Mikielewicz *et al. Sports Medicine - Open (2026) 12:99*
https://doi.org/10.1186/s40798-026-01076-z

Sports Medicine - Open

ORIGINAL RESEARCH ARTICLE

Open Access

Is Non-dominant Leg a Key Factor for Endurance Performance in Male Youth Soccer Players? Data-Driven Knowledge-Adjusted Causal Analysis and Literature Synthesis

Magdalena Mikielewicz[1], Kacper Korzeniewski[1], Robert Makuch[2], Jakub S. Gąsior[3*] and Marcel Młyńczak[1]

Abstract

Background Soccer performance in youth players arises from a complex interaction of anthropometric, physiological, technical, and maturational factors. However, most studies emphasize correlation analyses, offering limited insight into causal mechanisms that shape athletic development and physical performance. This study aimed to identify causal pathways underlying potential targets for practical intervention in male youth soccer players.

Results Data from 275 male Caucasian youth soccer players aged 8–18 years from youth soccer academy (Mazovian region) were collected during the pre-season and analyzed using the Greedy Fast Causal Inference algorithm to generate a data-driven directed acyclic graph. Complementarily, a scoping review of publications indexed in PubMed and Web of Science (search conducted up to July 2025) identified 102 eligible studies on associations between parameters in apparently healthy male youth soccer players. Data from studies were used to construct a chord diagram illustrating associations among players' characteristics. This approach revealed sprint ability, countermovement jump, agility as well as maturity as central nodes in performance networks. However, causal modeling and literature synthesis highlighted the non-dominant leg and functional deficits as a potentially modifiable determinants linked to sport-specific skills and endurance-related performance.

Conclusions The integration of data-driven causal discovery and review-based associations offers a methodological bridge from observational evidence toward hypothesis generation. The findings establish a rationale for a future randomized controlled trial aimed at testing whether intervention focused on reducing interleg asymmetries (i.e., differences in power/strength between lower extremities) can improve endurance capacity and specific soccer skills in male youth soccer players.

*Correspondence:
Jakub S. Gąsior
jakub.gasior@wum.edu.pl
Full list of author information is available at the end of the article

Key points

- Endurance performance in male youth soccer players is shaped by a network of interacting factors with age, maturity, experience, advancement, functional deficits and body composition emerging as central nodes.
- While age and maturity are non-modifiable, literature synthesis and data-driven causal modeling identified the interleg asymmetry as correlates of sprint, agility, sport-specific skills such as passing accuracy and non-dominant leg performance as a potentially modifiable determinant linked to endurance-related performance.
- Reducing interleg asymmetries may represent a practical training target and provide a rationale for future randomized trials verifying whether balancing lower-limb power and strength can improve aerobic capacity and sport-specific skills in youth soccer players.

Keywords Soccer, Youth, Endurance performance, Inter-limb asymmetry, Causal inference

Background

Soccer, leading youth sport in Europe [1], encompasses physiological, physical, technical, tactical, and psychological contributions to performance [2], all of which are related to athletes' maturation status [3]. Soccer is an intermittent sport consisting of short bouts of intense activity that are superimposed amongst longer periods of low–moderate intensity activity. This intermittent profile makes match demands highly contextual and complex, requiring players to perform varied actions during match play. Understanding the association between player's performance and match demands are important for implementing training strategies that are aimed at development within soccer [2]. Implementation of individualized training strategies aimed at specific parameters may influence an athlete's improvement.

Most studies on performance parameters in youth soccer players emphasize correlation analyses rather than examining the underlying causal mechanisms among performance variables, creating ambiguity in understanding how these variables influence one another. It is crucial to identify which factors act as primary drivers and which serve as outcomes. While correlation-based approaches can provide initial insights into the strength of relationships, they fail to capture the directionality and complexity of these interdependencies [4].

To move beyond these limitations, more advanced tools are available that enable clearer identification of causal relationships. One of the options to consider is "discovering" causal diagram (DAG—directed acyclic graph), providing framework for mapping variable dependencies and identifying potential confounders. Controlling for various confounders is a crucial element in analyzing the performance of young athletes, as—for instance—maturity and chronological age, are often closely linked to performance outcomes [5–8]. This approach allows for better understanding of what training plan should be applied to get the expected outcome—while also helping to minimize potential risks of injury [9]. However, the gold standard for identifying and confirming causal mechanisms remains randomized controlled trials (RCTs). Despite their strength, RCTs face important barriers that limit their application in youth sport research, such as much higher cost for recruitment, larger sample size to detect meaningful effects, ethical considerations or long-time commitment of participants [10]. As an intermediate solution between correlation analysis and RCTs, causal discovery methods such as Fast Causal Inference (FCI), Fast Greedy Search (FGES), and Greedy Fast Causal Inference (GFCI) algorithms may be used, at least as a first step, before conducting the interventional study [11]. It goes beyond simple correlation by attempting to infer causal relationships from observational data. The rationale of such an analysis would be to generate a proper hypothesis, rather than conclude from the data.

The aim of this study is to identify a data-driven causal diagram and synthesize literature on potential relationships between performance variables identified in male youth soccer players. These findings may support the development of a targeted research protocol aimed at defining effective intervention strategies.

Methods

The study design combined two complementary analytical streams: one focused on a data-driven discovery approach, and the other employed a scoping review. Together, these two streams yielded a knowledge-adjusted DAG (Fig. 1).

Data Collection (Participants and Procedures)

Given the observational design and the use of data-driven causal model discovery with the GFCI algorithm for continuous variables, the study was designed to include as many eligible players as possible during the data collection period. This approach was chosen, because causal discovery methods assess multiple conditional

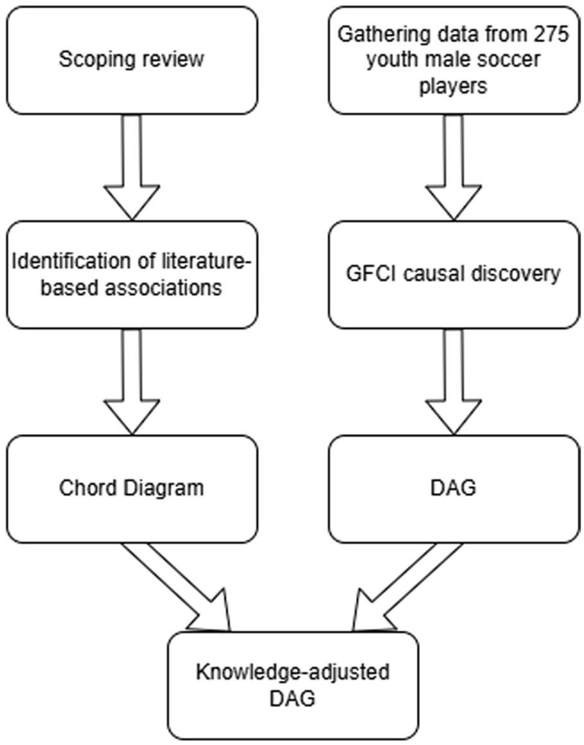

Fig. 1 Methodological flow. *GFCI* Greedy Fast Causal Inference, *DAG* directed acyclic graph

