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Predictive Methods for Estimating Growth in Children: Clinical and Sports Perspectives

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ABSTRACT

Background: Accurate growth estimation in children is crucial in pediatric medicine and youth sports. It enables early detection of hormonal or systemic disorders and supports talent identification, structured training, and injury prevention. Traditional methods include mid-parental height calculation and skeletal age assessment using radiographs of the left hand and wrist via Greulich–Pyle (GP) atlas or Tanner–Whitehouse (TW2/TW3) scoring. Accuracy may decline during rapid growth phases, especially puberty.

Aim: This review synthesizes evidence on growth prediction methods, comparing conventional techniques with emerging data-driven and automated approaches, highlighting clinical and sports applications.

Materials and Methods: Literature analysis focused on conventional radiography, ultrasound (BonAge®), MRI, and computer-assisted systems (CASAS, CASMAS, BoneXpert). Evaluations considered observer variability, efficiency, suitability for serial monitoring, and correlation with chronological age.

Results: GP atlas allows rapid assessment but has higher inter-observer variability. TW scoring improves reproducibility for longitudinal tracking. Ultrasound is non-invasive, radiation-free, and correlates well with radiographs but may misestimate advanced or delayed bone age. MRI provides detailed growth plate visualization with high reliability but is costlier and time-consuming. Automated systems reduce observer bias: CASAS enables semi-automated multi-bone scoring, CASMAS focuses on single phalanx automation, and BoneXpert performs fully automated multi-bone analysis with high accuracy. Mid-parental height remains a valuable adjunct for contextualizing skeletal age.

Conclusions: Skeletal age assessment has evolved toward safer, reproducible, and automated approaches. Combining conventional and advanced methods with mid-parental height allows comprehensive growth evaluation, optimizing monitoring and decision-making in healthcare and sports.

Keywords: *growth estimation, growth in children, pediatric endocrinology, skeletal age, mid-parental height, machine learning, longitudinal cohort studies, youth athletes, biological maturation, growth velocity in children, Tanner stages*

1. Introduction

Prediction of adult height represents a core component of pediatric endocrinology, particularly when a child's stature deviates from age- and sex-specific reference ranges (e.g., below the 3rd percentile or above the 97th percentile). Such predictions may reassure families in cases of constitutional growth variation or, conversely, prompt further diagnostic evaluation aimed at identifying endocrine, genetic, or systemic conditions affecting growth. Consequently, accurate growth prediction supports both clinical decision-making and longitudinal monitoring of therapeutic interventions [1].

Beyond clinical practice, estimation of final height has gained increasing relevance in pediatric exercise science and sport performance research. Growth prediction is frequently applied in

talent identification, athlete selection, long-term athlete development frameworks, and considerations related to early sport specialization [2]. Although stature alone does not determine athletic success, it influences biomechanical leverage, movement efficiency, and positional demands across many sports. Shorter stature may be advantageous in disciplines such as gymnastics or weight-category sports, whereas taller stature is often associated with competitive benefits in sports including basketball, volleyball, and swimming [3]. Therefore, predicted adult height may inform sport participation pathways, training load distribution, and role allocation within team environments.

Accurate height prediction is closely linked to biological maturation rather than chronological age alone. Skeletal age reflects physiological development and may differ substantially between individuals of the same chronological age due to variability in the timing and tempo of pubertal growth. The sequential appearance, development, and fusion of ossification centers follow relatively predictable patterns from infancy to skeletal maturity, allowing radiographic evaluation to serve as a validated indicator of maturation status [4]. Importantly, reliance solely on chronological age may obscure meaningful inter-individual differences during the pubertal growth spurt, a period characterized by marked heterogeneity in developmental timing [5].

