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Using a smart app method Maturo for precisely estimating maturation status for young basketball athletes

Utilización de un método de aplicación inteligente Maturo para estimar con precisión el estado de maduración de jóvenes deportistas de baloncesto

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Abstract

This study evaluates the effectiveness of Maturo, a smartphone application designed to estimate maturation status in youth basketball athletes. The sample comprised 41 basketball players (mean age ± SD: boys, 13.44 ± 1.32 years; girls, 13.21 ± 1.04 years) aged between 10 and 15 years. Maturo provides automated assessments of biological maturation indicators, including PHV speed, PHV age, maturation timing (early, on-time, late), and maturation status (prepubescent, pubescent, postpubescent). The validity of the Maturo application was assessed against traditional expert evaluation methods. Intraclass correlation coefficients (ICCs) and Pearson correlation coefficients revealed strong correlations between Maturo and expert assessments for PHV speed (ICC = 0.955, r = 0.96) and moderate correlations for PHV age (ICC = 0.673, r = 0.78). Bland-Altman analysis indicated minimal systematic error, confirming reliable estimations by Maturo. Additionally, Kappa coefficients demonstrated excellent agreement in classifying maturity status (κ = 0.95) and timing (κ = 0.87). Maturo's non-invasive, cost-effective, and user-friendly approach makes it valuable for routine monitoring of growth and maturation. The integration of Maturo assessments with other growth indicators could enhance the comprehensive understanding of youth athletes' development, thereby informing training programs and improving athlete safety and performance.

Keyword: Artificial Intelligence; Monitoring; Growth and Maturation; Youth; Basketball

Resumen

Este estudio evalúa el uso de un método de aplicación inteligente para estimar con precisión el estado de maduración de jóvenes atletas de baloncesto. En comparación con las evaluaciones tradicionales de expertos, los coeficientes de correlación intraclase (CCI) y los coeficientes de Pearson demostraron altas correlaciones y acuerdos significativos en métricas como la velocidad PHV (CCI = 0,955, R = 0,96) y la edad PHV (CCI = 0,673, R = 0,78). Los gráficos de Bland-Altman confirmaron su fiabilidad, mostrando un error sistemático bajo. Los análisis de regresión lineal arrojaron altos valores R-cuadrado ajustados, indicando exactitud en las predicciones de Maturo. El software clasificó de forma fiable a los adolescentes según su estado madurativo y momento de maduración, con coeficientes Kappa de 0,95 y 0,87, respectivamente, mostrando una concordancia casi perfecta con los métodos de expertos. Su naturaleza no invasiva, su bajo coste y su facilidad de uso hacen de Maturo una herramienta clave para el seguimiento y la clasificación del crecimiento y la maduración en jóvenes deportistas. Maturo se integra con otros indicadores para comprender mejor el desarrollo físico de los deportistas, contribuyendo al diseño de programas de entrenamiento más eficaces y seguros en deportes como el baloncesto.

Palabra clave: Inteligencia artificial; Seguimiento; Crecimiento y maduración; Jóvenes; Baloncesto.

Introduction

The home-court advantage (HA) refers to the phenomenon in which teams playing on their home court experience an advantage over visiting teams (Pollard & Gomez, 2014; Pollard & Gómez, 2015). The concept of HA was first defined by Koppet (1972), who analyzed multiple competitions to establish a statistical link between match location and competitive outcome. Since then, numerous studies have confirmed the presence of HA across different sports (Bermejo & Gómez Ruano, 2012; Pollard & Gomez, 2014; Pollard & Pollard, 2005). In basketball, HA is widely recognized by fans, players and coaches as a significant determinant of success in competitive games, offering a measurable benefit to the home team (Alonso et al., 2022; Inan, 2020; Smith, 2005). Research suggests that basketball exhibits one of the strongest HA effects among team sports (Pollard et al., 2017). Furthermore, some studies indicate that HA has fluctuated over time due to factors such as changes in game rules, improvement in travel logistics or advancements in player conditioning (Pollard & Gomez, 2014). Biological maturation refers to the progressive process through which individuals transition toward an adult state during growth and development. This process is manifested in increments in height and weight, skeletal development, and the gradual maturation of sexual organs (Lloyd et al., 2014). Biological maturation is typically defined in terms of status, timing, and tempo (Cumming et al., 2017; Malina et al., 2015). Maturation status denotes a specific stage of development observed at a given point in time (e.g., skeletal age, pubertal stage), while maturation timing refers to the age at which specific maturation events occur (e.g., the age of PHV) (Alejandro et al., 2024; Hill et al., 2023). Tempo, on the other hand, describes the rate at which maturation occurs within a given system (Malina, 2004). During adolescence, individual differences in biological maturity arise from both genetic and environmental influences (Mirwald et al., 2002).

