. Three attempts were made, with 1 minute of rest between attempts. The protocol followed the normalization of (Guedes, 2006).

Back extensor muscle's' strength

The BMS data were collected using one dorsal dynamometer model Crown, Filizola® (Brasil), with a range of mensuration of 0-200 kg-f, and precision of 1 kg-f. The volunteers stood on the dynamometer platform, knees fully extended, the trunk slightly bent forward, forming an angle of approximately 120°, and the head following the extension of the trunk with the gaze fixed ahead, and then they performed maximum strength on the legs in the standing position (knee and hip extension). Three attempts were made, and with 1 minute of rest between attempts, the greater attempt was noted (Guedes, 2006).

Lower limb power

The LLP was analyzed using a contact platform Multi Sprint, Hidrofit®, Brazil,with a 1000 x 600 x 8 mm dimension. The volunteer did the vertical jump with the arm's help, characterizing a countermovement jump for each attempt. Three attempts were made, with 1 minute of rest between attempts; the greater attempt was noted (Guedes, 2006).

Lower limb flexibility

The lower limb flexibility was collected using the Wells bench, Physical® brand, Brazil, with a scale of 0.01 meters. The volunteer was positioned sitting on a mat, with the feet in full contact with the anterior face of the bench and with the knees fully extended, and subsequently, the volunteers were instructed to reach the bench's scale as much as they could, performing a trunk flexion. Three attempts were made, with 1 minute of rest between attempts. The greater score was noted (Guedes, 2006).
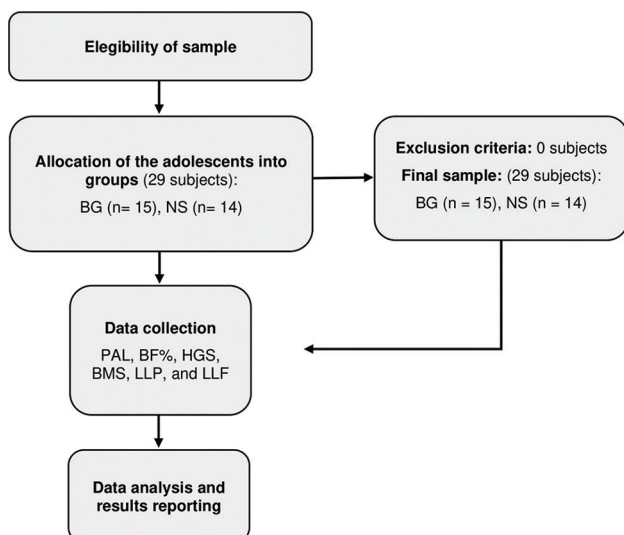

Figure 1. Flowchart of the study

Statistical Analysis

The data bank was saved and organized in a Microsoft® Excel worksheet (Microsoft Corporation, USA). All statistical analysis and data visualization were performed using the R version 4.0.0 program, in which the researcher programmed the analysis inside Rstudio (Field et al., 2012). The normality of the data was analyzed by using the Shapiro-Wilk test, and the homogeneity of the variance was verified by using the Levene test. The normal data was analyzed through the independent T-test, and the non-parametric data were analyzed through the Mann-Whitney U test. Normal data was reported as mean, and standard deviation, and non-normal data were reported as median and interquartile range. For the effect size (ES), the calculation of Cohen's r (r) adopting the normalization of 0,10: small, 0,30: moderated, 0,50: large was used (Cohen, 2013). Additionally, the analysis of covariance (ANCOVA) between the independent covariables and the dependent variables selected for the analysis was calculated. All statistical presupposes for ANCOVA were attended, thus hoc comparisons were performed using the Tukey post-hock test. The sample means were adjusted for the model. The data for the ANCOVA was reported using the mean and standard error. For the ES, the calculation of the Eta partial squared analysis ($\eta p2$) adopted the normalization of 0,10: small, 0,30: moderated, and 0,50: large (Cohen, 2013). A significance levels of $p < 0.05$ was adopted for all the analyses. The results were presented in the body of the text and tables. a linear regression machine learning algorithm was applied to predict the adolescent´s' physical components. For this purpose, a feature selection was performed to explore the data through the correlation coefficients between all variables in the dataset (Unpingco, 2016). After exploratory analysis, the best features were chosen as variables of interest for the linear regression. Next, the two most correlated variables were split into a predictive array (X for the independent variable) and a target variable (y) for the predicted variable. To train the model, 70% of the data was chosen, and the remaining 30% was directed to testing the predictions. The intercept values (βo), the average predicted value for the dependent variable, the coefficients of regression (β), and the R^2 were the main regression outputs (Haslwanter, 2016; Unpingco, 2016). RMSE was used validate the model (Chai & Draxler, 2014).