Traditional predictive approaches remain widely implemented in clinical settings. Calculation of mid-parental height provides a rapid estimation of genetic growth potential, while skeletal age assessment using radiographic standards such as the Greulich–Pyle Atlas and the Tanner–Whitehouse Method constitutes a cornerstone of biological maturation evaluation [6,7]. Despite their long-standing utility, these methods present recognized limitations, including observer-dependent variability, population-specific bias, and reduced predictive precision during periods of rapid pubertal acceleration [8]. Furthermore, many classical predictive models were derived from historical reference cohorts that may not adequately reflect contemporary, ethnically diverse pediatric populations. These methodological constraints highlight the need for more individualized, data-driven, and integrative predictive frameworks [6]. Recent technological developments—including ultrasound-based assessment, magnetic resonance imaging, and automated computer-assisted analysis—seek to improve reliability, reproducibility, and safety of skeletal maturity evaluation.These approaches aim to reduce subjective interpretation, minimize radiation exposure, and enable more individualized growth prediction. However, uncertainty remains regarding the comparative validity, practical feasibility, and optimal integration of traditional and emerging methods within clinical and sport contexts [9,10,11]. Therefore, the aim of this review is to synthesize current approaches to skeletal age assessment and mathematical height prediction, evaluate their methodological strengths and limitations, and discuss their relevance for clinical growth monitoring and youth sport development.

Table 1. Methods for Skeletal Age Assessment Abbreviations

Method / Approach	Imaging Modality	Assessed Structures	Evaluation System / Scoring Method
Conventional manual	Radiograph	Hand and wrist bones	Greulich-Pyle Atlas (Atlas method)
	Radiograph	Radius, ulna, short bones (RUS), 20 bones	Tanner-Whitehouse 2 (Scoring method)
Ultrasonographic	Ultrasonogram	Radius and ulna epiphyses	BonAge® (Sound velocity measurement)
Magnetic resonance	MR imaging	RUS	Open compact MR imager (Scoring method)
Computer-assisted	Radiograph	RUS, carpal, and 20 bones	CASAS
	Radiograph	Third phalanges	CASMAS
	Radiograph	RUS	BoneXpert (automated scoring method)

RUS = radius, ulna, and short bones;
MR = magnetic resonance;
CASAS = computer-assisted skeletal age score;
CASMAS = computer-aided skeletal maturity system.

2. Mid-parental height calculation (MPH)

Since its introduction in 1970, the MPH has been recommended for evaluating the growth of individual children. The formulas for calculating MPH, adjusted for the child's sex and expressed in centimeters, are as follows: for girls – (father's height − 13 + mother's height) / 2; for boys – (father's height + mother's height + 13) / 2. The results of these calculations are reported with a range of ±10 cm (i.e., ±2 standard deviations) [12].

Clinicians completed surveys for a significant portion of cases and reported that: In 79% of cases, the MPH tool confirmed their initial clinical judgment about the child's growth status. In 4% of cases, access to MPH data changed their assessment, leading clinicians to pursue more comprehensive evaluation (for example, additional monitoring, tests, or referrals) [13].

Mid-parental height remains a valuable clinical tool for assessing child growth and estimating target adult height. While it does not wholly predict individual outcomes, it captures a

meaningful portion of growth variability and supports clinical decision making when used appropriately and with accurate height measurements [14].

3. Traditional Radiographic Methods

The two bone age assessment techniques most frequently applied in clinical and research settings are the Greulich–Pyle (GP) atlas method [15] and the Tanner–Whitehouse 2 (TW2) method [16]. Both approaches are based on radiographic imaging of the left hand and wrist. This anatomical region is particularly suitable for skeletal age evaluation because it contains numerous bones at different stages of development, and obtaining a hand–wrist radiograph is technically simple and minimally burdensome.

The preference for imaging the left hand rather than the right has several explanations. Since the majority of individuals are right-hand dominant, the right hand is more exposed to trauma and potential deformities, which could interfere with assessment [15].

The radius, ulna, metacarpals, and phalanges develop through endochondral ossification, whereas the carpal bones primarily form via intramembranous ossification. Carpal bones demonstrate considerable individual variability in maturation rate and typically complete their development earlier than the long and short bones. Furthermore, intramembranous ossification is less influenced by growth hormone (GH) compared with endochondral ossification. For these reasons, carpal bones are considered less reliable indicators of skeletal maturity and are generally excluded from detailed bone age scoring systems [17].