relationships simultaneously, and larger sample sizes improve the stability and robustness of the inferred model structure. Therefore, all players who met the inclusion criteria were recruited. Inclusion criteria were: (1) a minimum of 1 year of soccer training experience; and (2) no musculoskeletal injuries in the lower extremities (knee, ankle, or hip joints) within the previous 12 months. Two hundred and seventy-five male Caucasian youth soccer players aged 8–18 years from one youth soccer academy—"Akademia RKS Radomiak Radom" (Mazovian region, Radom, Poland) voluntarily participated in the study during the off-season, prior to the start of the competitive season. Two researchers (R.M. and J.S.G.) supervised the data collection process conducted by the coaches of the selected age-groups. Participants underwent a comprehensive set of assessment designed to capture demographic, maturational, anthropometric, physiological and physical performance characteristics. Youth players were asked to refrain from strenuous exercise at least 48 h prior to testing. Selected information were gathered using a questionnaire completed by the coaches: chronological age, training start date to calculate experience in years (training experience defined as years of systematic training performed at least three times per week), advancement level (1–4 scale, with 1 representing the highest level of proficiency, based on individual assessment conducted by the team coach, reflecting the athlete's overall technical and tactical competence), playing status (starting or reserve) and leg dominance (self-reported by players based on their natural preference for kicking and performing technical soccer skills). Biological maturation was estimated using Moore's equations to calculate maturity offset, expressed as years from peak height velocity [12]. Anthropometric and body composition measurements were obtained using a Tanita MC-980 MA body composition analyzer. Standing height was measured to the nearest 0.1 cm and body mass to the nearest 0.1 kg. Body mass index (BMI) was calculated as body mass divided by height squared ($kg \cdot m^{-2}$). Body composition variables included percentage and absolute fat mass (FATP and FATM, respectively), fat-free mass (FFM), predicted muscle mass (PMM), bone mineral mass (BONEM), total body water (TBW), basal metabolic rate (BMR), and whole-body electrical impedance (IMP). Impedance reflects the resistance of body tissues to a low-level electrical current and serves as a physiological indicator associated with hydration status and tissue composition, particularly lean mass distribution. Upper-limb strength was evaluated through maximal handgrip strength (HGS) testing performed for both dominant and non-dominant hands under standardized conditions (seated position, 90° elbow flexed). Lower-limb strength was assessed using vertical jump testing on an Optojump system, including countermovement jump (CMJ), countermovement jump without arm swing, and squat jump (SJ). Unilateral jumping performance and inter-limb asymmetry were further examined using the Drift protocol [13]. The Back Squat Assessment was used to verify functional deficits and technical factors that limit performance [14]. Aerobic capacity was evaluated using the Yo-Yo Intermittent Recovery Level 1 test (YYIR1), from which running distance, training load and estimated maximal oxygen uptake (VO_2max) were derived. Anaerobic performance was assessed using the running-based anaerobic sprint test (RAST), from which power outputs, fatigue index, and fastest sprint time were derived. Change-of-direction ability was assessed using the 505 Agility Test. Cardiovascular measures (heart rate and blood pressure; Beurer BM 58, Germany) were recorded to provide a holistic characterization of the youth athletes.

Statistical Analysis and Data-Driven Causal Model Discovery

The normality of distribution for continuous variables was assessed using the Shapiro–Wilk test. Continuous variables with normal distribution are presented as mean ± standard deviation, whereas variables deviating from normality are presented as median [interquartile range]. Categorical variables are reported as number (n) and percentage (%).

The data-driven causal model discovery was performed using the GFCI technique intended for continuous variables [11]. The GFCI approach integrates and enhances two existing algorithms: FCI and FGES. FCI starts with a fully connected undirected graph, while FGES begins with an empty graph, incrementally adding necessary edges and later removing redundant ones. In GFCI, FGES is first used to construct a "supergraph" representing the underlying structure of connections. Then, FCI refines this supergraph by pruning it and determining the final edge orientations. Analyzed data were used as an input. All variables were stored as raw numeric values without prior standardization, as the causal discovery method itself relies on linear correlations, making manual scaling unnecessary (any manual scaling would not change the graph structure at all). The default settings for the GFCI method intended for continuous variables were chosen, specifically utilizing the Bayesian Information Criterion scoring function with a penalty discount of 1.0 for the FGES phase, and the cutoff for p value at the level of 0.01 for the FCI phase, no bootstraps (not applied to preserve the exploratory nature of the analysis, as well as to prevent the excessive pruning of potentially meaningful hypothesis-generating pathways in a moderately sized sample dataset), ensemble method: the highest. The whole analysis was performed utilizing Tetrad 6.5.3 software [15].

Scoping Review

This scoping review was conducted in accordance with the PRISMA Extension for Scoping Reviews (PRISMA–ScR) guidelines [16]. A search of the PubMed and Web of Science databases was performed from inception to July 2025. The search was limited to titles using the following Boolean string: *(young OR youth) AND (football OR soccer) AND players* (e.g., "youth soccer players"[All Fields]). Eligibility was restricted to original, English-language studies examining associations between selected parameters in apparently healthy male youth soccer players. The source selection process was conducted in two stages. First, titles and abstracts and second full-text articles were screened for relevance to the research aims by two authors independently. Studies were excluded if: (i) not focused on correlation/association between physiological, physical, technical, tactical, psychological, performance parameters, (ii) combine data from youth and adult soccer players, (iii) focused solely on playing positions, (iv) reported associations between two tests concerning one ability/skill, (v) identified no statistically significant correlations, (vi) concern youth soccer players with disabilities. To ensure a comprehensive search, reference lists of all included articles were manually checked for additional eligible studies. The initial search yielded a total of 997 publications. Following the screening of titles and abstracts, 780 studies were excluded. A total of 217 full-text papers were analyzed. Finally, 89 English-language original studies related to associations between selected parameters in apparently healthy male youth soccer players were included for detailed analysis. An additional 13 studies meeting the inclusion criteria were identified in the references of the accepted articles (see list of final sample of 102 references in Supplementary Materials). The flow chart is presented in Fig. 2.

The methodological quality and risk of bias of the included studies were evaluated using the Newcastle–Ottawa Scale (NOS) [17, 18]. Recognizing the diversity of study designs, specific versions of the tool were applied to match each study type:

i) Cross-sectional studies: Quality was assessed using an adapted 16-point version of the NOS. This version evaluates four key domains: clearness of the stated aim (0–2 points), sample selection (0–8 points), comparability (0–2 points), and outcome (0–4 points). Following established guidelines, studies were categorized as high quality (13–16 points), moderate quality (9–12 points), or low quality (≤ 8 points), or
ii) Cohort and case–control studies: These were evaluated using the original star system of the NOS. The assessment focused on three major categories/domains: selection of the study groups (maximum 4 stars), Comparability of the groups based on design or analysis (maximum 2 stars), and Exposure/Outcome (maximum 3 stars). Each domain can receive a maximum of one star, except for comparability, which can be awarded up to two stars. Articles that received between 7 and 9 stars were classified as having a low risk of bias; those scoring between 4 and 6 stars were considered to have a moderate risk; and those with scores between 0 and 3 stars were classified as having a high risk of bias.

To ensure the reliability of the synthesis, all assessments were conducted independently by two authors. In cases where discrepancies in scoring occurred, they were resolved through discussion with other authors to reach a consensus. This approach was adopted to mitigate the subjectivity inherent in qualitative appraisal tools and to enhance the transparency of the systematic review process. NOS scoring for articles included to analysis is presented in Supplementary Materials.