RESULTS

Figure 2 shows the general characteristics of the BG and NS groups. It was observed that the BG presented higher values of height than NS group (BG: 1.84 ± 0.05 meters vs. NS: 16.2 ± 0.7 meters, $t = 2.87$, $df = 22.84$, $p = 0.008$, $r = 0.32$), and a lower BF% than NS group (BG: 26% (15) vs. NS: 34% (7), $w = 33$, $p = 0.02$, large ES, $r = 0.85$), There were no differences between BG and NS for age, body weight, and BMI ($p > 0.05$).

Figure 3 shows the results of comparing HG, BMS, LLP, and LLF. It was observed that the BG group presented greater values HG (BG: 124 ± 31 kgf vs. NS: 105 ± 18 kgf, $p = 0.005$, $t = 3.12$, $df = 19.16$, moderate ES, $r = 0.34$, greater

values of BMS (BG: 134 ± 26 Kgf vs. NS: 105 ± 18 Kgf, $t = 3.12$, $df = 19.16$, $p = 0.005$, moderate ES $r = 0.33$), greater values of LLP (BG: 34 ± 4 cm vs. NS: 30 ± 3 cm, $t = 2.95$, $df = 20.41$, $p = 0.007$, moderate ES, $r = 0.30$), and greater values for LLF (BG: 30.5 ± 10 cm vs. NS: 22.4 ± 8 cm, $t = 2.35$, $df = 25.71$, $p = 0.02$, small ES, $r = 0.17$). Moreover, the BG group presented an upper number of adolescents classified with high PAL than the NS group (BG, n = 15 (100%) vs. NS, n = 4 (28%), $X^2 = 13.34$, $df = 1$, $p = 0.0002$, large ES, $V = 0.73$), and a lower number of adolescents classified with low PAL than the NS group (BG, n = 0 (0%) vs. NS, n = 10 (71%), $X^2 = 13.34$, $df = 1$, $p = 0.0002$, large ES, $V = 0.73$). Therefore, through the ANCOVA analysis a positive effect of high PAL compared with low PAL was found in HG (high PAL: 50.8 ± 3.3 Kg-f vs. Low PAL: 31.6 ± 4.7Kg-f, $t (19) = 3.11$, $p = 0.005$, moderate ES, $r = 0.24$) and also for high PAL in LLF (high PAL: 29.2 ± 2.03 cm vs. Low Pal: 17.7 ± 2.93 cm, $t (19) = -3.02$, $p = 0.006$, moderate ES, $r = 0.23$). No significant differences were found between high PAL and low PAL for LLP, BMS, and BF% ($p > 0.05$).

Table 1 shows the machine learning outputs. In general, the models expressed good generalization performance, with R^2 ranging from 0.77 to 0.88, RMSE from 1.01 to 3.92, and four and average mean difference of four points between the predicted and real values. The worst model was a random forest regressor ($R^2 = 0.77$, RMSE = 3.92), and the best model was Bayesian regression ($R^2 = 0.88$, RMSE = 1.01).

DISCUSSION

This study aimed to compare the physical activity level, body composition, strength, and flexibility of teen basketball players and adolescent non-practitioners of sports. The main findings reveal that our hypothesis was confirmed, in which the EG showed better results than NS in PAL, BF%, HG, BMS, LLP, and LLF.

As mentioned, basketball is an intermittent and high-intensity sport characterized by sprints and jumps, and anaerobic/aerobic resistance is necessary (Sacot et al., 2022). Thus, as a consequence of continuous practice, basketball can stimulate body composition and physical capacities such as muscle strength and power, and aerobic resistance, improving overall health (Castagna et al., 2020). In the present study, the BG presented higher PAL than the NS, with all teen basketball players (n = 15, 100%) classified with high PAL, while only four (28%) adolescents from the NS presented high PAL. The literature shows that increasing the PAL across sports practice is a relevant intervention for improving the health of adolescents (DiFiori et al., 2018; Sánchez-Díaz et al., 2021). Increasing PAL improves muscular and cardiorespiratory fitness and is also associated with the accumulation of adipose tissue, thus reducing the risk of diabetes and dyslipidemia in adolescence (Woodforde et al., 2021).