Although the biological mechanisms underlying skeletal maturation are fundamentally similar across populations, the tempo of maturation varies between ethnic groups. A major factor contributing to these differences is variation in the timing of pubertal onset, which significantly influences the rate of skeletal development [18].

3.1 Tanner Whitehouse method

The method focuses on a set of bones collectively known as the RUS bones — the Radius, Ulna, and Short bones (metacarpals + phalanges). Each bone is evaluated for its maturation stage according to specific criteria: shape, size, ossification centers.
Traditional TW systems (including TW2 and TW3) categorize each bone's maturity into stages (e.g., A to I) that correspond to progressive development from immature to mature. Each stage for each bone is assigned a numerical score based on standardized reference data. This bone-by-bone scoring yields a total maturity score [17, 19].

3.2 The Greulich and Pyle atlas

Bone age assessment using the GP method involves obtaining a standard radiograph of the left hand and wrist. The radiograph is then compared against a series of reference images (atlas plates), each representing typical skeletal maturation at specific ages ranging from infancy to late adolescence. An evaluator performs a visual comparison, identifying the plate that most closely resembles the child's radiograph, and assigns the corresponding bone age [15]. The atlas provides distinct reference images for boys (0–18 years) and girls (0–19 years), presented at varying age intervals ranging from three months to one year. Each image is accompanied by a description of the progressive, age-related changes occurring in the bones at that stage, along with individual bone-specific bone ages (BAs). Because bone maturation can naturally vary

within a single person, some bones may appear more or less advanced compared to the standard they are intended to represent [15].

3.3 Comparison the Tanner–Whitehouse Method with the Greulich and Pyle atlas method.

A large multicase comparison of GP and TW2 found that the two methods do not produce equivalent bone age estimates and recommended that when serial measurements are made (e.g., monitoring growth over time), one consistent method should be used, with preference for TW2 because of tighter confidence limits in intra-observer variation [20].
In an audit of 50 radiographs, the inter-observer spread was slightly smaller for TW2 (0.74 years) than GP (0.96 years), but this difference was not statistically significant. GP was markedly faster to perform, leading to its continued use in some clinical settings [21].
Systematic reviews indicate that both methods remain widely used, but automation and AI-assisted approaches are increasingly evaluated to reduce variability inherent in both GP and TW scoring [22].

Table 2. Comparative table summary

Feature / Criterion	Greulich–Pyle (GP)	Tanner–Whitehouse (TW)
Method Type	Atlas-matching (visual)	Scoring system (quantitative)
Complexity	Low (simple visual match)	Higher (scoring multiple bones)
Time to Perform	Short (~1–2 min)	Long (~7–9 min)
Observer Variability	Higher	Lower to moderate
Reproducibility	Acceptable but more variable	Often more consistent
Suitability for Serial Monitoring	Less optimal	Better
Population Bias	Based on mid-20th century Caucasian children	Also based on older cohorts; improved in TW3
Accuracy vs Chronological Age	Good but may vary by ethnicity	Slightly more precise in some studies
Clinical Ease of Use	Very high (common)	Moderate (requires training)
Preferred in Research Growth Studies	Less often	More often
Summary	Fast & widely used; some observer bias	Structured & consistent; more work