Data from included articles were extracted using a standardized data-charting form developed specifically for this review. To ensure consistency and reliability,

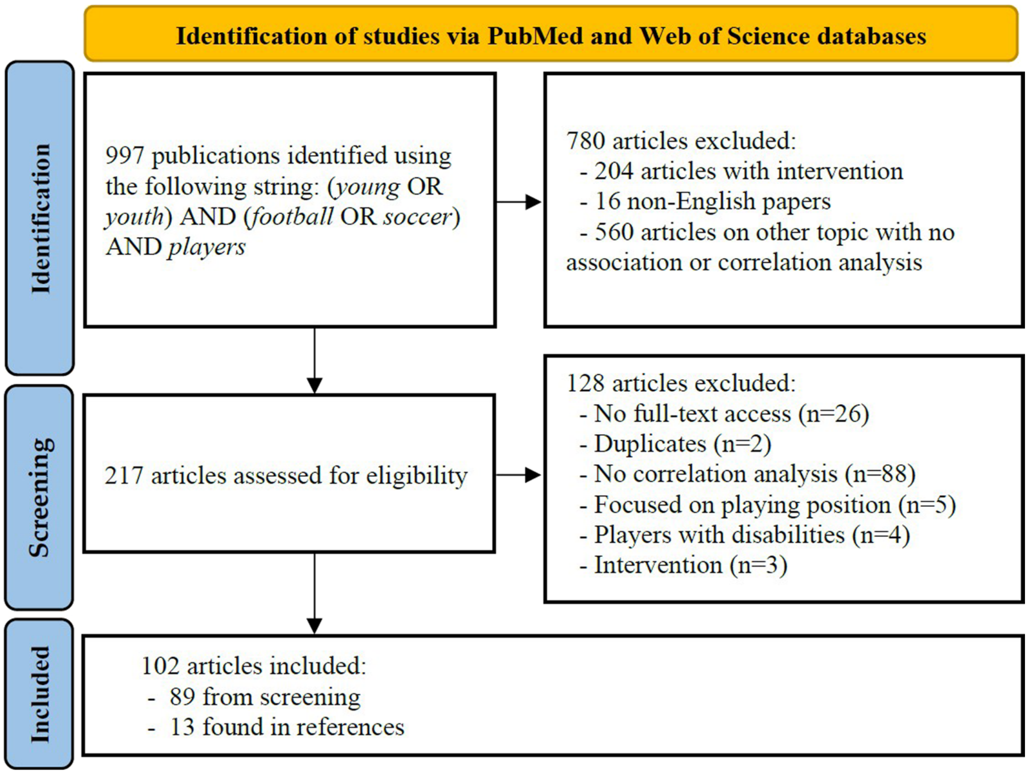

Fig. 2 PRISMA 2020 flow diagram

two authors independently charted the data from each included study. Any discrepancies or disagreements between the two authors were resolved through consensus-based discussion with other authors.

To summarize all of the connections between the analyzed parameters found in the literature, a chord graph was created using R 4.5.2 [19].

Results

Participants Characteristics

None of the players reported injuries at the time of testing. A total of 275 male youth soccer players participated in the study; however, 61 were excluded due to lack of complete data (absence during selected examinations). Results of 214 players were analyzed, among them 120 starters (56.1%) and 94 substitutes (43.9%); 109 (50.9%), 49 (22.9%), 46 (21.5%) and 10 (4.7%) assessed by the team coaches as 1, 2, 3 and 4 advancement level, respectively. Right leg was dominant for 185 (86.4%) players. Players' characteristics are presented in Table 1.

Data-Driven Causal Model Discovery

The GFCI algorithm for continuous variables enabled the DAG model creation. As stated in the section above, missing data were ignored (complete-case analysis). We decided not to apply any imputation techniques to avoid introducing artificial correlations. Features that were not found to be related to any other features were not presented in the graph. The graph was improved by adjusting a few knowledge-based information, as follows: the direction of information flow was changed for Advancement and Experience, the direction of information flow was changed for Advancement and Aerobic capacity (YYIR1), the direction of information flow was changed for Back Squat Assessment and Aerobic capacity (YYIR1). The final result is presented in Fig. 3.

Review-Based Flow Chart

The methodological quality assessment of the 102 included studies demonstrated a generally high to moderate standard of evidence. For the cross-sectional studies ($n=94$), which were evaluated using the adapted 16-point NOS, 25 studies (26.6%) were classified as high quality (scoring 13–16 points), representing a low risk of bias. The remaining 69 studies (73.4%) were identified as being of moderate quality (scoring 9–12 points). Notably, no cross-sectional studies were categorized as low quality (≤ 8 points), as the minimum score recorded in this group was 9 points. The cohort and case–control studies ($n=8$) all achieved high-quality ratings according to the original NOS star system, with scores ranging from 6 to 7 stars out of a possible 9.

Table 1 Player's characteristics. Continuous variables with normal distribution are presented as mean ± standard deviation, whereas variables deviating from normality are presented as median [interquartile range]

Variable	Data
Age (years)	13.26 ± 1.98
Maturation (years relative to peak height velocity)	– 0.07 [– 1.6–1.32]
Training experience (years)	3.43 [1.51–5.40]
Standing height (cm)	163.50 [150.45–175.82]
Body mass (kg)	49.6 [39.32–63.50]
BMI (kg/m^2)	18.7 [16.8–21.2]
Fat mass (%)	15.50 [12.42–18.62]
Absolute fat mass (kg)	7.30 [5.82–9.38]
Fat-free mass (kg)	41.85 [32.48–53.30]
Predicted muscle mass (kg)	39.65 [30.78–50.60]
Bone mineral mass (kg)	2.2 [1.7–2.7]
Total body water (litres)	31.15 [23.90–39.20]
Basal metabolic rate (kJ)	6673.8 [5801.9–7743.6]
Whole-body electrical impedance (ohms)	631.5 [559.8–705.5]
Handgrip strength—dominant hand (kg)	26.7 [19.8–34.7]
Handgrip strength—non-dominant hand (kg)	24.9 [19.1–33.6]
Countermovement jump with arm swing (cm)	30.35 ± 8.07
Countermovement jump without arm swing (cm)	25.99 ± 6.85
Squat jump (cm)	25.21 ± 6.19
Unilateral jump—dominant leg (cm)	11.35 [9.10–15.38]
Unilateral jump—non-dominant leg (cm)	12.15 [9.9–16.08]
Asymmetry in unilateral jump (cm)	0.4 [-9.52–12.02]
Yo-Yo running distance (m)	1000.0 [640.0–1480.0]
Yo-Yo VO$_2$max (ml/kg/min)	44.8 [41.8–48.8]
Yo-Yo training load	46.5 [30.0–69.5]
Running-Based Anaerobic Sprint Test—power (W)	275.77 [172.39–412.37]
Running-Based Anaerobic Sprint Test—fatigue index	2.85 [1.80–5.04]
Running-Based Anaerobic Sprint Test—fastest sprint (s)	5.70 [5.24–6.26]
Change-of-direction ability—505 Agility Test (s)	2.71 [2.59–2.86]
Functional deficits—Back Squat Assessment (points)	5.0 [4.0–7.0]
Heart rate (bpm)	81 [73–89]
Systolic blood pressure (mmHg)	119.8 ± 15.9
Diastolic blood pressure (mmHg)	73.3 ± 9.3

Although most of the studies focus on correlation as main relationship detected, it is crucial to have a look at overall associations within the data. Some of the studies refer to the correlation of parameter to the group of parameters indicating some kind of sport performance, rather than identify direct relationships—those studies were not included in the chart, as it focuses mostly on one to one relations. Results of the review, which consist of a list of relations defined in those studies, are gathered in Tables 1–7 provided in the Supplementary Material, with respect for the categories of a parameter for easier reading. The analyzed parameter is indicated in the first column of each table, while the second column represents all variables identified as correlated or associated with it. The graph demonstrating relationships between parameters is presented in Fig. 4. An interactive table can be found under: https://mmikielew.github.io/causal-discovery/

The parameters that most often are being pointed out as related to other parameters are: maturity (35 relations), sprint (34 relations), countermovement jump (28 relations) and agility (24 relations).

