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RESEARCH ARTICLE

LiDAR and X-ray: A Retrospective Comparison of Spinal Alignment

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ABSTRACT

The study explores the potential of LiDAR (Light Detection and Ranging) technology as a non-invasive alternative for measuring spinal alignment, particularly focusing on the correlation between LiDAR generated data and traditional X-ray measurements. The research involved 275 patients who underwent both full spine X-rays and LiDAR scans. The study compared measurements of Cobb angle, lumbar lordosis, and thoracic kyphosis derived from X-rays and the Spine3D LiDAR system by Sensor Medica. The results demonstrated a strong positive correlation between LiDAR and X-ray measurements across all conditions. The findings suggest that while LiDAR cannot replace X-rays for initial diagnostic purposes, it offers a promising tool for ongoing monitoring of spinal deformities, potentially reducing the frequency of exposure to ionising radiation, and improving patient compliance through engagement. This research highlights the potential for integrating LiDAR technology into clinical practice.

Keywords: LiDAR, X-ray, ionising radiation, Cobb angle, scoliosis, non-invasive measurement, spine, spinal, posture, deep learning, spinal deformities.

Introduction

Traditionally, spinal measurements such as Cobb angle in scoliosis, lordosis and kyphosis and are measured using X-rays[1-3], which is an ionising radiation and require careful analysis by medical professionals. Previous studies have shown a correlation between cancer risk and the repeated exposure to ionising radiation during scoliosis management[4-8]. With the advent of advanced technologies such as LiDAR[9] (Light Detection and Ranging), sometimes referred to as 'light-Radar' there is potential for accurate, rapid, and automated prediction of these spinal angles to supplement the use of X-ray and reduce the lifetime ionising radiation dose to the patient.

The integration of LiDAR technology and deep learning models into clinical practice could revolutionise the way spinal deformities are diagnosed and importantly, monitored[10]. With the ability to rapidly and accurately predict and monitor spinal angles without the use of ionising radiation, clinicians could benefit from a safe tool that supports decision-making and treatment planning. This technology could also enhance patient outcomes by enabling more precise monitoring of disease progression or response to treatment, something that is often not possible by the limitation on frequency of ionising radiation assessments. Lastly, patient compliance is higher in cases where the patient fully understands their condition and their responsibilities[11-12]. The Spine3D LiDAR by Sensor Medica used in this study allows for easy report generation to show patients their condition and their progress. It has been utilised in a paper by Marin et al[13] to show patients how effective their exercise programme is by performing LiDAR scans whilst holding specific exercise positions that improve their spinal alignment.

Whilst the literature regarding the use of LiDAR on the spine is limited to date, it holds great promise for improving the assessment of spinal deformities[14]. As research in this area continues to evolve, it is expected that these technologies will become increasingly integrated into clinical workflows, offering a more advanced, non-invasive, and efficient approach to spinal measurement.

There are no studies available to the author directly comparing LiDAR to X-ray for predicting spinal angles and it's important to note that LiDAR and X-ray are fundamentally different technologies with distinct applications. LiDAR uses laser light to measure distances and create detailed 3D maps of the visible environment. There are studies and applications that utilise LiDAR technology for various purposes, including mapping and scanning objects or environments[15-17]. LiDAR can provide high-resolution data and has been used in fields such as 3D scanning/printing, architecture, archaeology, topographic surveys, infrastructure inspection, and vegetation analysis[18-19].

On the other hand, X-ray imaging is a medical imaging technique that uses ionising radiation to visualise internal structures of the body. X-ray machines emit ionising X-ray radiation, which passes through the body with variable absorption by different tissues. This differential absorption creates an image that can be used for diagnostic purposes.

The key difference between LiDAR and X-ray is the type of information they capture. LiDAR provides detailed 3D spatial information of the external environment, while X-ray captures internal structures of the body. Therefore, the results obtained from LiDAR and X-ray are fundamentally different in terms of the data they provide. Nonetheless, recent advancements in deep learning have led to the development of systems capable of locating vertebral centre points from external data and measuring spinal alignment with high accuracy.[20-25]