4. Ultrasound-Based Bone Age Assessment

Ultrasound (USG) has become a promising, non-invasive method for evaluating bone age, offering the advantage of no exposure to ionizing radiation, which is particularly important for children requiring repeated assessments [17]. This technique works by sending high-frequency sound waves through bones and cartilage, mainly at the distal radius and ulna, to examine the development of ossification centers and growth plates [9]. Systems like BonAge® use an ultrasound probe along with dedicated software to provide rapid estimates of skeletal maturity directly at the bedside [23]. Measurements such as the speed of sound and transducer spacing reflect the density and maturity of the ossifying cartilage, allowing estimation of bone age [9, 23]. Research by Mentzel et al. and Shimura et al. showed that USG-based results closely match conventional methods such as the Greulich-Pyle (GP) and Tanner-Whitehouse (TW2) standards [23,24]. Nevertheless, studies involving larger numbers of patients, including that by Khan et al., indicated that BonAge® may overestimate delayed bone age and underestimate advanced bone age, suggesting that ultrasound cannot fully replace radiographs yet [25]. The technique offers benefits such as safety, immediate results, and the ability to examine soft tissues, but it also has limitations, including dependence on operator skill, technical variability, and a lack of comprehensive reference data for all age groups [9, 26]. Ultrasound has also been applied to other skeletal sites, such as the anterior femoral head cartilage and iliac crest apophysis, showing promising correlations with chronological age, height, and weight [26, 27]. Despite encouraging results, USG is still infrequently used in routine clinical practice compared to standard hand-wrist X-rays [17,23]. As the technology advances and more normative data become available, ultrasound may become a reliable, safe alternative for assessing skeletal maturity in children [9,25].

5. Magnetic Resonance Imaging (MRI) for Skeletal Age

MRI has emerged as a radiation-free alternative for assessing skeletal (bone) age, which reflects the degree of skeletal maturation important in growth evaluation and clinical decision-making. MRI scans visualize growth plates and bone structure without exposing patients, especially children, to ionizing radiation as in traditional X-rays, and can be applied to regions such as the wrist, knee or humerus epiphyses [10].

Studies using MRI to determine bone age often adopt standard reference methods originally designed for X-rays, such as the Greulich-Pyle (GP) atlas or Tanner-Whitehouse (TW) scoring, and show high inter-rater reliability and good agreement with conventional radiographic results [28]. For example, in a study of healthy boys, MRI assessments using GP and TW produced reliable ages with excellent inter-rater concordance, indicating feasibility of MRI in clinical practice [28]. Advanced analytical approaches, including texture analysis of MRI wrist images, also correlate strongly with chronological age, suggesting that quantitative MRI features can further improve bone age estimation [29]. Compared with X-ray, MRI can offer detailed soft-tissue contrast and visualization of cartilage and growth plates, potentially improving the precision of maturation staging [30]. Despite these advantages, MRI remains more costly and time-consuming, and requires patient cooperation during scans, considerations that may limit widespread use [10]. Overall, MRI methods for predicting bone age represent a promising, safe alternative to radiography, with ongoing research focused on standardization and integration with automated image analysis [28].

6. Computer-Assisted Bone Age Methods Computerized

Digital and computational tools now allow more objective, reproducible bone age assessment. Systems range from semi-automated platforms to fully automated software, aiming to reduce observer variability, improve efficiency, and provide precise skeletal maturity estimates. Key examples include CASAS, CASMAS, and BoneXpert.

6.1 CASAS – Computer-Assisted Skeletal Age Scoring

CASAS emerged in the early 1990s as an attempt to improve the reproducibility and objectivity of conventional radiographic bone age methods. Among the earliest structured systems was the Computer-Assisted Skeletal Age Score (CASAS), developed to support the Tanner–Whitehouse 2 (TW2) methodology by introducing digital image analysis into the evaluation of hand and wrist radiographs [11].

CASAS was designed as a semi-automated system integrating human expertise with quantitative image processing. The method applies the TW2 scoring framework to the radius, ulna, and short bones (RUS), including the carpal bones and a total of 20 skeletal structures in the hand and wrist. Unlike fully automated systems developed later, CASAS requires manual identification and localization of each epiphysis on a digitized radiograph. Once positioned, the software performs quantitative morphometric analysis, comparing extracted radiologic features with internal reference standards. A key methodological innovation was the generation of continuous maturity scores rather than discrete TW letter stages, thereby reducing stepwise transitions in longitudinal assessments and allowing smoother growth tracking over time [11].