Basketball is a widely popular sport in the world, a high number of young population are involved in this landscape (Bonal et al., 2020; Kalén et al., 2021; Zeng, 2021). And it requires a high demand for physical fitness and biological maturity as basketball is an intensely competitive sport. And in the context of research and practice related to youth physical activity, variations in biological maturity are often identified as a primary factor contributing to selection biases in talent identification and development (Johnson et al., 2017; Lovell et al., 2015) . Adolescents of the same chronological age can exhibit substantial differences in biological maturity (Rojas et al., 2024; Gamonales et al., 2021; Hill et al., 2023; McAuley et al., 2023) . For instance, beginning in late childhood, differences in skeletal age and somatic maturity among peers of the same age cohort can reach as much as six years, both of which are established indicators of biological maturity in youth (Borms, 1986; Gundersen et al., 2022). Based on comparisons of biological and chronological age, individuals can be classified as early maturers, average maturers, or late maturers (Malina, 2004). Studies have demonstrated that, compared to their later-maturing peers, early-maturing adolescent athletes tend to exhibit advantages in key physiological attributes such as height, weight, bone density, muscle mass, and maximal oxygen uptake (de Gouvêa et al., 2017; González et al., 2022; Junior et al., 2020). These physiological advantages can be further translated into superior athletic performance, particularly in attributes such as speed, strength, power, and agility, which allow early maturers to excel in selection processes and gain opportunities to join elite academies or teams for training and competition (de Oliveira et al., 2024; Konarski et al., 2021). This bias is particularly pronounced in team sports such as soccer and basketball (Abad-Robles et al., 2014; Arenas et al., 2024; Leyhr et al., 2024).

Furthermore, the changes in biological maturity experienced during adolescence can significantly impact physical health, particularly during the phase of accelerated growth referred to as the PHV (PHV) period (Monasterio et al., 2023; Rommers et al., 2020). During this phase, elevated levels of growth hormones lead to rapid, yet asynchronous, growth across different parts of the body. These changes affect limb length, muscle mass, and moments of inertia (Hawkins & Metheny, 2001). However, these newly acquired physical attributes often do not align with the previously developed neuromuscular control capabilities, resulting in a temporary decline in movement coordination. Consequently, adolescent athletes in this stage face a significantly increased risk of injury, a phenomenon commonly referred to as the “adolescent awkwardness period” (Quatman-Yates et al., 2012).

To mitigate selection biases in talent identification and development among adolescent athletes and to scientifically adjust training loads to reduce injury risks, it is both necessary and critical to understand the concept of biological maturity and conduct precise assessments (Pérez et al., 2024; Meylan et al., 2010).

Traditionally, the evaluation of biological maturity has relied primarily on techniques such as skeletal age assessment and secondary sexual characteristic examinations. Among these, skeletal age is considered the gold standard for assessing biological maturity. This method typically requires specialists to evaluate the maturity of hand and wrist bones using X-rays or magnetic resonance imaging (MRI) (Malina et al., 2018). However, X-rays pose a certain risk of radiation exposure, and frequent use may have potential health implications for adolescents (Malina et al., 2015). Although MRI avoids radiation exposure, its relatively high cost and the complexity of equipment requirements reduce its accessibility and convenience (Dvorak et al., 2007). Moreover, skeletal age assessment requires highly specialized expertise when applied in adolescent settings. Secondary sexual characteristic assessments, which involve physical palpation of reproductive organs, are also considered invasive and raise concerns about privacy infringement (Malina et al., 2012). These traditional methods are not only intrusive but also inefficient in terms of data collection and processing, limiting their application in resource-constrained sports clubs or schools.

