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A comparison of two artificial intelligence-based methods for assessing bone age in Turkish children: BoneXpert and VUNO Med-Bone Age

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PURPOSE

This study aimed to evaluate the validity of two artificial intelligence (AI)-based bone age assessment programs, BoneXpert and VUNO Med-Bone Age (VUNO), compared with manual assessments using the Greulich–Pyle method in Turkish children.

METHODS

This study included a cohort of 292 pediatric cases, ranging in age from 1 to 15 years with an equal gender and number distribution in each age group. Two radiologists, who were unaware of the bone age determined by AI, independently evaluated the bone age. The statistical study involved using the intraclass correlation coefficient (ICC) to measure the level of agreement between the manual and AI-based assessments.

RESULTS

The ICC coefficients for the agreement between the manual measurements of two radiologists indicate almost perfect agreement. When all cases, regardless of gender and age group, were analyzed, an almost perfect positive agreement was observed between the manual and software measurements. When bone age calculations were analyzed separately for boys and girls, no statistically significant differences were found between the two AI-based methods in any subgroup. For boys regardless of age, the ICCs were 0.995 for VUNO and 0.994 for BoneXpert ($z = 1.597$, $P = 0.110$), while for girls, the ICCs were 0.994 and 0.995, respectively ($z = -1.303$, $P = 0.193$). The overall agreement with manual measurements was high for both VUNO and BoneXpert. In both boys and girls, the agreement remained consistent across different age groups. These findings indicate that both AI-based bone age assessment tools have a high degree of agreement with manual measurements across all age and gender groups, with no significant superiority of one method over the other.

CONCLUSION

Both BoneXpert and VUNO demonstrated high validity in assessing bone age, with no statistically significant differences between the two methods across gender or pubertal status groups. Notably, this study represents the first evaluation of both BoneXpert and VUNO for bone age assessment in Turkish children, highlighting their potential as reliable and clinically relevant tools for this population.

CLINICAL SIGNIFICANCE

Investigating the most suitable AI program for the Turkish population could be clinically significant.

KEYWORDS

Bone age, BoneXpert, VUNO, artificial intelligence, deep learning

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Bone age is a marker of skeletal maturation and is measured routinely by pediatricians, radiologists, and pediatric endocrinologists for the assessment of the maturation progress of children.¹ The most commonly used manual method for bone age measurement is the Greulich–Pyle (GP) method.² According to this method, the determination of bone age is based on the similarity between the image in the GP atlas and the patient's left-hand wrist radiography. Thus, the GP method is very subjective and has higher inter and intraobserver

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variability in addition to inter and intra-institutional variability.³ Besides, there is no standardized protocol for assessing bones, and it is unclear which bones should be included in the assessment.⁴ With the development of deep learning, which is a subclass of artificial intelligence (AI) that exploits artificial neural networks, several software programs have been developed to automate and standardize bone age assessment, thereby reducing interobserver variability. It has been reported previously that AI-based assessment methods have high accuracy, reproducibility, and time efficiency when compared with manual methods.⁴ Although BoneXpert version 2.4.5.1 and 3.0.3 (Visiana, Denmark) is one of the most frequently used methods of these, there are other AI-based bone age calculation software packages, including VUNO Med-Bone Age version 1.0.3 (VUNO) (VUNO, Seoul, Korea). The Turkish population is composed of various ethnic groups. As far as we know, no data compares these software packages, and no published report compares the manual method with these AI-based bone age assessment methods in Turkish children. This study aims to analyze the accuracy of two AI-based bone age assessment programs, namely BoneXpert and VUNO, in comparison with manual assessments using the GP bone age atlas.

Methods

Study design and population

This retrospective cohort study was approved by the Ethics Committee of Koç University Faculty of Medicine (2024.050. IRB2.023) and conducted in accordance with the Declaration of Helsinki's ethical principles. Informed consent was not obtained from the participants due to retrospective design of the study.

Main points

- Our study reveals that both VUNO Med-Bone Age (VUNO) and BoneXpert correlated well with the manual assessment and Greulich-Pyle atlas.
- Neither VUNO nor BoneXpert showed a statistically significant difference in performance across gender or pubertal status groups, indicating similar effectiveness for bone age assessment in Turkish children.
- The results of our study are particularly important as they represent the first evaluation of both VUNO and BoneXpert in the Turkish pediatric population, addressing the gap in research on the applicability of AI-based bone age calculations for this demographic.