From a technical perspective, CASAS operates through three principal stages: (1) digitization of the radiograph and manual bone localization, (2) feature extraction and template matching, and (3) conversion of quantitative parameters into a skeletal maturity score equivalent to TW2-derived bone age. Because scoring is continuous, small maturational changes can be captured more precisely than in conventional manual TW staging. This feature is particularly advantageous in longitudinal monitoring of growth disorders, where subtle temporal changes are clinically relevant [31].

Clinical validation studies demonstrated that CASAS improved intra- and interobserver reproducibility compared with purely manual Greulich–Pyle (GP) or TW assessments. In comparative analyses, CASAS-derived bone age values showed closer concordance with TW2 scores than with GP estimates, and variability between observers was reduced due to computer-assisted standardization [11,31]. However, the system retained dependence on operator input, particularly during the manual delineation phase. Abnormal skeletal morphology, dysplastic changes, or radiographs of suboptimal quality could reduce analytical reliability and sometimes required corrective intervention by experienced readers [31].

The advantages of CASAS include improved reproducibility, quantitative continuous scoring, and partial reduction of subjective variability. It represented an important conceptual step toward full automation and demonstrated that digital morphometric analysis could meaningfully enhance traditional maturity scoring. Additionally, its compatibility with the established TW2 framework facilitated integration into existing clinical paradigms without fundamentally altering interpretation standards [31,32].

Nevertheless, several limitations prevented widespread clinical adoption. First, the semi-automated nature limited workflow efficiency compared with later fully automated systems.

Second, the system required dedicated software and structured digitization protocols at a time when digital radiography was not yet universal. Third, its performance in cases of skeletal dysplasia, significant deformity, or non-standard populations was less robust, reflecting the inherent constraints of template-based modeling [32]. As digital radiology matured and machine learning–based segmentation algorithms became feasible, fully automated platforms such as BoneXpert gradually supplanted earlier hybrid systems [33].

In terms of clinical application, CASAS was primarily used in pediatric endocrinology and growth evaluation, including assessment of constitutional delay of growth and puberty, growth hormone deficiency, and monitoring of therapeutic interventions. Its ability to reduce observer variability made it particularly attractive in research settings and longitudinal clinical trials, where reproducibility is critical. However, it did not become standard practice in routine radiology departments, largely due to workflow constraints and the rapid technological evolution that followed [32,33].

In summary, CASAS represents an important transitional technology in the evolution of computerized bone age assessment. It bridged manual TW scoring and modern automated image analysis by demonstrating that quantitative morphometric evaluation could enhance reliability and provide continuous maturity indices. While ultimately superseded by fully automated systems, CASAS contributed substantially to methodological development in pediatric skeletal age assessment [11, 31, 33].

6.2 CASMAS – Computer-Aided Skeletal Maturity Assessment System

CASMAS represents one of the early fully automated approaches to bone age estimation, developed to reduce observer dependency and improve reproducibility compared with traditional manual methods. Unlike semi-automated systems such as CASAS, which are based on the Tanner–Whitehouse (TW) RUS scoring framework and require manual identification of multiple skeletal elements, CASMAS focuses on a single, anatomically consistent structure: the third middle phalanx of the hand. This focus was chosen because the phalanx exhibits clear, sequential morphological changes during growth, making it amenable to automated segmentation and quantitative analysis [34,35].

Methodologically, CASMAS uses digitized radiographs to identify and isolate the third phalanx automatically. Once segmented, the software extracts multiple morphometric parameters, including metaphyseal width, epiphyseal width, cortical thickness, and proportional indices describing epiphyseal–metaphyseal relationships. These quantitative features are then processed using regression-based statistical models to predict skeletal age, producing continuous numerical output rather than discrete categorical stages [34, 36]. The continuous nature of CASMAS scoring allows for the detection of subtle maturational changes, which is particularly valuable in longitudinal monitoring of growth, pubertal progression, and therapeutic interventions such as growth hormone treatment [35].