To address some of the limitations of traditional methods, researchers have recently proposed non-invasive methods for assessing biological maturity based on anthropometry and mathematical modeling. These approaches have been widely applied in the maturity assessment and talent selection processes for youth sports such as soccer and basketball (Arenas et al., 2024; Torres-Unda et al., 2013). For instance, a survey on biological maturity assessment in UK football academies identified “maturity offset (MO)” and “predicted percentage of adult height (PPAH)” as commonly used non-invasive methods (Salter et al., 2021). The MO method estimates the time offset from PHV using regression models that require data on the individual’s chronological age, height, weight, sitting height, and leg length (Mirwald et al., 2002). In contrast, PPAH estimates an individual’s predicted adult height using variables such as parental height, current height, and weight, and calculates the percentage of current height relative to the predicted adult height to determine maturation status (Khamis & Roche, 1994). Although these non-invasive methods are relatively convenient, recent studies have highlighted their limitations. The accuracy and applicability of the MO method and its modified version, the Maturity Ratio, have been questioned in recent research (Sullivan et al., 2023) . Similarly, PPAH may yield inaccurate predictions due to errors in reporting parental height (Towlson et al., 2021) . These limitations affect the precision of such methods to varying degrees. Additionally, the low level of automation in these methods, which still require manual measurement and calculation, makes them susceptible to the subjectivity and expertise of the operators, further impacting their reliability.

Current researchers recommend constructing longitudinal growth trajectories through regular monitoring, using more frequent measurements—such as monthly assessments—to accurately identify the actual stage of PHV during adolescence (Rommers et al., 2020). To address the challenges posed by differences in biological maturity and the limitations of existing testing methods, particularly in adolescent sports contexts, there is a pressing need for a non-invasive method that is convenient, accurate, and broadly applicable to monitor the biological maturity of adolescent athletes comprehensively. In response to this need, a maturity assessment method based on the smartphone application Maturo has been developed. By integrating modern information technology with traditional evaluation metrics, this method aims to achieve automated measurements, precise assessments, and long-term monitoring of the biological maturity of adolescent athletes.

The primary objectives of this study are to evaluate the accuracy and reliability of the Maturo application in adolescent basketball athletes, specifically bya): validating the consistency of Maturo with traditional expert evaluation methods in assessing biological maturity indicators; b): analyzing Maturo’s effectiveness in classifying athletes across different maturity status.

Methods

Participants

This study assesses the accuracy and consistency of the Maturo software, an automated methodology for estimating biological maturation stages of 41 teenage athletes aged 10 to 15, compared to traditional expert evaluations.

Participants were selected based on the following inclusion criteria: age range 10-15 years, regular participation in organized basketball training for at least 1 year, and absence of injuries or medical conditions affecting growth. The final sample comprised 41 youth basketball players. The mean age (± standard deviation) was 13.44 ± 1.32 years for boys and 13.21 ± 1.04 years for girls.

Validation Procedure

The research strictly adhered to ethical protocols, ensuring that written informed consent was obtained from participants and their guardians. We used expert estimate method and Maturo software demonstrated significant efficiency by evaluating all athletes within 2 days.

Initially, athletes underwent a conventional evaluation where three operators were involved (see Figure 1). Two operators measured weight (with shoes removed) to the nearest 0.1 kg using a SECA scale (model Clara 803, Hamburg, Germany). They also measured standing height and sitting height (with shoes removed) to the nearest 0.1 cm using a stadiometer (SECA model 213, Hamburg, Germany). The third operator recorded the data and measurements manually.

Following the conventional evaluation, participants underwent an initial assessment using the Maturo app (Figure 2). The setup involved ensuring the unit was horizontal and level using the spirit level feature on an iPhone. The phone was positioned 2 meters from the background wall and 1 meter from the ground. One operator assisted athletes in completing a questionnaire and took photos to measure their height, as illustrated in Figure 2.

Figure 1. Data collection of human expert method.

Figure 2. Data collection of Maturo method.

Statistical Analyses

A comprehensive set of statistical studies was used to impartially evaluate the accuracy and reliability of Maturo's AI-driven maturation evaluations. The purpose of these investigations was to measure the level of agreement between Maturo's automated predictions and the results acquired using conventional expert methods. The focus was on important metrics linked to development and maturation.