Verification of DAG with Literature-Based Chord

The analysis of the DAG revealed relationship between aerobic performance (measured by YYIR1) and advancement, BSA, age and non-dominant leg performance (i.e., height of jump on this leg). While the associations between Yo-Yo test results with age and experience has already been observed (Fig. 5), BSA and non-dominant leg performance has not yet described. According to the diagram (Fig. 3), changes in non-dominant leg performance appears to be a cause of the Aerobic capacity (YYIR1). However, although there were 17 relationships identified between the Yo-Yo test and other parameters (Fig. 5), and 5 between interleg asymmetry and other parameters (Fig. 6), no direct relationship between these two variables has been observed yet.

Summarizing, the general alignment was presented in Table 2.

Discussion

This study combined a data-driven causal discovery with literature synthesis to explore potential targets for practical intervention in male youth soccer players. The integration of these two approaches highlighted interleg asymmetry, specifically non-dominant leg performance, as a potentially modifiable determinant linked to sport-specific skills and endurance-related performance.

Soccer not only includes physical factors but also depend on many tactical, technical and psychological parameters [2]. The review has confirmed the complexity of relationships found in this sport. Furthermore, the assessment of physical performance in youth soccer players is confounded by the concurrent processes of physical growth and biological maturation, which significantly influence physical fitness development [3]. The chord diagram constructed based on results from more than one hundred observational studies demonstrates that parameters such as sprint, maturity, age and agility

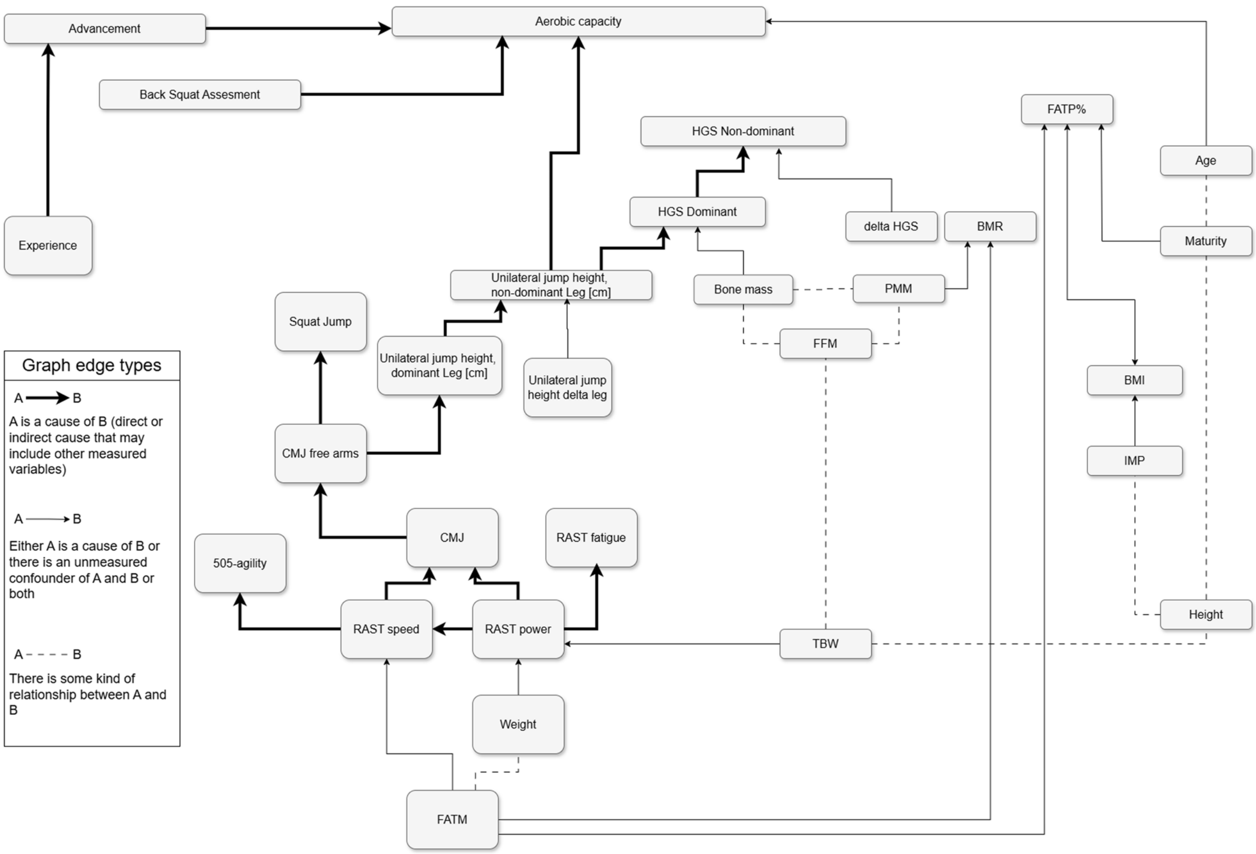

Fig. 3 Data-driven directed acyclic graph presenting hypothetical relations between the data. *CMJ* countermovement jump, *RAST* Running-Based Anaerobic Sprint Test, *FATM* absolute fat mass, *HGS* handgrip strength, *FFM* fat-free mass, *TBW* total body water, *PMM* predicted muscle mass, *BMR* basal metabolic rate, *FATP%* percentage of fat mass, *BMI* body mass index, *IMP* whole-body electrical impedance

are most often identified as related to other variables. It is also worth noting that age and maturity are parameters that cannot be controlled through training, which requires special treatment when planning interventional studies and when interpreting cross-sectional associations. Correlation itself does not allow to get clear path we could follow to make significant improvements. It is easy to conclude, that too many correlations are defined for one variable (example) and it is hard to define clearly which value is indeed crucial. Taking into account each possible indicator leads to the data overload. The number of connections within the chord can lead to overcomplicating the results. It is hard to say which factors are influencing the others and which are being influenced by them. Moreover, correlation can often be misleading, as certain factors may be influenced by an external variable that genuinely drives the relationship rather than acting as a confounder. The relationships determined by DAG created from the gathered observational data are to some extent consistent with the relationships defined in the literature-biased chord. This visualization allowed to identify key causal effects, where multiple factors simultaneously influence one or more outcomes, providing insights that cannot be easily captured through traditional correlation analyses. By mapping these complex pathways, diagrams provide a more holistic framework for optimizing training programs and monitoring athlete development over time.