CASMAS provides several advantages over manual and semi-automated methods. The system significantly reduces inter- and intraobserver variability and eliminates the need for repeated subjective scoring, which can be a source of error in traditional TW or Greulich–Pyle methods. Its fully automated workflow also shortens processing time and facilitates standardized evaluation, making it suitable for research settings and clinical studies requiring repeated measurements [32, 35].

However, CASMAS has inherent limitations. Since it relies on a single phalanx, it may not fully represent global skeletal maturity, particularly in cases of asynchronous bone development, skeletal dysplasia, or localized pathologies affecting the phalanx. Segmentation inaccuracies can also propagate into bone age predictions, emphasizing the importance of high-quality radiographic images and robust image-processing algorithms. Moreover, while CASMAS demonstrated promising accuracy in early studies, it lacks large-scale multicenter validation comparable to that of more widely adopted automated systems such as BoneXpert, which analyze multiple bones with integrated quality control [35,36].

Despite these constraints, CASMAS played an important role in the evolution of automated skeletal maturity assessment. It demonstrated that regression-based analysis of morphometric features could provide continuous, reliable bone age estimates, paving the way for modern AI-driven and multi-bone automated systems. The system continues to be cited in methodological reviews as an example of early automation in bone age evaluation and serves as a historical bridge between semi-automated approaches like CASAS and fully validated clinical tools such as BoneXpert [17, 35,36].

6.3 BoneXpert – Automated Bone Age Determination

BoneXpert is a fully automated software platform developed for the analysis of left-hand and wrist radiographs to determine bone age without the need for manual scoring. Since its clinical introduction in 2009, it has been widely adopted in radiology departments worldwide due to its speed, reproducibility, and integration with standard bone age scales [17,33]. The software operates through a multi-layered algorithm: it first performs automated localization of up to 21 bones—including radius, ulna, metacarpals, and phalanges—using generative appearance models and machine learning [33]. Next, it extracts quantitative features related to bone shape, density, and texture, which are then synthesized into an intrinsic bone age score and mapped to standard scales such as Greulich–Pyle or Tanner–Whitehouse variants. BoneXpert also incorporates self-validation mechanisms that automatically exclude images or bones failing quality checks, ensuring measurement reliability [33,37].

Clinical validation studies have consistently demonstrated BoneXpert's accuracy and precision. Early reports showed a root mean square error of approximately 0.71–0.72 years compared with manual TW or GP ratings, with excellent precision around 0.17–0.18 years and successful analysis of over 98% of images [33]. More recent validation of version 3 across large and diverse datasets reported overall errors between 0.45 and 0.62 years relative to multi-expert consensus and fewer extreme deviations than manual assessment [37]. BoneXpert has been tested across different ethnic groups and clinical conditions, including short stature and precocious puberty, making it a robust tool for both research and routine clinical use [17].

Its main strengths lie in full automation, integrated quality checks, high reproducibility, and compatibility with multiple bone age standards [17,33,37]. Limitations include potential underperformance in rare skeletal anomalies not represented in the training set and the occasional need for visual verification by practitioners for broader diagnostic context, such as dysplasias [37,38]. Overall, BoneXpert represents a mature, validated platform that significantly reduces variability and workload in pediatric bone age assessment.

Table 3. Comparative overview of computerized bone age assessment systems: CASAS, CASMAS, and BoneXpert

Feature / System	CASAS	CASMAS	BoneXpert
System type	Semi-automated	Fully automated	Fully automated
Bones analyzed	RUS (radius, ulna, short bones) + carpal bones (20 bones)	Single bone: third middle phalanx	Multi-bone (radius, ulna, metacarpals, phalanges; up to 21 bones)
Assessment method	TW2 framework, manual localization +digital morphometrics	Regression-based morphometric analysis	Generative appearance models + feature extraction + mapping to GP/TW scales
Advantages	Reduces subjectivity, continuous scoring, compatible with TW2	Reduces inter-/intraobserver variability, automation, detects subtle changes	Full automation, self-validation, high reproducibility, extensive clinical validation
Limitations	Requires manual input, limited workflow efficiency, affected by dysplasia	Based on single bone, sensitive to segmentation errors, limited large-scale validation	May underperform in rare skeletal anomalies, occasional need for manual verification
Clinical applications	Pediatrics, endocrinology, growth monitoring, therapy follow-up	Pediatrics, endocrinology, growth and puberty monitoring, clinical studies	Pediatrics, endocrinology, growth monitoring, therapy follow-up, routine radiology