Pediatric cases who underwent left-hand X-ray imaging between January 2016 and December 2023 in the hospital due to suspicion of an endocrinological pathology and whose left-hand X-ray evaluation revealed that their chronological age and bone age were compatible were determined. Patients whose bone age was compatible with chronological age but who had known endocrinologic genetic or orthopedic disorders were excluded from the study list. Cases were also excluded if the radiological images were of poor quality, as this could make bone age estimation difficult.

After that, these cases were anonymized and grouped according to their age and gender, and the groups were randomized within themselves. Due to the limited number of male and female cases in the 1-year age group (aged 1–2 years), 6 cases for each gender were selected from this group. In the evaluation made for the other age groups, it was determined that the group of 15-year-old girls had the fewest case numbers, and there were 10 cases in this group. For this reason, in the other groups, the first 10 cases from the randomized list for both genders were selected. The specific age distribution included 6 boys and 6 girls aged 1–2 years, and 10 boys and 10 girls were included for each subsequent age group (aged 2–16 years).

Radiological assessment

Left-hand wrist posterior to anterior X-ray images were used for the evaluation of bone age. Two radiologists with 15 and 5 years of experience and unaware of the results determined by AI independently evaluated bone ages according to the GP bone age atlas. Bone age was determined to be the midpoint when a case exhibited some, but not all, of the typical bone characteristics of a particular age (e.g., aged 8 years) and had all the characteristics of the previous age (e.g., aged 7 years). This approach was adopted to provide a more detailed and precise assessment of bone maturity. A third radiologist, aware of the cases' clinical details but blind to the manual bone age assessments, documented the AI assessments using BoneXpert version 3.0.3 and VUNO version 1.0.3 (Figure 1).

Statistical analysis

Correlation analysis was performed using the Statistical Package for the Social Sciences, version 28.0 (IBM SPSS Statistics, Armonk, NY, USA).⁵ Comparing correlation coefficients was done by the MedCalc Statistical Software version 12.7.7 (MedCalc Software bvba, Ostend, Belgium; <http://www.medcalc.org>; 2013). The test used by MedCalc is a z-test on Fisher's z-transformed correlation coefficients.⁶ The inter-reader agreement between the manual evaluations of two radiologists was measured to ensure consistency in the

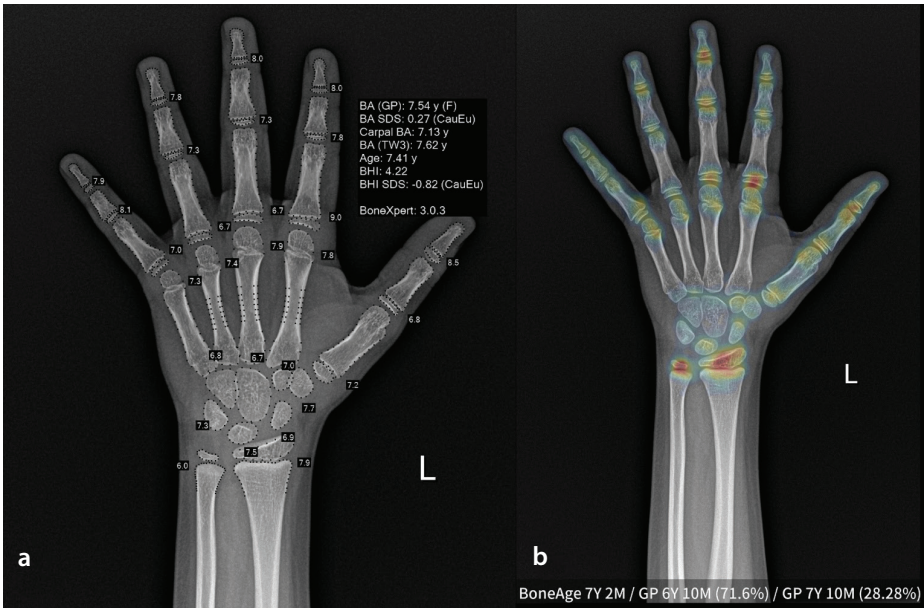


Figure 1. BoneXpert and VUNO images of a patient. In the 7.4-year-old female case, BoneXpert showed the bone age as 7.54 years (a) and VUNO indicated the bone age as 7 years 2 months (b). As illustrated in the accompanying image, the BoneXpert version 3.0.3 system additionally evaluates carpal bones and provides separate carpal bone age, whereas the VUNO system assesses carpal bones as well as tubular bones and provides one bone age accordingly. Upon receipt of the image to be analysed, VUNO Med-Bone Age suggests three probable estimated bone ages (i.e., first- and second-rank artificial intelligence bone ages) based on probabilities, accompanied by similar images for comparison, while BoneXpert provides standard deviation information.