It is widely recognized that youth soccer players exhibit a high prevalence of asymmetric movement patterns [20, 21]. These imbalances often emerge early in adolescence, as evidenced by significant performance asymmetries in dynamic stability tasks—such as the posterolateral direction of the Modified Star Excursion Balance Test—which tend to favor the stability-dominant leg in players aged 13–14 [22]. While traditional field tests often focus on absolute performance, asymmetries in vertical ground reaction forces (vGRF) during take-off, rather than muscle torque alone, have been identified as a critical limiting factor for vertical jump height [23]. Interestingly, in bilateral tasks like the deep squat, the non-dominant side has been shown to generate higher peak forces, likely reflecting its repetitive role as a stabilizing limb during unilateral soccer-specific technical actions [24, 25]. The

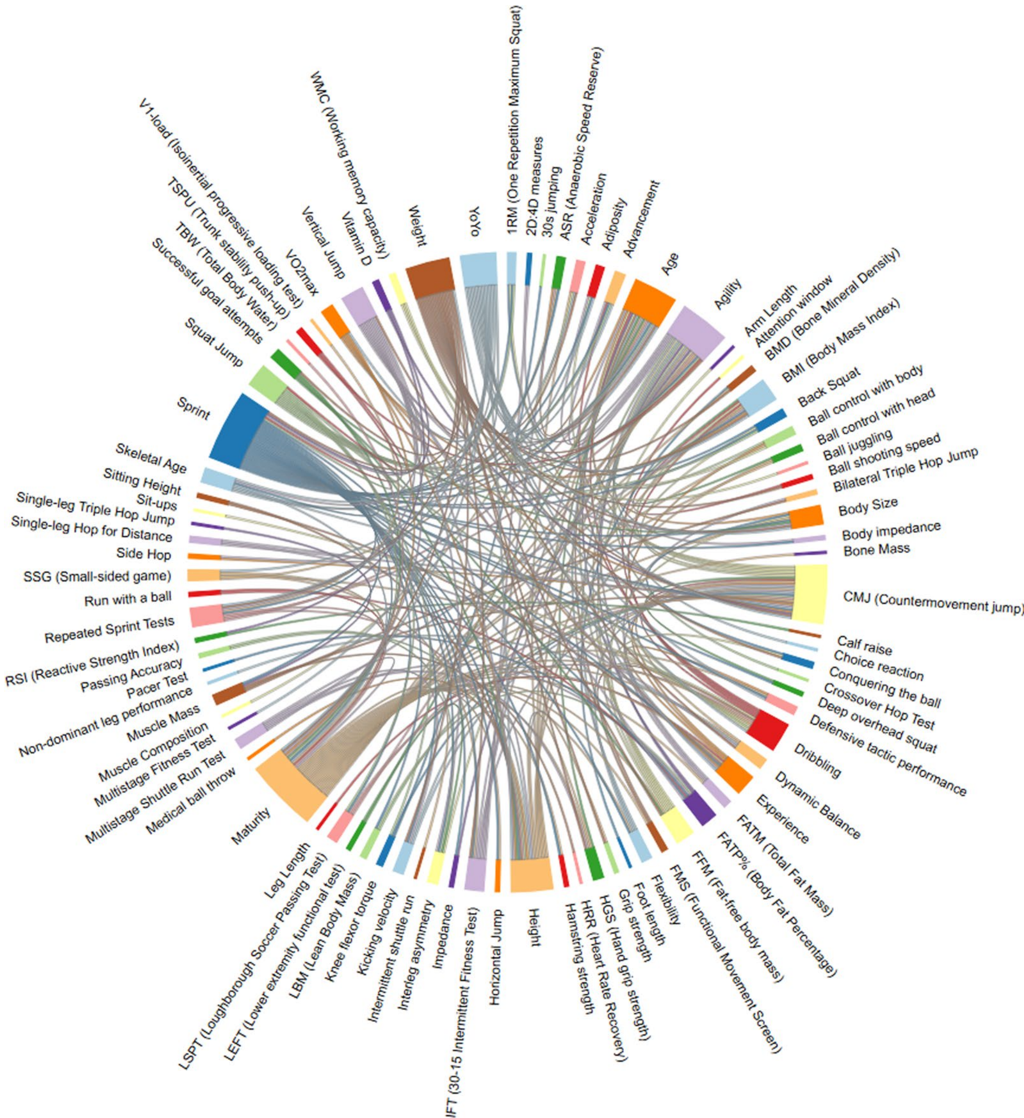

Fig. 4 Chord graph presenting every relation between the data presented in literature

developmental trajectory of these asymmetries is closely linked to biological maturation [26]. For instance, landing force asymmetries in jumping tasks often become more pronounced around the period of peak height velocity (PHV) [21]. In contrast, pre-PHV players may exhibit greater asymmetry in technical tasks, such as linear and change-of-direction (COD) dribbling [26]. Notably, authors suggest that while inter-limb asymmetry scores in jumping and COD tasks remain relatively stable across chronological age categories from U12 to U17 [27], biological maturation acts as a significant moderator of their impact on physical performance [28]. Specifically, higher asymmetry scores (particularly in single leg countermovement jump and 505 tests) are significantly associated with poorer sprint and COD performance in post-PHV players, whereas these relationships are often non-significant in pre-pubertal youth soccer players [28]. Furthermore, recent study highlights that neuromuscular efficiency is highly task-specific; vertical jump asymmetry does not necessarily correlate with asymmetries in movement economy during COD maneuvers [29]. Performance level further moderates these outcomes, as elite youth players consistently display smaller bilateral muscle mass differences and more favorable body composition profiles compared to their lower-level counterparts [30]. The relationship between inter-limb imbalances and athletic performance remains complex. The concept of bilateral deficit—where the sum of unilateral force production