Furthermore, it was verified that the BG showed a lower BF% than the NS, thus revealing the positive effects of the sports practice above on body composition. Basketball can reduce the body fat percentage because of the high-intensity physiologic demands during a training session or a match,
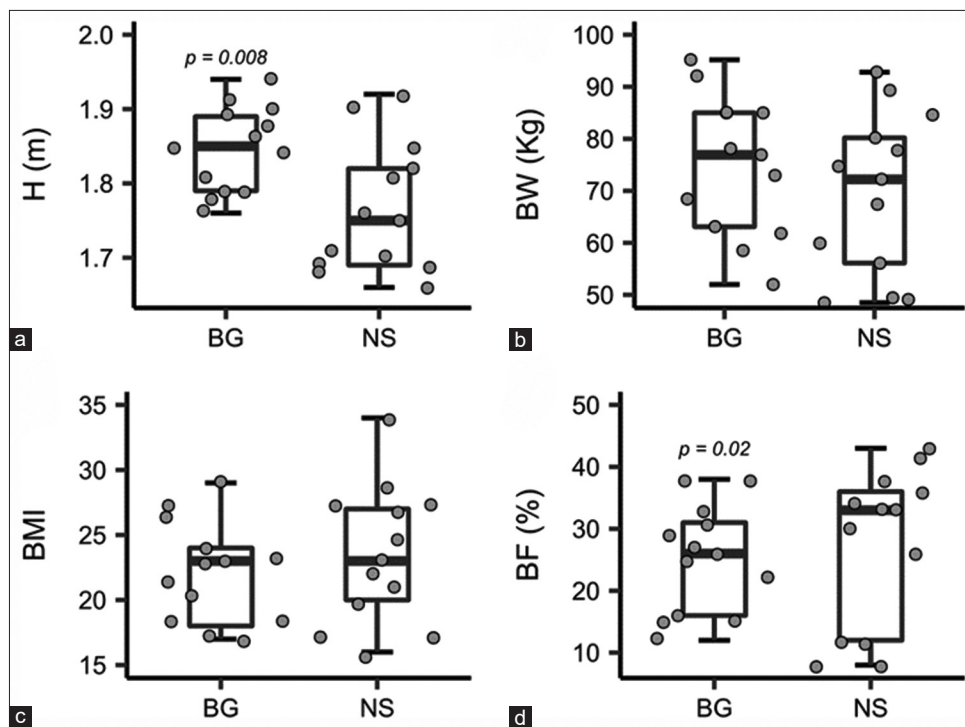
Figure 2. General characteristics of the participants the BG and NS groups. Note: Data are shown in mean and standard deviation and median and interquartile range. Panel (a): height (H), Panel (b): body weight (BW), Panel (c): Body Mass Index (BMI), Panel (d): body fat percentage (BF%)., *p*, p-value < 0.05
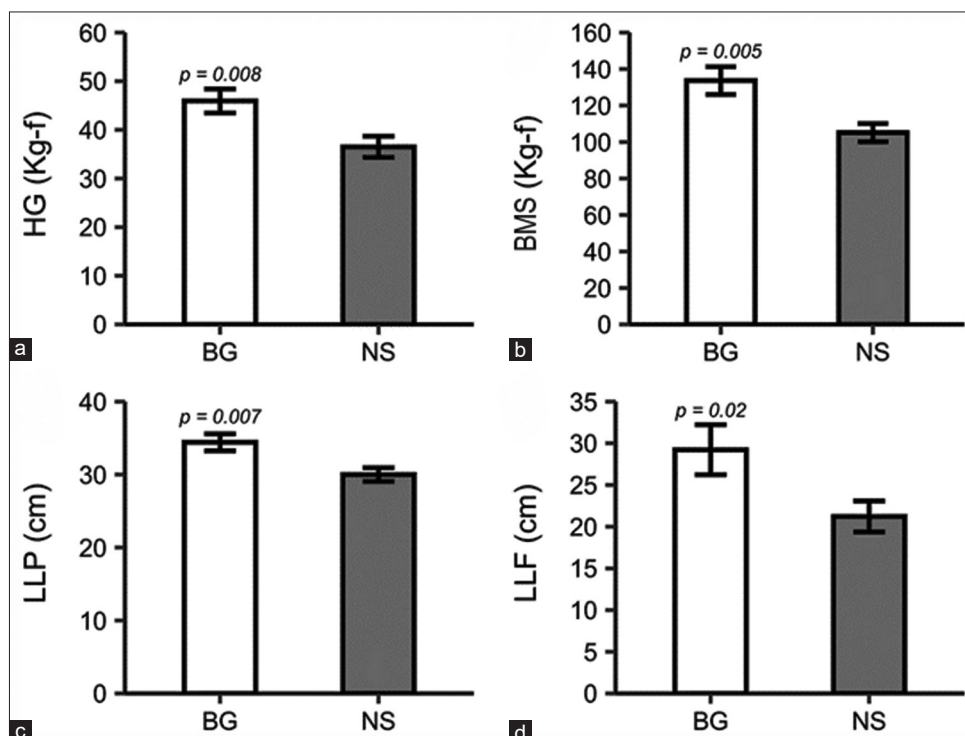