The statistical analysis was conducted using RStudio software (RStudio Integrated Development Environment (IDE), Version 1.4.1717; RStudio, Inc.) (Wang et al., 2015). The tools used for data processing and visualization were stats (Version 4.4.3), pwr (Version 1.3.0), and ggplot2 (Version 3.5.0). Statistical analyses were performed to evaluate the agreement between Maturo's automated estimation of maturity status, maturity timing and the reference standards. This study employed a range of software tools for data visualization and statistical analysis. The analytical findings were shown using Excel (Version 2208, Microsoft Corp) and SPSS (Version 25, IBM Corp) through the creation of tables and charts.

A post-hoc power analysis was performed using the pwr package in R to assess the sufficiency of the statistical power for correlation studies. The study was conducted using a sample size of 41 individuals. The expected effect size was r = 0.5, and the significance threshold was set at α = 0.05. The findings demonstrated that the statistical power was adequate, with a computed power of 0.93.

Since all the maturation estimation techniques were designed specifically for each gender, separate analyses were performed for male and female subjects. The analysis revealed that both the male and female participants had sufficient statistical power to detect differences. For the male participants, the statistical power was adequate (n = 18, r = 0.5, sig.level = 0.05, power = 0.59). Similarly, the analysis for female participants alone also showed sufficient statistical power (n = 23, r = 0.5, sig.level = 0.05, power = 0.71), indicating that we have enough power to detect differences in this group as well.

To assess the agreement between Maturo's automatic maturity estimations and known reference standards (expert assessed), we calculated ICC for the variables PHV speed, and PHV age. High ICC values imply a robust agreement between the two approaches. In addition, TEM (Technical Error of Measurement) and R.TEM (Relative TEM) were employed to ascertain the extent of disparities between the automated estimates and reference standards.

Cross-tabulation was utilized to classify athletes into different maturation stages (prepubescent, pubescent, postpubescent) and maturation timing (early, on-time, late) using both Maturo's and the traditional method's classifications. Additionally, Cohen's Kappa coefficient was calculated to assess the agreement between the two classification methods. The Cohen's Kappa coefficient was subsequently computed to evaluate the degree of concordance between these two categorization systems. A Kappa value around 1 would suggest nearly flawless agreement.

To further investigate the correlation between Maturo's assessments and the outputs of the conventional technique, regression models were utilized. These models were used to analyze the prediction ability of Maturo's measures for important variables as maturity category. The models took into account any confounding factors.

Internal consistency of Maturo's assessments was examined using Cronbach's alpha for questionnaire items and interrater reliability assessments for repeated measurements, ensuring the stability and reproducibility of the results.

Results

The study presents detailed descriptive statistics for age, biological age (BA), as well as stratified by sex, in Table 1. The results of the analysis indicate that, in our samples, females typically have higher chronological and biological ages than males. Specifically, the mean chronological age for females was 13.21 years (SD = 1.04) compared to 13.44 years (SD = 1.32) for males. While there are minor discrepancies between the Expert and Maturo software in estimating biological age and related metrics, the overall trends are consistent across both methods.

Table 1. Descriptive statistics for chronological age and estimated biological age (BA) across methods by sex and for the total sample.

Statistics Parameters	Males (n=18) M (SD)	Females (n=23) M (SD)	Total (n= 41) M (SD)
Chronological age	13.44(1.32)	13.21(1.04)	12.31(1.68)
PHV SPEED_Expert	-2.16(1.07)	-0.26(-1.35)	-1.63(1.21)
PHV SPEED_Maturo	-2.03(1.03)	-0.15(1.07)	-1.50(1.04)
PHV AGE_Expert	13.60(0.61)	14.01(0.35)	13.89(0.58)
PHV AGE_Maturo	13.56(0.64)	14.00(0.34)	13.88(0.47)

In order to thoroughly assess the level of agreement between Maturo's automated predictions and the results obtained from expert methods, ICCs were computed. The ICCs were used to evaluate the strength and direction of the relationships between the automated estimations of maturation and the reference method, using a combination of mixed effects and absolute agreement. The results may be seen in Table 2.

The Maturo software exhibited high reliability, with ICC values exceeding 0.9 for PHV speed, indicating excellent agreement. The smallest mean differences and TEM values were observed that suggesting minimal discrepancies between the methods. However, the ICC for PHV age was 0.673 (95% CI: 0.578-0.758), indicating moderate reliability. This suggests that further refinement may be needed for this variable when using the Maturo. Scatter plots illustrating the correlations between the automated method (Maturo software) and the expert method are depicted in Figure 3, Figure 4. These plots visually reinforce the high degree of agreement between the methods.