manual evaluation process. Intraclass correlation coefficients (ICC) were calculated for agreement between two radiologists using a two-way random-effects model, assessing absolute agreement. According to Shrout and Fleiss⁷ (1979), this corresponds to ICC (2,1) for single measures and ICC (2,2) for average measures. Since the agreement was very high, manual evaluation was calculated with the arithmetic mean of these two measurements. The ICC values were used for assessing the agreement between software measurements and the mean radiologist measurements using a two-way random-effects model. According to Shrout and Fleiss⁷ (1979), this corresponds to ICC (2,1) for single measures. To test the difference between two dependent correlations, the online tool "calculation for testing the difference between two dependent correlations" by Lee and Preacher (2013; <https://quantpsy.org/corrttest/corrttest2.htm>) was used. Bland-Altman analysis was used to further evaluate the agreement between manual and AI-based assessments. To also see the effect of gender and age on the measurements, all analyses were repeated for all combinations of subgroups: girls, boys, and different age groups. Boys over the age of 9 years and girls over the age of 8 years were considered to be pubescent.⁸ The statistical significance level was accepted as 0.05.

Results

All pediatric patients aged 1–15 years with left-hand X-ray images generated in our institution were included in the study. Thirty-six patients with poor-quality radiological images and 54 patients with known endocrinologic genetic or orthopedic disorders were excluded from the study. The final study cohort included 292 cases with an equal distribution of genders across all age groups, ranging from 1 to 15 years (Figure 2). The ICC coefficients for the agreement between the manual measurements of two radiologists were calculated as 0.990 for ICC (2,1) and 0.995 for ICC (2,2) (Table 1). These values indicate almost perfect agreement. Based on these measurements, the average of the two observer values was taken and accepted as the manual measurement.

For the manual vs. software comparison, the ICC (2,1) values were calculated for single measurements. When all cases, regardless of gender and age group, were analyzed, an almost perfect agreement was observed between the manual and software measure-

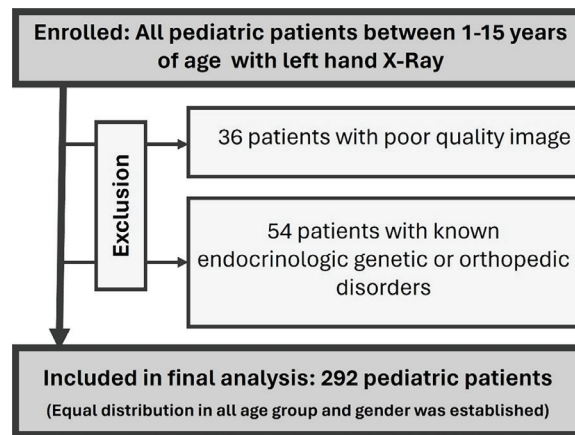


Figure 2. Flowchart of the study.

Table 1. Correlations for agreement between two radiologists

	Intraclass correlation ^b
Single measures ICC (2,1)	0.990 ^a
Average measures ICC (2,2)	0.995

Two-way random effects model where both people effects and measures effects are random. ^a, the estimator is the same, whether the interaction effect is present or not; ^b, type A intraclass correlation coefficients using an absolute agreement definition; ICC, intraclass correlation coefficient.

Table 2. Intraclass Correlations for Agreement Between Software and Manual Measurements

Group	ICC (2,1) ^a		Difference between 2 correlation coefficients ^b		
		Vuno	BoneXpert	z	2-tailed P
Overall	ICC	0.995	0.995	0.000	1.000
	95% CI	0.993–0.996	0.991–0.997		
Males	ICC	0.995	0.994	1.597	0.110
	95% CI	0.989–0.997	0.970–0.998		
Females	ICC	0.994	0.995	–1.303	0.193
	95% CI	0.992–0.996	0.993–0.997		
≤9 years males & ≤8 years females	ICC	0.990	0.988	1.294	0.196
	95% CI	0.985–0.992	0.975–0.993		
>9 years males & >8 years females	ICC	0.977	0.978	–0.382	0.703
	95% CI	0.968–0.984	0.964–0.986		
≤9 years males	ICC	0.990	0.986	1.86	0.063
	95% CI	0.983–0.994	0.903–0.995		
>9 years males	ICC	0.977	0.976	0.262	0.793
	95% CI	0.902–0.991	0.906–0.99		
≤8 years females	ICC	0.988	0.992	–1.748	0.080
	95% CI	0.980–0.993	0.987–0.995		
>8 years females	ICC	0.977	0.980	–0.800	0.423
	95% CI	0.965–0.985	0.969–0.987		