7. Mathematical Methods for Predicting Adult Height

Mathematical prediction methods provide an alternative or complementary approach to skeletal age assessment, allowing estimation of final adult height based on measurable parameters such as current height, chronological age, and parental stature. These methods are widely used in clinical pediatrics when radiographic assessment is not feasible or to supplement bone age evaluation.

7.1 Bayley–Pinneau Method

The Bayley–Pinneau method predicts adult height using skeletal age derived from hand–wrist radiographs, typically assessed by the Tanner–Whitehouse (TW) scoring system. This approach applies age- and sex-specific multipliers to the child's current height to estimate final height [16]. It is frequently used in pediatric endocrinology for evaluating children with growth disorders, including constitutional growth delay and growth hormone deficiency [39,40]. While reasonably accurate, the method may be less precise during rapid pubertal growth or in populations differing from the original reference cohort [15].

7.2 Khamis–Roche Method

The Khamis–Roche method estimates adult height without the need for radiographs. It uses a child's current height and weight along with mid-parental height to calculate a predicted adult height, providing a non-invasive and easily applicable alternative [41,42]. This method has been validated in North American populations and demonstrates comparable accuracy to radiograph-based methods in non-obese children [41]. However, its precision may decrease in children with atypical growth patterns or in ethnically diverse populations not represented in the original dataset [43].

7.3 Roche–Wainer–Thissen (RWT) Method

The Roche–Wainer–Thissen model integrates chronological age, skeletal age, and current anthropometric measurements to provide a regression-based prediction of adult height [44,45]. By combining multiple predictors, this method aims to improve accuracy relative to single-variable approaches, particularly in children undergoing rapid pubertal growth. While effective in research settings, it requires skeletal age assessment and is more complex to calculate in routine clinical practice and requires skeletal age assessment [46].

7.4 Other Regression- and Growth-Based Models

Several additional models have been proposed to improve height prediction, including bone-age–height ratio models and updated regression equations that incorporate longitudinal growth data [47]. These methods aim to account for variability in pubertal timing, secular trends in growth, and population-specific differences. They are particularly useful in research or specialized pediatric endocrinology clinics but may be less practical for routine clinical use.

Mathematical models complement skeletal age assessment by providing quantitative height predictions that can guide clinical decision-making, monitor growth trajectories, and assist in family counseling. Their main limitations include population specificity, reduced accuracy during rapid growth phases, and potential underestimation or overestimation in children with atypical growth patterns. Combining these methods with skeletal age evaluation and mid-parental height provides a more robust and comprehensive framework for predicting final adult height [48,49].

8. Future directions

Recent technological developments are reshaping how skeletal maturity and adult height are predicted in pediatric and sport science contexts. Traditional radiographic methods remain fundamental, but integrating genetic and biomarker-based information with machine learning (ML) and artificial intelligence (AI) models holds strong potential to improve individualized growth assessment and performance profiling in youth athletes.

Emerging studies suggest that skeletal maturity prediction can be enhanced by incorporating additional biological indicators beyond hand-wrist radiographs, such as dental maturation stages and morphologic parameters, alongside demographic variables, within ML frameworks. These integrated models have demonstrated high discriminative performance and strong predictive accuracy for skeletal maturity stages compared with models based solely on chronological age or single measures [50]. Such multidimensional models may allow more precise characterization of biological age, which can inform training load adjustments, injury prevention strategies, and equitable talent development.