Table 2. Comparison of methods for estimating biological age against the expert method for the youth.

Measurement Comparison	Mean (SD)	ICC (95% CI)	A.TEM	R.TEM
PHV SPEED _Expert vs Maturo	-0.09(0.39)	0.955(0.911-0.967)	0.09	0.85
PHV AGE _Expert vs Maturo	0.17(0.46)	0.673(0.576-0.784)	0.17	0.78

Note: ICC = Intraclass correlation, A.TEM = Absolute Technical Error of Measurement, R.TEM = Relative Technical Error of Measurement,

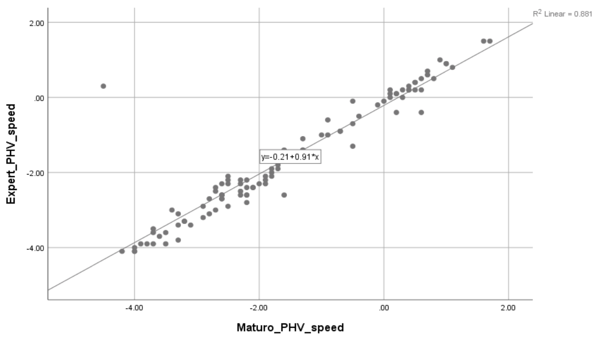

Figure 3. Intraclass correlations and scatterplots for estimates of PHV speed derived from the Maturo software and expert protocol.

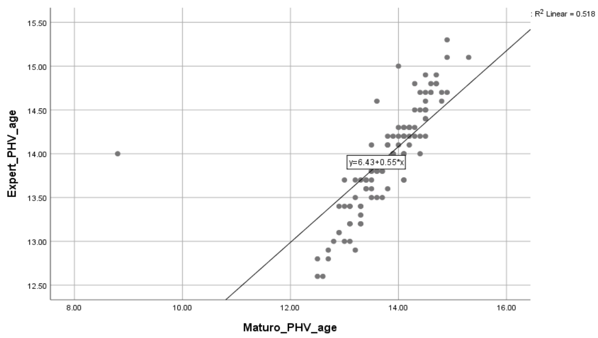

Figure 4. Intraclass correlations and scatterplots for estimates of PHV age derived from the Maturo software and expert protocol.

The Bland-Altman plots provide a detailed graphical representation of the agreement between the two estimate methods across several parameters. For PHV speed, the mean difference between the expert and Maturo estimates is close to zero, with the majority of points falling within the 95% limits of agreement (LOA), indicating high agreement. However, the plot for PHV age reveals a slightly higher mean difference of 0.18 years (95% LOA: -0.94 to 1.30 years), suggesting moderate agreement and the presence of systematic bias. These visualizations provide clear evidence of the Maturo software 's accuracy and reliability for most measurements.

Further analysis using Pearson correlation coefficients reinforced the high level of consistency between Maturo and the expert method. For PHV speed, the correlation was also high ($R = 0.96$, $p < 0.001$). However, for PHV age, the correlation was lower ($R = 0.78$, $p < 0.001$), suggesting moderate agreement with some systematic bias.

Table 3. Bland Altman analyses and Pearson Correlation Coefficients comparing methods for estimating maturity from Maturo against the expert method for the youth.

Measurement Comparison	t. Bias (SD)	ULOA (95%)	LLOA (95%)	LOA Range	R
PHV SPEED _Expert vs Maturo	-0.09 (0.58)	1.01	-1.18	2.10	0.96***
PHV AGE _Expert vs Maturo	0.17 (0.46)	1.28	-0.93	2.13	0.78***

Note: t. Bias (SD) = Paired T test. Bias (Standard Deviation); ULOA = Upper Level of Agreement; LLOA = Lower Level of Agreement; LOA Range: Limits of Agreement Range.
***= p < 0.001.

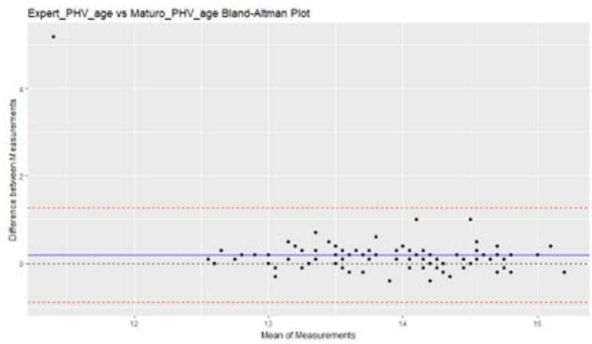

Figure 5. Bland-Atlman plot illustrating the degree of agreement between estimates of PHV speed derived from the Maturo software and expert protocol.