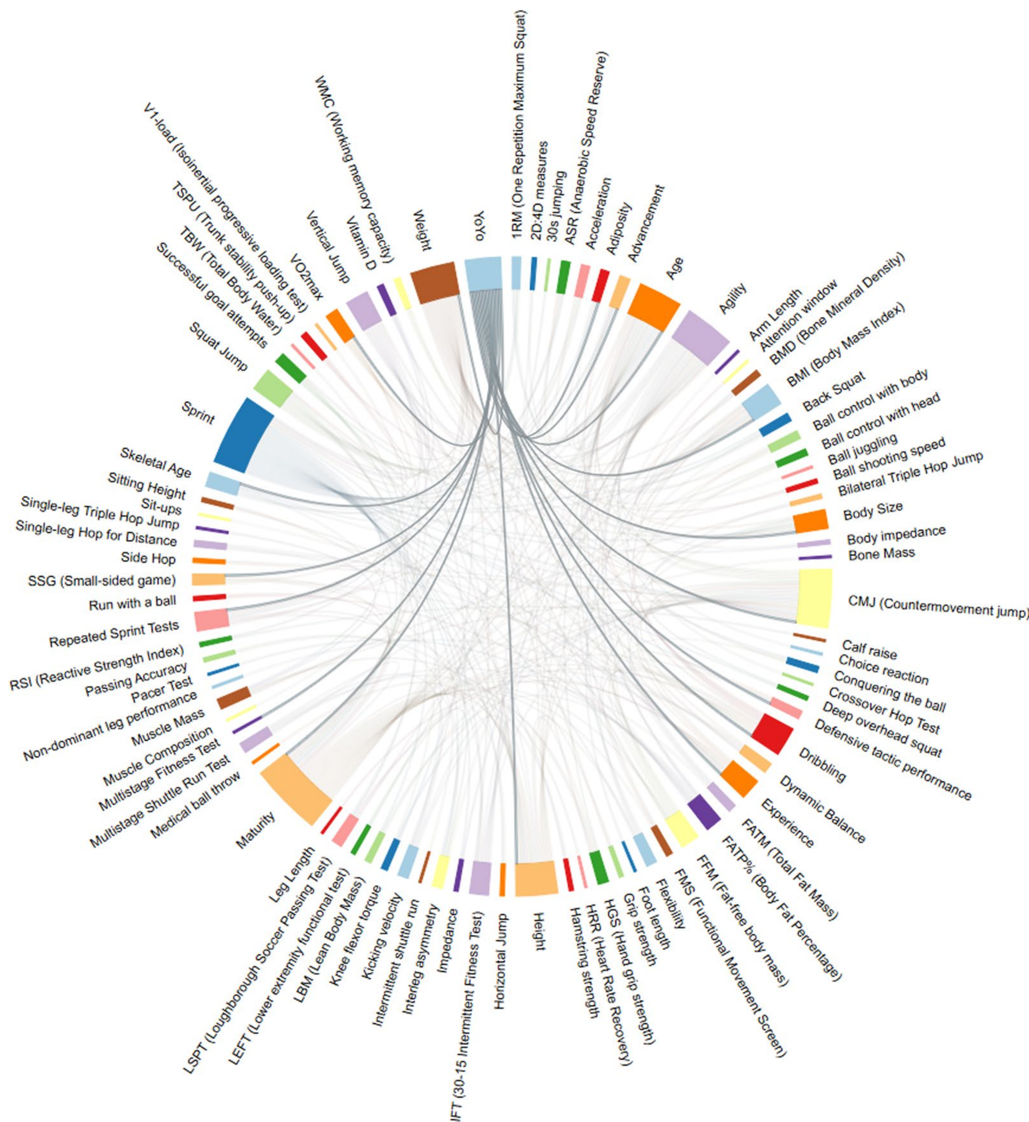

Fig. 5 Relations proven with YoYo test result and other parameters based on literature review

exceeds bilateral capacity—is highly sensitive to motor tasks and loading conditions, but it may not serve as a direct predictor for linear sprint performance [31]. Leg dominance significantly influences specific agility tasks, for example, players are often faster in 180° turns (505 test) when braking with their dominant leg [25]. Furthermore, a novel biomechanical link has been established, where lateral trunk rotation asymmetries are significantly correlated with knee extensor and vGRF asymmetries, suggesting that trunk stability is essential for optimizing lower body kinematics [32]. Against this background, targeted training of the non-dominant leg is a justified strategy to enhance overall performance and technical proficiency [33]. Interventions focusing on lower-limb function have been shown to positively influence physical performance. Specifically, 8-week plyometric jump training programs have demonstrated significant capacity to improve physical fitness components while simultaneously reducing inter-limb asymmetry scores in pre-pubertal players [34]. Moreover, the implementation of bilateral training protocols—practicing technical skills equally with both legs—has been shown to improve agility and task-specific accuracy for both preferred and non-preferred limbs [35]. While long-term corrective exercise programs can effectively reduce the frequency of dysfunctional movements [20], integrating neuromuscular training that addresses the interconnectedness of trunk stability and lower-limb kinematics remains essential for

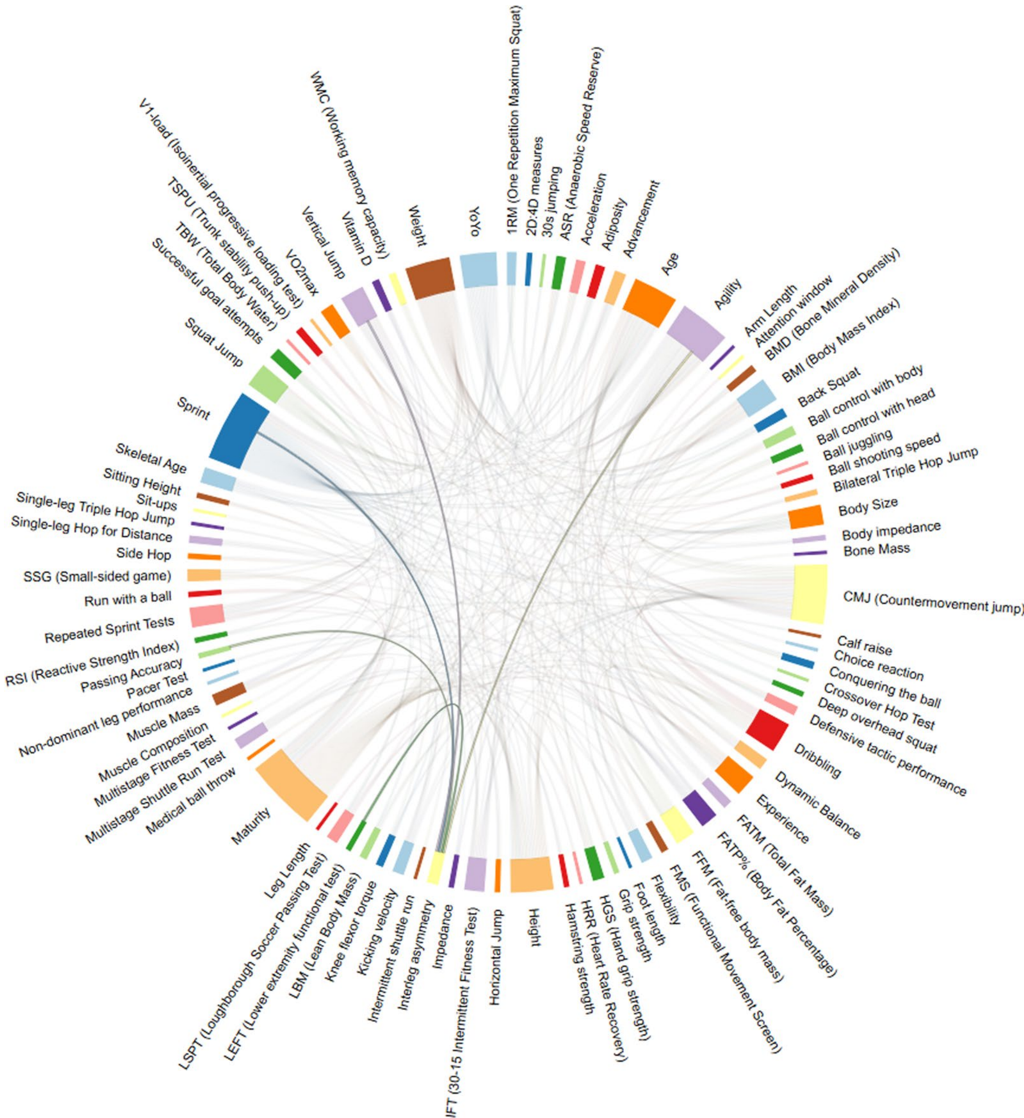

Fig. 6 Relations proven with interleg asymmetry and other parameters based on literature review

optimizing athletic development and injury prevention [32].