^aICC estimates and their 95% confident intervals based on a single measures, absolute-agreement, 2-way random effects model. ^bTest of the difference between two dependent correlations with one variable in common. ICC, intraclass correlation coefficient; CI, confidence interval.

ments. When all cases, regardless of gender and age groups, were analyzed, an almost perfect positive agreement was observed between the manual and software measurements. The ICC was calculated as 0.995 for both VUNO and BoneXpert. No statistical difference was found between two AI-based methods.

When bone age calculations were analyzed separately for girls and boys, an ICC coefficient of 0.995 and 0.994 was calculated for VUNO and BoneXpert, respectively, for boys, and this difference was not significant ($z = 1.597$, $P = 0.110$). For girls, ICC coefficients of 0.994 and 0.995 were calculated for VUNO and BoneXpert, respectively, and this difference was not significant ($z = -1.303$, $P = 0.193$).

Upon categorization of all cases by age, a slight decrease in the software–manual agreement was observed for measurements of the older group. While the ICC coefficient was 0.990 for VUNO, it was calculated as 0.988 for BoneXpert in the younger age group (≤ 9 years for boys, ≤ 8 years for girls). Accordingly, it was evaluated that, in the measurements of prepubescent children, no significant difference was detected between two AI-based tools ($z = 1,294$, $P = 0,196$). After the age of 8

years for girls and 9 years for boys, the compliance of both software and manual measurements was calculated as 0.977 for VUNO and 0.978 for BoneXpert, and no significant difference was detected between the software ($z = -0,382$, $P = 0,703$) (Table 2).

Although there was no statistical significance between VUNO and BoneXpert, the difference between the agreements demonstrated by the two software packages with manual measurements in the prepubescent group was much more pronounced than older age group. The ICC values in prepubescent girls were calculated as 0.988 for VUNO and 0.992 for BoneXpert, and the difference was not significant ($z = -1,748$, $P = 0,080$). In prepubescent boys, the ICC value was 0.990 for VUNO and 0.986 for BoneXpert; the difference was not statistically significant ($z = 1.86$, $P = 0.063$).

For girls aged >8 years and boys aged >9 years, the agreement between manual measurements and both AI software packages was similar. While the ICC values were 0.977 for VUNO, 0.976 for BoneXpert in boys aged >9 years, these values were 0.977 for VUNO and 0.980 for BoneXpert in girls aged >8 years (Table 2).

When examining Bland–Altman plot graphs, higher variability is observed on the left side of the graphs. Therefore, it can be seen that both AI-based bone age calculations tend to diverge more from manual measurements in the older group.

Discussion

This study represents the inaugural investigation into the comparative efficacy of AI-based systems, namely BoneXpert and VUNO, in the determination of bone age among a Turkish pediatric population. The results of our study indicate that both AI-based systems demonstrated a high level of agreement with each other and with manual methods in all our subgroups, including both genders and age groups. This is consistent with the findings of previous studies in the field. This highlights the potential for integrating AI-based bone age calculation into clinical practice, with the aim of enhancing the effectiveness of bone age assessment.

The GP method is the most widely used and well-known manual method, and according to Martin et al.⁹, it is the method preferred by 76% of pediatric endocrinologists and radiologists.¹⁰ The GP method is based