AI and deep learning approaches continue to evolve with novel architectures designed to capture complex image features reflective of bone development. Recent transformer-based and graph-neural-network frameworks have achieved low mean absolute error (MAE) in automated bone age assessments across diverse datasets, demonstrating improved robustness and stability across age groups and image variations [51]. Cascaded deep learning models have also shown high correlation with clinician-annotated bone age and adult height predictions, providing rapid, reliable assessments suitable for longitudinal monitoring in sport environments [52]. Additionally, deep learning systems have been validated in complex clinical subgroups, such as rare growth disorders, underscoring the capacity of AI to handle atypical maturation patterns [53].

Beyond image analysis, there is growing interest in incorporating genetic markers and circulating biomarkers that reflect growth dynamics, hormonal milieu, and bone metabolism into predictive frameworks. Genetic polymorphisms related to growth hormone, IGF-1, and estrogen receptor pathways have been associated with variations in pubertal timing and skeletal maturation, providing potential predictive value when combined with anthropometric and imaging data [54,55]. Similarly, circulating biomarkers such as serum IGF-1, alkaline phosphatase, and osteocalcin have been shown to correlate with growth velocity and peak height velocity (PHV), offering dynamic insight into individual maturation tempo [56, 50].

Although research in this area remains emergent, integrating physiological, genetic, and biochemical data with machine learning models could enhance trait-specific prediction and identify subtle deviations from expected growth trajectories [50,52]. Multimodal approaches may also capture inter-individual variability more effectively than skeletal age alone, enabling personalized growth monitoring and the optimization of training loads in youth athletes during periods of rapid growth [50,53,55]. Early evidence suggests that combining genetic and biomarker data with AI-driven prediction models improves forecasting of maturation timing and adult height, potentially supporting bio-banding strategies and injury prevention programs in competitive youth sport [33, 52,53].

Despite these promising advances, limitations such as dataset heterogeneity, population-specific biases, cost of genetic and biomarker assessments, and ethical considerations must be addressed. Future research should aim to validate multimodal predictive models across diverse youth athlete populations, integrating real-time monitoring with AI-driven analytics to optimize training and talent development while ensuring data privacy and equitable practice [50–56].

9. Conclusions

Accurate assessment of skeletal maturity and adult height remains a cornerstone of both pediatric endocrinology and youth sport science. Traditional radiographic methods, such as the Greulich–Pyle atlas and Tanner–Whitehouse scoring, provide reliable baseline evaluations but are limited by observer variability, population-specific biases, and reduced precision during

rapid pubertal growth. Mid-parental height calculation continues to offer valuable context for genetic growth potential, while mathematical models complement skeletal age assessment by enabling quantitative adult height predictions.

Recent advancements in non-invasive imaging, including ultrasound and MRI, as well as semi-automated and fully automated systems, have enhanced reproducibility, reduced radiation exposure, and improved longitudinal tracking of growth. In parallel, the integration of machine learning and AI approaches with multimodal data—including radiographs, morphologic parameters, genetic markers, and circulating biomarkers—demonstrates considerable potential for individualized growth prediction, optimized training load management, injury prevention, and equitable talent identification in youth athletes.

Despite these promising developments, challenges remain. Dataset heterogeneity, population-specific limitations, cost, and ethical considerations must be addressed before widespread clinical and sports application. Future research should focus on validating multimodal and AI-driven predictive models across diverse populations, incorporating real-time monitoring, and integrating physiological, genetic, and biochemical markers to achieve precise, personalized growth assessment.

In conclusion, the convergence of traditional assessment methods with emerging automated, AI, and biomarker-informed approaches represents a transformative shift in pediatric growth evaluation and youth athlete development. By leveraging these integrative strategies, clinicians, coaches, and sports scientists can make more informed decisions, promote safe and individualized training, and enhance long-term athlete development pathways.

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Author's Contribution:
Conceptualization: AM, ACH, AS, AJ
Methodology: NK, KK, MP
Software: ACH, NK, JŁ
Check: MP, AJ, MS, KF
Formal analysis: JŁ, MP
Investigation: AM, ACH, AS
Resources: AJ, AS, AM
Data curation: NK, JŁ, KF
Writing rough preparation; MS, KK
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