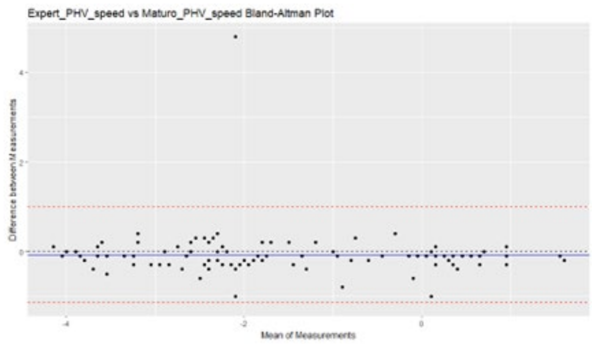

Figure 6. Bland-Atlman plot illustrating the degree of agreement between estimates of PHV age derived from the Maturo software and expert protocol.

The regression analysis (Table 4) shows that the Maturo software has a high level of accuracy in predicting adult height compared to the expert approach. The examination of PHV speed reveals an adjusted R-squared value of 0.92 and a slope of 0.98, demonstrating a strong linear connection with high agreement and no systematic bias, as indicated by the non-significant intercept. Nevertheless, the examination of PHV age reveals an adjusted R-squared value of 0.62, suggesting a reasonable level of agreement. Additionally, the slope of 0.97 indicates a significant albeit imperfect linear association when compared to other data. The lack of a substantial intercept indicates that the Maturo approach has to be further improved for this particular statistic.

A series of one-sample t-tests were conducted to compare the average maturity estimations obtained from the Maturo approach with those obtained from the expert method. The results (Table 5) for PHV speed indicated no significant differences, with mean differences approaching zero. This further reinforces the coherence across the employed methodologies. The p-value for PHV speed was 0.52, with a mean difference of -0.03. This suggests that there is no statistically significant difference.

Table 6 illustrates a strong correlation between the Maturo approach and the expert method in accurately determining the maturity status and time for young individuals. The high Kappa values of 0.95 and 0.87, together with statistically significant T values and low standard errors, indicate that the Maturo approach is a dependable substitute for the expert method in evaluating maturity. The extremely low p-values (both 0.00) provide additional evidence supporting the strength and reliability of these findings.

Table 4. Linear Regression Analysis comparing methods for estimating maturity from Maturo against the expert method for the youth.

Measurement Comparison	Intercept (SE)	Slope (SE, p-value)	Adjusted R-squared	Residual SE	F-statistic
PHV SPEED _Expert vs Maturo	0.03 (SE = 0.07)	0.98 (SE = 0.03***)	0.92	0.61	741.17 ***
PHV AGE _Expert vs Maturo	0.55 (SE = 1.26)	0.97 (SE = 0.08***)	0.62	0.62	109.27 ***

***= p < 0.001.

Table 5. One sample means t-tests Results comparing methods for the mean value of estimating maturity from Maturo against the expert method for the youth.

Measurement Comparison	t	p-value	Mean Difference
PHV SPEED_Expert vs Maturo	-0.45	0.52	-0.03
PHV AGE_Expert vs Maturo	0.03	0.38	0.05

The Maturo approach demonstrated a high level of dependability in classifying teenagers into groups based on their maturity status and timing. The Kappa coefficients of 0.93 for maturity status and 0.82 for maturity timing indicate a nearly perfect agreement with the expert technique.

Table 6 illustrates a strong correlation between the Maturo approach and the expert method in accurately determining the maturity status and time for young individuals. The high Kappa values of 0.93 and 0.82, together with statistically significant T values and low standard errors, indicate that the Maturo approach is a dependable substitute for the expert method in evaluating maturity. The extremely low p-values (both 0.00) provide additional evidence supporting the strength and reliability of these findings.

Table 6. Cross-Tabulation and Cohen's Kappa Coefficient from Maturo against the expert method.