Importantly, non-dominant lower-limb function is amenable to targeted, relatively low-risk training interventions in youth. Thus, the knowledge-adjusted DAG derived in this study does not prove causality but provides a structured, empirically informed rationale for designing a RCT to test whether reducing strength and power asymmetries between lower extremities can improve endurance capacity in developing soccer player. The analysis in this study relied on observational data, and although the GFCI algorithm enables data-driven causal discovery, the resulting DAG remains contingent on model assumptions and on the specification of included variables. The method cannot exclude the presence of unmeasured confounders, and therefore, the directions and strengths of the indicated relationships should be interpreted as hypotheses rather

Table 2 Alignment of relationships identified by the data-driven GFCI model and the literature-based review

Relationship	Detected in DAG	Supported in literature
Age →Yo-Yo test result	Yes	Yes
Advancement →Yo-Yo test result	Yes	Yes
Experience → Yo-Yo test result	Indirectly	Yes
Non-dominant leg performance → Yo-Yo test result	Yes	No, hypothesis for RCT

than definitive causal effects. Although the search was systematic and an additional backward search of references was performed, relevant studies indexed in other databases or published in other languages may have been missed. Furthermore, only studies reporting associations between selected parameters were included, and publications focusing exclusively on positional differences or very narrow, low-level associations were excluded. These decisions, while necessary for graphical synthesis, introduce a degree of subjectivity and may bias the representation of the literature in the chord diagram. Regarding the data-driven component, the DAG was built from a single, cross-sectional dataset of male Caucasian youth soccer players aged 8–18 years from one academy from a specific competitive context. The broad age range introduces considerable biological heterogeneity, as participants encompassed pre-pubertal, pubertal, and post-pubertal stages of maturation. To account for this, maturity status was estimated and incorporated into analyses. However, this method provides only a non-invasive estimate of maturational timing based on anthropometric variables, rather than a direct assessment. More precise methods, such as skeletal age (e.g., via radiographic assessment), or direct hormonal assays, could offer a more accurate classification of maturity status and should be considered in future studies. In addition, although maturity offset was accounted for, players at different developmental stages were pooled together in the analyses, which may complicate interpretation given that physical, physiological, and psychological characteristics vary substantially across maturational phases. Therefore, the findings may not be generalizable to female players, different competitive and cultural contexts. Finally, endurance capacity was operationalized using the YYIR1, which, although widely used and validated as a field measure related to VO_2max in soccer, remains an indirect estimate rather than a direct physiological measurement.

Conclusions

Our findings support the need to design a randomized controlled study in which the dedicated training program on non-dominant leg to equal the strength and/or power able to be generated by both legs is prescribe for one group, with a control group with the standard training. We aim to test whether such intervention will translate into greater improvements in aerobic, anaerobic and other soccer-specific skills in experimental group of male youth soccer players.

Abbreviations

BMI	Body mass index
BONEM	Bone mineral mass
CMJ	Countermovement jump
DAG	Directed acyclic graph
FATM	Absolute fat mass
FATP/FATP%	Percentage of fat mass
FCI	Fast Causal Inference
FFM	Fat-free mass
FGES	Fast Greedy Equivalence Search
GFCI	Greedy Fast Causal Inference
IMP	Whole-body electrical impedance
IQR	Interquartile range
PMM	Predicted muscle mass
PRISMA–ScR	PRISMA Extension for Scoping Reviews
RAST	Running-Based Anaerobic Sprint Test
RCT	Randomized controlled trials
SJ	Squat jump
TBW	Total body water
VO_2max	Maximal oxygen uptake
Yo-Yo/YYIR1	YoYo intermittent recovery test

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40798-026-01076-z.

Supplementary Material 1.

Acknowledgements

We thank all youth soccer players for participation in the study.

Author Contributions

M.Mi. conceptualized the study, conducted the literature search, performed data processing, and drafted the manuscript. K.K. performed data processing and critically revised the manuscript. R.M. conducted data collection. J.S.G. conceptualized the study, conducted the literature search and drafted the manuscript. M.Mł. conceptualized the study and performed the GFCI analysis. All authors critically reviewed and edited the manuscript, contributed to its intellectual content, and approved the final version.

Funding

This research was founded by the POB Biotechnology and Biomedical Engineering of Warsaw University of Technology within the Excellence Initiative: Research University (IDUB) program. In addition, this work was supported by the National Science Centre, Poland, under project number 2025/57/B/NZ4/01470.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics Approval and Consent to Participate

The study was conducted in accordance with the principles of the Declaration of Helsinki for research involving human subjects. Ethical approval was obtained from the appropriate ethics committee (approval number: KB/55/N02/2019). All participants and their legal guardians were fully informed about the purpose, procedures, potential benefits, and risks of the study. Written informed consent was obtained from the parents or legal guardians of the participants prior to the study.

Consent for Publication

Not applicable.

Competing interests

The authors declare that they have no competing interest.

Author details

[1]Faculty of Mechatronics, Institute of Metrology and Biomedical Engineering, Warsaw University of Technology, św. Andrzeja Boboli 8, 02-525 Warsaw, Poland. [2]Department of Physical Education, Faculty of Philology

and Pedagogy, Casimir Pulaski University of Radom, Malczewskiego 20a, 26-600 Radom, Poland. [3]Department of Pediatric Cardiology and General Pediatrics, Medical University of Warsaw, Żwirki i Wigury 63A, 02-091 Warsaw, Poland.