Figure 3. Strength, power, and flexibility the BG and NS groups. Note: Data is shown in mean and standard deviation. Panel (a): handgrip strength (HG), Panel (b): back extensor muscle's' strength (BMS), Panel (c): lower limb power (LLP), Panel (d): lower limb flexibility (LLF). Cm: centimeter, Kg-f: kilogram-force., *p*, p-value < 0.05

which leading to better performance in the modality (Mancha-Triguero et al., 2019). Furthermore, maintaining an adequate body fat percentage through sports practice during adolescence improves body composition and well-being and also reduces the risk of obesity and metabolic imbalances (Morais et al., 2021).

In the present study, it was verified that the BG group presented greater HG values than the NS group. In addition,

Table 1. Algorithm's' performance in predicting the basketball player's' vertical jump based on their body fat percentage

	B_0	β	R^2	RMSE	Real (cm)	Predicted (cm)
LR	38.7	-0.17	0.77	1.4	31	35.45
RR	38.7	-0.17	0.77	1.4	31	35.45
RFR	NA	NA	0.77	3.92	31	34.4
BR	38.1	-0.15	0.88	1.01	31	35.22
Average of the metrics	38.5	-0.16	0.79	1.9	31	35.13

LR: linear regression; RR: Ridge regression; RFR: random forest regression; BR: Bayesian regression

the analysis of covariance found a moderate effect of high PAL in HG, indicates a positive influence of the increased PAL of BG on their HG. The literature reveals that HG is an indicator of strength manifestation and general vitality and functionality in children, adolescents, and elderly people (Dooley et al., 2020; Soysal et al., 2021). Moreover, important studies have revealed that having good HG is strongly associated with high functionality and a good quality of life (García-Hermoso et al., 2019).

Furthermore, the BG presented greater values of BMS than NS, indicating the positive effects of basketball practice on this strength variable. Muscle strength is a physical capacity that can be measured in many ways, and each strength manifestation means different health or health indicators, such as sports performance, physical fitness, and quality of life (de Lima et al., 2021). Specifically, BMS is considered an important physical capacity for preventing low back pain in children and adolescents because it is responsible for improving muscle activation and joint stability in the lumbar spine, thus preventing lower back pain and consequently the low quality of life during adolescence (Jung et al., 2020). Likewise, BMS is relevant to maintaining quality in the realization of the activities of daily living (ADLs), such as holding objects with the help of trunk stabilization, stabilizing the spine while climbing stairs, clean the garden, among others (Castro et al., 2022).

Moreover, for the LLP, it was verified that BG had greater values than NS, revealing the effectiveness of basketball training on the muscle power of adolescents. It is known that the jump is one of the most important determinants of basketball performance, accompanied by sprint speed and change of direction speed (Cui et al., 2019). The LLP is not only important for basketball performance but also is positively associated with better physical fitness, aerobic resistance, and physical capacity; additionally, LLP is inversely correlated with sedentary behavior and obesity in adolescents (Almeida-Neto et al., 2021; He et al., 2019).

Therefore, it was found that the BG group showed better values of LLF than the NS group. Flexibility is a physical capacity important for avoiding movement asymmetries through the training process, helping technical development, leading to better sports performance, and injury prevention (Cejudo et al., 2020). Moreover, LLF is inversely associated with functional limitations throughout life, thus helping in ADLs such as walking in crooked terrain, overcoming obstacles, and getting on a bus (Pfeifer & Berkman, 2018). In addition, the ANCOVA verified a positive effect of the high PAL in the LLF of the adolescents, thus, revealing the benefit

of participating in basketball training and keeping physically active during high school.

In the present study, the application of a linear regression machine learning algorithm predicting of adolescent physical components yielded insightful results, as presented in Table 1. The machine learning models demonstrated worthy generalization performance across the board, with R^2 values ranging from 0.77 to 0.88 and RMSE values spanning 1.01 to 3.92. Notably, a consistent average mean difference of four points was observed between the predicted and actual values. Among the four models assessed, the Bayesian regression emerged as the top-performing model. Furthermore, in the context of machine learning analysis, the Bayesian regression model consistently outperformed its counterparts. It is noteworthy that the BG group consistently outperformed the NS group across various physical components, including PAL, BF%, HG, BMS, LLP, and LLF. Specifically, body fat percentage emerged as a precise predictor of the player's' VJ.