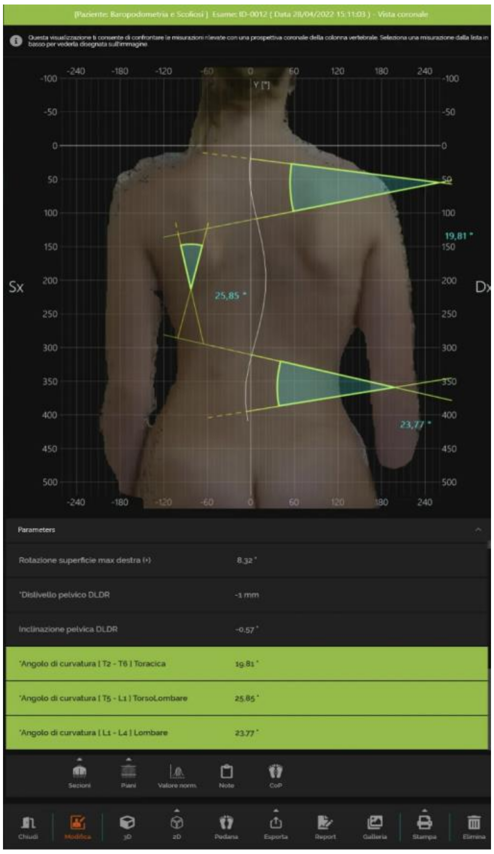
Lastly, it is worth making clear that the author does not suggest that LiDAR should replace the use of X-ray. Initial assessments should still use upright X-ray, or standing MRI (with increasing availability) to accurately assess internal weight-bearing data. As LiDAR provides surface data, it cannot replace X-ray, CT or MRI for ruling out pathology such as fractures, tumours and visceral issues in addition to congenital conditions such as hemi-vertebra. However once the initial assessment has been performed, X-rays are usually repeated regularly to visualise the spinal measurements, especially in scoliosis to assess Cobb angle. With repeated exposure to ionising radiation children with scoliosis are at a higher risk of certain cancers[26-27].

Method

Data was collected from the Dorsi Spinal Institute, a research and teaching clinic in Nottingham, UK. The X-ray database was screened for patients that had full spine (Posterior-Anterior and Lateral) X-rays and a LiDAR scan taken at the same time. X-ray measurements were performed by two experienced clinicians, if the measurements between the two clinicians varied by more than 8 degrees the case was rejected, only the senior consultants measurements were recorded for this research. No other inclusion or exclusion criteria were used. The age range for patients was 12-77 years old. 275 patients were identified to have full spine X-rays of adequate quality to measure Cobb angle, lumbar lordosis and thoracic kyphosis. At the time of the study the LiDAR machine from Sensor Medica did not have the function to measure cervical lordosis.

X-rays were analysed using QuantorMed+ DICOM software version 2.2.24. The clinicians measured Cobb angle (if present), lumbar lordosis and thoracic kyphosis for each patient.

The Spine3D LiDAR machine by Sensor Medica (Sensor Medica, Guidonia Montecelio, Rome, Italy) software version 1.4.2.26 automatically generates clinical data in all planes from one scan. The Spine3D LiDAR utilises a proprietary triangulation algorithm and machine learning. Each machine is linked to the cloud, allowing artificial intelligence to improve data generation with increasing volumes of data and customer feedback. It should be noted that the Spine3D LiDAR does not generate a Cobb angle as this would require X-ray visualisation of the vertebral end plates. It generates a 'bending angle' which is an extrapolated measurement to determine Cobb angle (Figure 1.0). This article attempts to assess the correlation between X-ray Cobb angles and the Spine3D LiDAR bending angle, together with the assessments of Lumbar lordosis and Thoracic kyphosis.



[Paziente: Baropodometria e Scoliosi] Esame: ID-0012 (Data 28/04/2022 15:11:03) - Vista coronale

Questa visualizzazione ti consente di confrontare le misurazioni rilevate con una prospettiva coronale della colonna vertebrale. Seleziona una misurazione dalla lista in basso per vederla disegnata sull'immagine.

Parameters	
Rotazione superficie max destra (+)	8.32 °
*Dislivello pelvico DLDR	-1 mm
Inclinazione pelvica DLDR	-0.57 °
*Angolo di curvatura [T2 - T6] Toracica	19.81 °
*Angolo di curvatura [T5 - L1] TorsoLombare	25.85 °
*Angolo di curvatura [L1 - L4] Lombare	23.77 °

Figure 1.0 Spine3D LiDAR by Sensor Medica Bending angle visualisation

Prior to the automatic data generation step on the LiDAR machine, the clinical is presented with a screen that allows you to check and change several settings. Primarily it relates to certain anatomical markers seen in figure 2.0. They correspond to the Acromio-clavicular joint bilaterally, the vertebra prominens, the S2 spinous process and the P.S.I.S bilaterally. This allows the clinician greater levels of control and certainty. Whilst not common practice, for research purposes patients were marked at each of the core reference points in figure 2.0, and also on the spinous process of each vertebra from T1 to L5. In additional to the points in figure 2.0, the clinical can also double check the reference points for each vertebra that the machine has auto selected, they are shown in figure 2.1.

Three datasets were then extrapolated from the Spine3D LiDAR machine:

1. AI generated Data only. No human intervention.
2. Basic human intervention: Where a clinician checked the core reference points in figure 2.0 and moved if required.
3. Advanced human intervention: Where a clinician checked and moved if required the spinal process points in figure 2.1 in addition to the core reference points in figure 2.0

The data was then analysed using the datatab software with a focus on correlation. The goal of this study was to determine how closely the LiDAR data correlates with the X-ray data.