Received: 5 April 2026 Accepted: 6 July 2026
Published online: 15 July 2026

References

1. Emmonds S, Till K, Weaving D, Burton A, Lara-Bercial S. Youth sport participation trends across Europe: implications for policy and practice. Res Q Exerc Sport. 2024;95(1):69–80. https://doi.org/10.1080/02701367.2022.2148623.
2. Reilly T, Bangsbo J, Franks A. Anthropometric and physiological predispositions for elite soccer. J Sports Sci. 2000;18(9):669–83. https://doi.org/10.1080/02640410050120050.
3. Malina RM, Eisenmann JC, Cumming SP, Ribeiro B, Aroso J. Maturity-associated variation in the growth and functional capacities of youth football (soccer) players 13-15 years. Eur J Appl Physiol. 2004;91(5–6):555–62. https://doi.org/10.1007/s00421-003-0995-z.
4. Janse RJ, Hoekstra T, Jager KJ, Zoccali C, Tripepi G, Dekker FW, et al. Conducting correlation analysis: important limitations and pitfalls. Clin Kidney J. 2021;14(11):2332–7. https://doi.org/10.1093/ckj/sfab085.
5. Kokstejn J, Musalek M, Wolanski P, Murawska-Cialowicz E, Stastny P. Fundamental motor skills mediate the relationship between physical fitness and soccer-specific motor skills in young soccer players. Front Physiol. 2019;10:596. https://doi.org/10.3389/fphys.2019.00596.
6. Malina RM, Cumming SP, Kontos AP, Eisenmann JC, Ribeiro B, Aroso J. Maturity-associated variation in sport-specific skills of youth soccer players aged 13-15 years. J Sports Sci. 2005;23(5):515–22. https://doi.org/10.1080/02640410410001729928.
7. Borges PH, da Costa JC, Ramos-Silva LF, Menegassi VM, Praça GM, Moura FA, et al. Maturity-associated variation in the body size, physical fitness, technical efficiency, and network-based centrality measures in young soccer players. Sci Rep. 2023;13(1):7693. https://doi.org/10.1038/s41598-023-34833-1.
8. Figueiredo AJ, Coelho e Silva MJ, Malina RM. Predictors of functional capacity and skill in youth soccer players. Scand J Med Sci Sports. 2011;21(3):446–54. https://doi.org/10.1111/j.1600-0838.2009.01056.x.
9. Towlson C, Salter J, Ade JD, Enright K, Harper LD, Page RM, et al. Maturity-associated considerations for training load, injury risk, and physical performance in youth soccer: one size does not fit all. J Sport Health Sci. 2021;10(4):403–12. https://doi.org/10.1016/j.jshs.2020.09.003.
10. Bullock GS, Ward P, Hughes T, Thigpen CA, Cook CE, Shanley E. Using randomized controlled trials in the sports medicine and performance environment: is it time to reconsider and think outside the methodological box? J Orthop Sports Phys Ther. 2023;53(6):331–4. https://doi.org/10.2519/jospt.2023.11824.
11. Ogarrio JM, Spirtes P, Ramsey J. A Hybrid Causal Search Algorithm for Latent Variable Models. JMLR Workshop Conf Proc. 2016;52:368–79.
12. Malina RM, Kozieł SM. Validation of maturity offset in a longitudinal sample of Polish boys. J Sports Sci. 2014;32(5):424–37. https://doi.org/10.1080/02640414.2013.828850.
13. Elliott D, Smith X. Unilateral dynamic balance assessment: the test-retest reliability of the OptoJump next drift protocol. J Bodyw Mov Ther. 2024;37:328–31. https://doi.org/10.1016/j.jbmt.2023.11.054.
14. Myer GD, Kushner AM, Brent JL, Schoenfeld BJ, Hugentobler J, Lloyd RS, et al. The back squat: a proposed assessment of functional deficits and technical factors that limit performance. Strength Cond J. 2014;36(6):4–27. https://doi.org/10.1519/SSC.0000000000000103.
15. Ramsey JD, Zhang K, Glymour M, Romero RS, Huang B, Ebert-Uphoff I, Samarasinghe S, Barnes EA, and Glymour C. Tetrad—a toolbox for causal discovery. In 8th international workshop on climate informatics, 2018.
16. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med. 2018;169(7):467–73. https://doi.org/10.7326/M18-0850.
17. Gualdi-Russo E, Zaccagni L. The Newcastle–Ottawa scale for assessing the quality of studies in systematic reviews. Publications (Basel). 2026;14:4. https://doi.org/10.3390/publications14010004.
18. Stang A. Critical evaluation of the Newcastle-Ottawa scale for the assessment of the quality of nonrandomized studies in meta-analyses. Eur J Epidemiol. 2010;25(9):603–5. https://doi.org/10.1007/s10654-010-9491-z.
19. R Core Team. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. 2025. https://www.R-project.org/.
20. Campa F, Spiga F, Toselli S. The effect of a 20-week corrective exercise program on functional movement patterns in youth elite male soccer players. J Sport Rehabil. 2019;28(7):746–51. https://doi.org/10.1123/jsr.2018-0039.
21. Read PJ, Oliver JL, Myer GD, De Ste Croix MBA, Lloyd RS. The effects of maturation on measures of asymmetry during neuromuscular control tests in elite male youth soccer players. Pediatr Exerc Sci. 2018;30(1):168–75. https://doi.org/10.1123/pes.2017-0081.
22. Gkrilias P, Zavvos A, Fousekis K, Billis E, Matzaroglou C, Tsepis E. Dynamic balance asymmetries in pre-season injury-prevention screening in healthy young soccer players using the Modified Star Excursion Balance Test-a pilot study. J Phys Ther Sci. 2018;30(9):1141–4. https://doi.org/10.1589/jpts.30.1141.
23. Rutkowska-Kucharska A. Asymmetry of lower limb strength and jumping ability of young soccer players. Acta Bioeng Biomech. 2020;22(1):79–85.
24. Atkins SJ, Bentley I, Hurst HT, Sinclair JK, Hesketh C. The presence of bilateral imbalance of the lower limbs in elite youth soccer players of different ages. J Strength Cond Res. 2016;30(4):1007–13. https://doi.org/10.1519/JSC.0b013e3182987044.
25. Clemente FM, González-Fernández FT, García-Delgado G, Silva R, Silva AF, Nobari H, et al. Leg dominance and performance in change of directions tests in young soccer players. Sci Rep. 2022;12(1):12900. https://doi.org/10.1038/s41598-022-17245-5.
26. Marzouki H, Cherni B, Sassi AE, Bouassida A, Bouhlel E, Chen YS, et al. Interlimb asymmetry across multiple soccer tasks varies with maturity status in young players: a cross-sectional study. Biol Sport. 2025;43:369–78. https://doi.org/10.5114/biolsport.2026.154159.
27. Michailidis Y. Relation of jump and change of direction inter-limb asymmetries with fitness in youth male soccer players. Medicina (Kaunas). 2023;59(10):1749. https://doi.org/10.3390/medicina59101749.
28. Robles-Palazón FJ, McMahon JJ, Ayala F, Comfort P. Things to keep in mind when selecting physical assessments in youth soccer: correlations between test performances, interlimb asymmetries, and effects of maturation. PLoS ONE. 2024;19(6):e0305570. https://doi.org/10.1371/journal.pone.0305570.
29. Frontani F, Prenassi M, Paolini V, Formicola G, Marceglia S, Policastro F. Dominant and nondominant leg kinematics during kicking in young soccer players: a cross-sectional study. Mot Control. 2022;27(2):327–37. https://doi.org/10.1123/mc.2022-0017.
30. Mala L, Hank M, Stastny P, Zahalka F, Ford KR, Zmijewski P, et al. Elite young soccer players have smaller inter-limb asymmetry and better body composition than non-elite players. Biol Sport. 2023;40(1):265–72. https://doi.org/10.5114/biolsport.2023.114840.
31. Ascenzi G, Ruscello B, Filetti C, Bonanno D, Di Salvo V, Nuñez FJ, et al. Bilateral deficit and bilateral performance: relationship with sprinting and change of direction in elite youth soccer players. Sports (Basel). 2020;8(6):82. https://doi.org/10.3390/sports8060082.
32. Maly T, Hank M, Verbruggen FF, Clarup C, Phillips K, Zahalka F, et al. Relationships of lower extremity and trunk asymmetries in elite soccer players. Front Physiol. 2024;15:1343090. https://doi.org/10.3389/fphys.2024.1343090.
33. Haaland E, Hoff J. Non-dominant leg training improves the bilateral motor performance of soccer players. Scand J Med Sci Sports. 2003;13(3):179–84. https://doi.org/10.1034/j.1600-0838.2003.00296.x.
34. Sammoud S, Negra Y, Bouguezzi R, Ramirez-Campillo R, Moran J, Bishop C, et al. Effects of plyometric jump training on measures of physical fitness and lower-limb asymmetries in prepubertal male soccer players: a randomized controlled trial. BMC Sports Sci Med Rehabil. 2024;16(1):37. https://doi.org/10.1186/s13102-024-00821-9.
35. Ben Kahla A, Elghoul Y, Ammar A, Masmoudi L, Trabelsi K, Glenn JM, et al. Bilateral training improves agility and accuracy for both preferred and non-preferred legs in young soccer players. Percept Mot Skills. 2022;129(6):1804–25. https://doi.org/10.1177/00315125221124373.

Publisher's Note