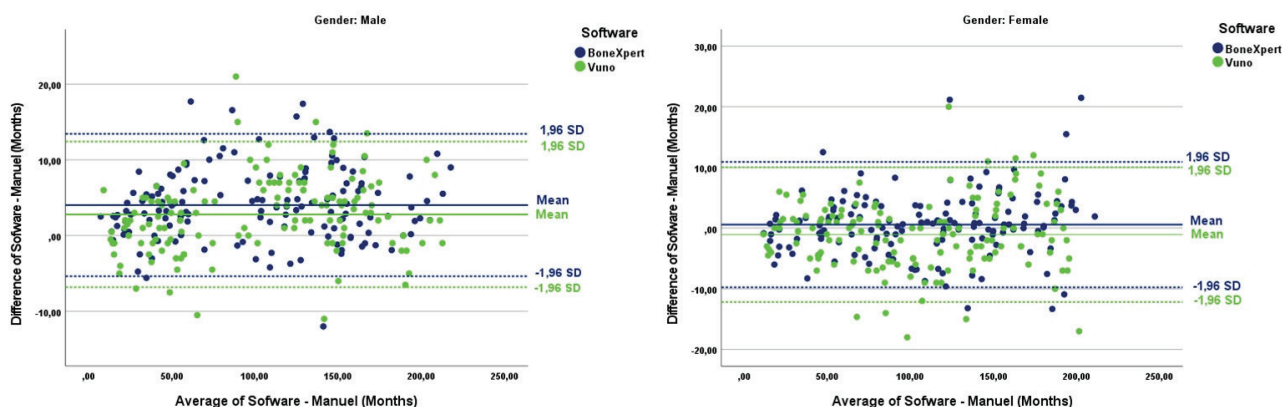


Figure 3. Bland–Altman plot. Difference between radiological bone age and automated bone age in boys and girls.

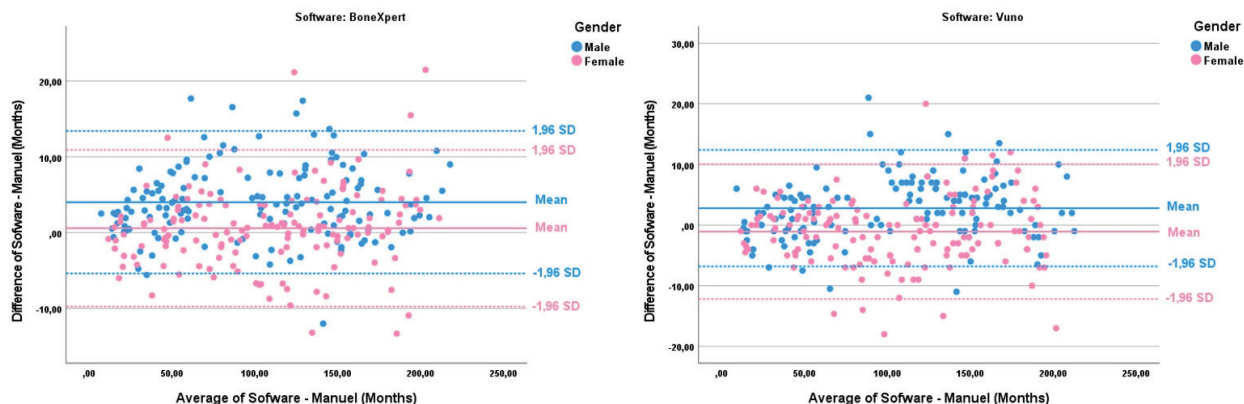


Figure 4. Bland–Altman plot. Difference between radiological bone age and automated bone age in BoneXpert and VUNO.

on the comparison of the cases' hand and wrist X-rays, with a standardized radiographic atlas compiled and standardized according to age and gender from birth to 18 years of age for girls and 19 years of age for boys.¹⁰ However, bone age is influenced by ethnicity, gender, genetic factors, socioeconomic level, nutritional metabolic status, and bone disorders.⁹⁻¹² The standardized radiographic images of the atlas were derived from healthy North American and Western European-originated children.¹³ They had good reliability in Australian and Middle Eastern ethnicity but were less reliable in Asian people. In addition to this, the evaluation of bone age with the GP method is also time-consuming; it takes a lot of time to evaluate the age of the bones individually with high accuracy when performed manually.¹⁴ Furthermore, one of the major disadvantages of manual bone age assessment with the GP method is the possible risk of high inter and intraobserver error.¹⁵ Therefore, before the comparison of manual bone age assessment with an AI-based system, the interobserver agreement between manual assessments performed by two radiologists was calculated and yielded an ICC of 0.990, thus establishing a solid basis for comparison of the AI-based measurements.