Measurement Comparison	Kappa	Standard Erro	p-value
Maturity Status_Expert vs MaturoMaturo	0.95	0.01	0.00***
Maturity Timing _Expert vs Maturo	0.87	0.03	0.00***

***= p < 0.001.

Discussion

This study investigated the validity of an automated method for estimating the maturity of athletes aged 10 to 15. The ICC indicated strong positive correlations between the automated maturity estimations and the expert reference technique. The Maturo software shown strong concordance with expert assessments across growth and maturation parameters. The differences between the Maturo software and expert methods were minimal.

The findings support using the Maturo software as an automated method for estimating the biological maturation of young athletes. The Maturo approach demonstrates a strong correlation with the expert technique in classifying adolescents into phases of maturity (prepubescent, pubescent, postpubescent) and timing (early, on-time, late). However, the fixed bias observed in comparisons suggests that Maturo tends to underestimate biological age. Therefore, caution is needed when interpreting maturity estimates from the Maturo software, and further optimization of the algorithms is recommended.

The Maturo software could offer substantial benefits, particularly in clinical and sports contexts, due to its non-invasive nature, cost-effectiveness, and compatibility with smartphones. It is especially advantageous for regular screening and monitoring of development and maturity. The Maturo technique demonstrates comparable performance to expert assessments, while yielding significantly lower estimates of maturity. It is important to use caution when interpreting Maturo's estimations at the individual level, just like with any other method.

One key limitation of relying solely on application-based assessments, such as Maturo, is their dependence on technological infrastructure and user compliance. In resource-limited contexts, factors such as restricted access to smartphones, poor internet connectivity, and limited digital literacy can compromise the feasibility and accuracy of implementation. Furthermore, while automated methods ensure consistency and scalability, they may lack the contextual judgment and nuanced interpretation that trained professionals provide, especially in borderline cases or when input data are incomplete or of low-quality input resources. Therefore, Maturo is best utilized as part of a hybrid system, integrating digital assessments with expert oversight, particularly in settings with diverse populations and constrained resources.Finally, although the Maturo software shows promise in calculating metrics linked to biological age, more study using bigger and more varied samples is required to validate the findings and improve the system's precision. The integration of Maturo's non-invasive estimates with other growth and maturation indicators can offer a comprehensive comprehension of the physical development of youth athletes, thereby optimizing their health, safety, athletic development, and training.

Looking ahead, the future of GAM is poised to be shaped by the development of methodologies that are non-invasive, cost-effective, and rapid. These tools must be easily accessible and dependable across a variety of settings to ensure broad applicability. Such innovations are expected to enable more timely and accurate interventions, as well as enhance the monitoring of growth and maturation processes. This is particularly vital for the health and optimal development of young athletes, where accurate assessments can significantly impact their training, health, and overall development. In addition to technological advancements, there is a need for a paradigm shift in the way growth and maturation data are approached. This includes fostering a culture of open data exchange and collaboration among researchers, clinicians, and institutions. Leveraging big data analytics and machine learning algorithms could offer new insights into growth patterns and maturation processes, potentially leading to more personalized and effective monitoring strategies. Considering the potential commercial and academic impact of the Maturo application, future efforts will focus not only on further algorithm refinement and validation studies but also on intellectual property protection. Specifically, we plan to initiate processes for trademark registration and patent applications for the Maturo software, in collaboration with the Innovation and Development Center of our university. These measures aim to secure its commercial viability and facilitate broader dissemination and application within sports and clinical settings.

Moreover, integrating GAM with holistic approaches that consider psychological, nutritional, and socio-economic factors will provide a more comprehensive view of a child's development. This aligns with the growing recognition of the interplay between physical growth, mental health, and overall well-being. In summary, the challenges in current GAM methods call for innovative solutions, interdisciplinary collaboration, and a holistic approach to understanding and supporting the growth and maturation of young individuals. Embracing these future directions will be pivotal in ensuring that GAM methodologies evolve to meet the diverse needs of the youth development effectively.

Conclusion

The findings support using the Maturo software as an automated method for estimating the biological maturation of young athletes. The ICCs and Pearson correlation coefficients showed strong positive correlations and significant agreement between the Maturo software and expert methods across multiple metrics of biological maturation.

The Maturo software could offer substantial benefits, particularly in clinical and sports contexts, due to its non-invasive nature, cost-effectiveness, and compatibility with smartphones. It is especially advantageous for regular screening and monitoring of growth and maturation, especially in basketball.

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