In uniformity with our machine learning analysis, it is pertinent to consider the insights provided by Caia et al. (2016), who sought to elucidate the variables influencing VJ performance when their findings underscore a robust negative association between BF% and VJ. Thus, the sole consideration of body BF% accounted for 57% of the variability in VJ performance. When incorporated with additional factors such as sex or body weight, this explanatory power increased to 66%. This observed inverse relationship between BF% and VJ aligns with expectations, given the non-force-producing nature of fat tissue. Our machine learning approach identified even a more robust variability in the VJ performance explained by BF% (R2 = 88%), revealing the importance of the body composition for the VJ performance in high school basketball players. Accordingly, previous findings have showing that a lower body fat percentage emerges as desirable for optimal VJ performance, as it signifies a lighter relative body mass to be propelled, facilitating the attainment of higher segment velocities during basketball practice (Ribeiro et al., 2015). These findings not only corroborate the importance of body composition in athletic performance but also provide valuable context for interpreting the predictive power of body fat percentage in our machine learning models.

Practical Implications

The benefits of basketball for the physical capacities related to health and sports performance during high school are

notorious. The results found in the present study draw attention to the necessity of effort in health and educational politics to introduce and institutionalize basketball practice in the scholarly environment in the same proportion as the other modalities more culturally practiced, thus keeping the adolescent population highly physically active and healthy for the next phase of their lives.

The success of machine learning algorithms, particularly the Bayesian regression model, in predicting key physical components like power, body fat percentage, and strength metrics offers valuable insights for tailored sports training programs. These precise predictions can empower coaches to customize interventions, optimizing the effectiveness of training strategies for adolescent athletes (Dwyer et al., 2022). In the perspective of sports performance, these outputs emphasize the importance of caring about the body composition of high school during the annual athletic seasons, especially during the preparatory periods where building a proper body shape is determinants to better athletic performance and prevent injuries overall the season moments (Dwyer et al., 2022). On the viewpoint of health, reducing body composition and improving VJ is directly correlated with good self-esteem and self-image perception in adolescents (Gualdi-Russo et al., 2022), and a significant reduction of non-communicable chronic disease during adolescence (Wells & Shirley, 2016).

Study Limitations and Perspectives

This study has some limitations, such as (i) a lack of baseline analysis that should permit effect analysis and enrich the results;, (ii) a lack of dietary control among the adolescents;, and (iii) the lack of collected biochemical data to explain more about the benefits of basketball practice. Future research should consider the randomized controlled design, verifying the long-term magnitude of the changes in the teen basketball practitioners' health and performance parameters. The comparison between different sports can also be analyzed in future studies.

CONCLUSIONS

In conclusion, our study not only highlights the superior physical performance of the BG group over the NS group across key metrics, including PAL, BF%, HG, BMS, LLP, and LLF, but also integrates the insightful predictive capabilities of machine learning. The machine learning models, particularly the Bayesian regression model, demonstrated exceptional accuracy in predicting essential physical components. These findings underscore the positive impact of basketball practice during high school, emphasizing its role in fostering higher outcomes in strength, body composition, and overall physical fitness. As we advocate for the importance of sustaining basketball practice, the integration of machine learning further refines and adapts training interventions for even greater efficacy. This holistic approach, combining traditional insights with cutting-edge technology, stands to enrich the lifelong benefits derived from the practice of basketball, contributing to the immediate physical well-being of adolescents and the enduring advantages reaped throughout their lives.

AUTHOR'S CONTRIBUTION

Samuel Gonçalves Almeida da Encarnação: conception, data acquisition, drafting the work, analysis and interpretation of the data, Vitor Hugo Santos Rezende: data acquisition, review and editing the original draft, Iarni Martins Gonçalves: data acquisition, review and editing the original draft, Patrícia de Oliveira Ramalho Prata: data acquisition, review and editing the original draft, Henrique Novais Mansur: data acquisition, review and editing the original draft, Tatiana Sampaio: data acquisition, review and editing the original draft, Pedro Forte: data curation, review and editing the original draft, José Eduardo Teixeira: data curation, review and editing the original draft, António Miguel Monteiro: data curation, review and editing the original draft, Ana Paula Muniz Guttierres: contributed to the conception of the work, data curation, review and editing the original draft.

DATA AVAILABILITY

The data from this research is available by contacting the authors.

Declaration of Competing Interest

The authors declare no conflicts of interest in the content of this research.

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