AI-based bone age calculation systems, developed to overcome all these disadvantages of manual calculation, can identify the morphological features of bone ossification automatically and provide rapid information about the patient's bone age. Therefore, this has resulted in a more objective and efficient method for assessing bone age.¹⁶

Numerous studies have demonstrated that newly developed AI technologies and software can accurately perform bone age assessments, surpassing the accuracy of the GP method.^{1,4,9,15} Furthermore, these studies have shown that AI-based assessments exhibit excellent agreement with assessments made by experienced human observers.¹ In their study to compare deep learning systems, including AlexNet, GoogleNet and Vgg19, in performing age estimation with the Turkish population, Senel et al.¹⁷ reported a success rate of 98.39%.

Similarly, we found a high level of agreement between manual assessments (using GP) and both AI-based systems, with an ICC of 0.995 for both VUNO and BoneXpert when the entire cohort was considered. This high correlation is particularly important given the lack of existing research on the applica-

bility of AI-based bone age calculations in the Turkish pediatric population.

BoneXpert is an AI-based automated bone age assessment system and is known as the first AI radiology system.¹³ This method, which is based on traditional machine learning methodology, predicts bone age by considering bone shape, density, and the degree of epiphyseal fusion.^{18,19} Image analysis predicts bone age by measuring shape, density, and texture scores at specific locations.¹⁴ If a bone's appearance falls outside the range covered by the machine learning process or if its bone age value deviates above the threshold value compared with the average of all tubular bones, it will not be included in the calculation. The final bone age is calculated using the evaluated bones. If fewer than eight bones are evaluated, the X-ray is not assessed due to possible inaccurate calculations, which is a major disadvantage of BoneXpert version 2.4.5.¹²⁰ However, BoneXpert version 3.0 introduced several significant advancements over its predecessor. These features improve accuracy. Additionally, version 3.0 also provides carpal bone age determination which is typically determined for boys up to 11.5 years and girls up to 9.5 years for additional information about skeletal maturity in younger children. In addition to that, new version reduces image rejection rates by improving adaptability to variations in image post-processing and achieving more precise bone localization. Both versions of BoneXpert have been validated for bone age calculation in North American, Caucasian, African American, Hispanic, and Asian children and has also been reported to be applicable in various ethnic groups.^{19,21,22} Many published reports show a notable distinction between bone ages determined by the GP method and chronological ages in Asian children.^{23,24} Similarly, Ontell et al.²⁵ reported delayed bone age in preadolescence and increased bone age in adolescence in Asian boys. The process of skeletal maturation in Korean children is initiated at a later age and completed at an earlier age than in Caucasian children. The VUNO Korean bone age assessment method, which is based on deep learning, has demonstrated superior performance compared with the manual assessment from the GP atlas. Compared with the manual assessment with the GP atlas, the Korean model has a lower root mean square error and lower mean absolute error. VUNO is the first AI-based bone age assessment system approved by the Korean Food and Drug

Administration. The system was developed by analyzing 18,940 left-hand wrist radiographs using the GP method.^{25,26} VUNO provides the most likely estimated bone ages based on the examined wrist radiography.

A subgroup analysis of the data revealed subtle differences between the calculated bone ages by BoneXpert and VUNO, particularly when examining data based on gender and age subgroups. Both VUNO and BoneXpert demonstrated a high level of agreement with manual assessments in boys and girls, with no statistically significant differences observed between the two methods across any subgroup. This suggests that both tools are equally effective in bone age assessment regardless of gender or pubertal status. The analysis provided valuable insights into the applicability of AI-based bone age programs, showing that BoneXpert and VUNO maintain high reliability across different age and gender groups, even among prepubertal individuals in contrast to previous version of BoneXpert. In a comprehensive validation study comparing previous and latest versions of BoneXpert revealed that previous version had a tendency to underestimate bone age in girls aged 6–7 years and 12–15 years, but the latest version showed significant improvements in this regard, highlighting the importance of usage most updated version of bone age softwares.²⁷

Our study had some limitations, including a small sample size and the fact that it focused on a single, heterogeneous ethnicity. Additionally, the study did not include participants aged <2 years or >15 years due to the unsuitability of the GP manual method for evaluating bone age in these age groups.

In conclusion, our study confirms that BoneXpert and VUNO are reliable AI-based systems for assessing bone age in the Turkish pediatric population. Both methods demonstrated comparable agreement with manual assessments across all gender and pubertal status groups, marking this study as a significant contribution to evaluating AI-based bone age assessment tools in this demographic.

Conflict of interest disclosure

Evrin Özmen, MD, is Section Editor in Diagnostic and Interventional Radiology. She had no involvement in the peer-review of this article and had no access to information regarding its peer-review. Other authors have nothing to disclose.

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