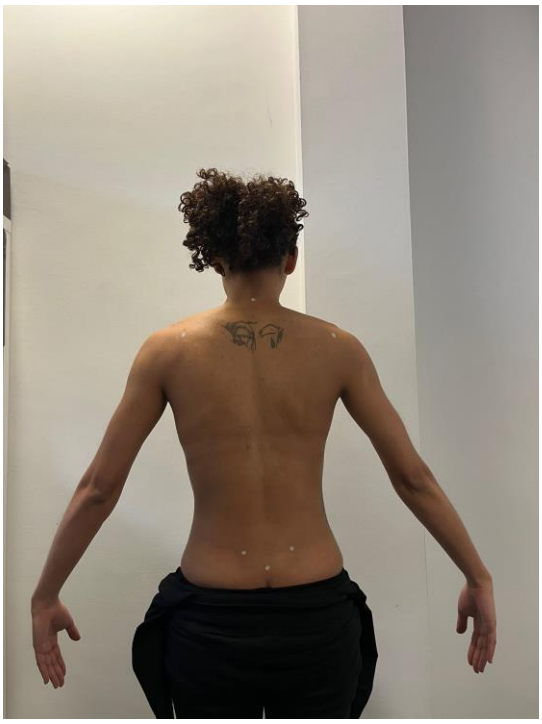


FIGURE 2.0.

FIGURE 2.1

Results

275 patients data was analysed using X-ray and LiDAR for the primary Cobb angle (bending angle on LiDAR) plus lumbar lordosis and thoracic kyphosis.

Cobb angle results - Descriptive Statistics

TABLE 1.0 Descriptive statistics and Pearson correlation coefficients comparing X-ray measurements of Cobb angle to the LiDAR AI only, LiDAR with BASIC human intervention and LiDAR with ADVANCED human intervention. The appropriate use of Correlation coefficient in medical research is documented in the article by Melaka[28]

	COBB XRAY	LiDAR AI - NO HUMAN	LiDAR - HUMAN BASIC	LiDAR ADVANCED HUMAN
Mean	31.64	35.56	34.27	33.4
Median	29.42	33.5	32.18	31.92
Std. Deviation	10.05	12.3	11.34	10.61
Minimum	13.85	10	14.65	14.76
Maximum	60.42	74	73.61	67.23
95% Confidence interval for mean	30.44 - 32.84	34.09 - 37.02	32.91 - 35.62	32.14 - 34.67
Mean ± Std.	31.64 ± 10.05	35.56 ± 12.3	34.27 ± 11.34	33.4 ± 10.61
Pearson Correlation p <.001	-	0.86	0.92	0.93

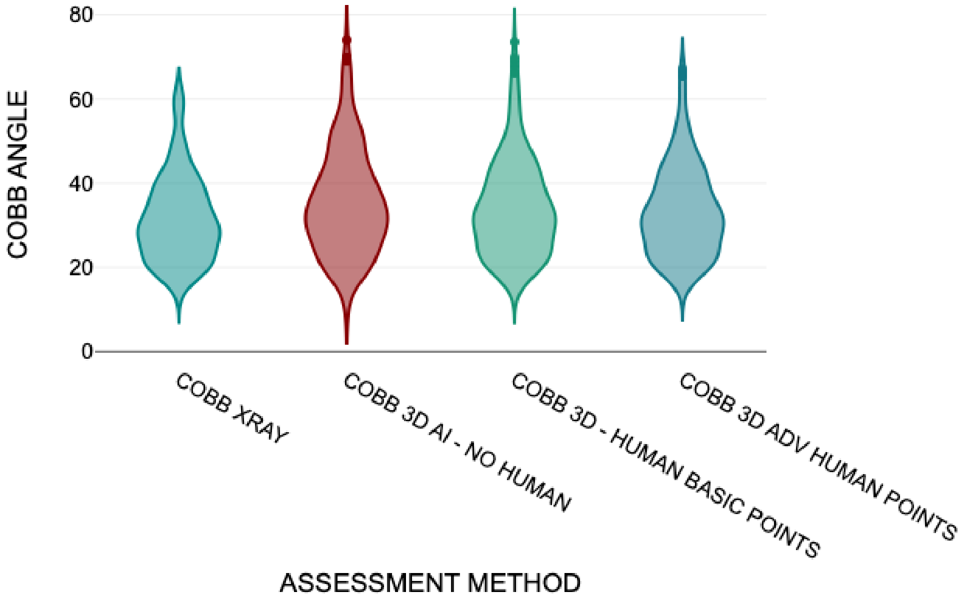


FIGURE 3.0 Violin plot for the Cobb angle assessment comparing X-ray to LiDAR

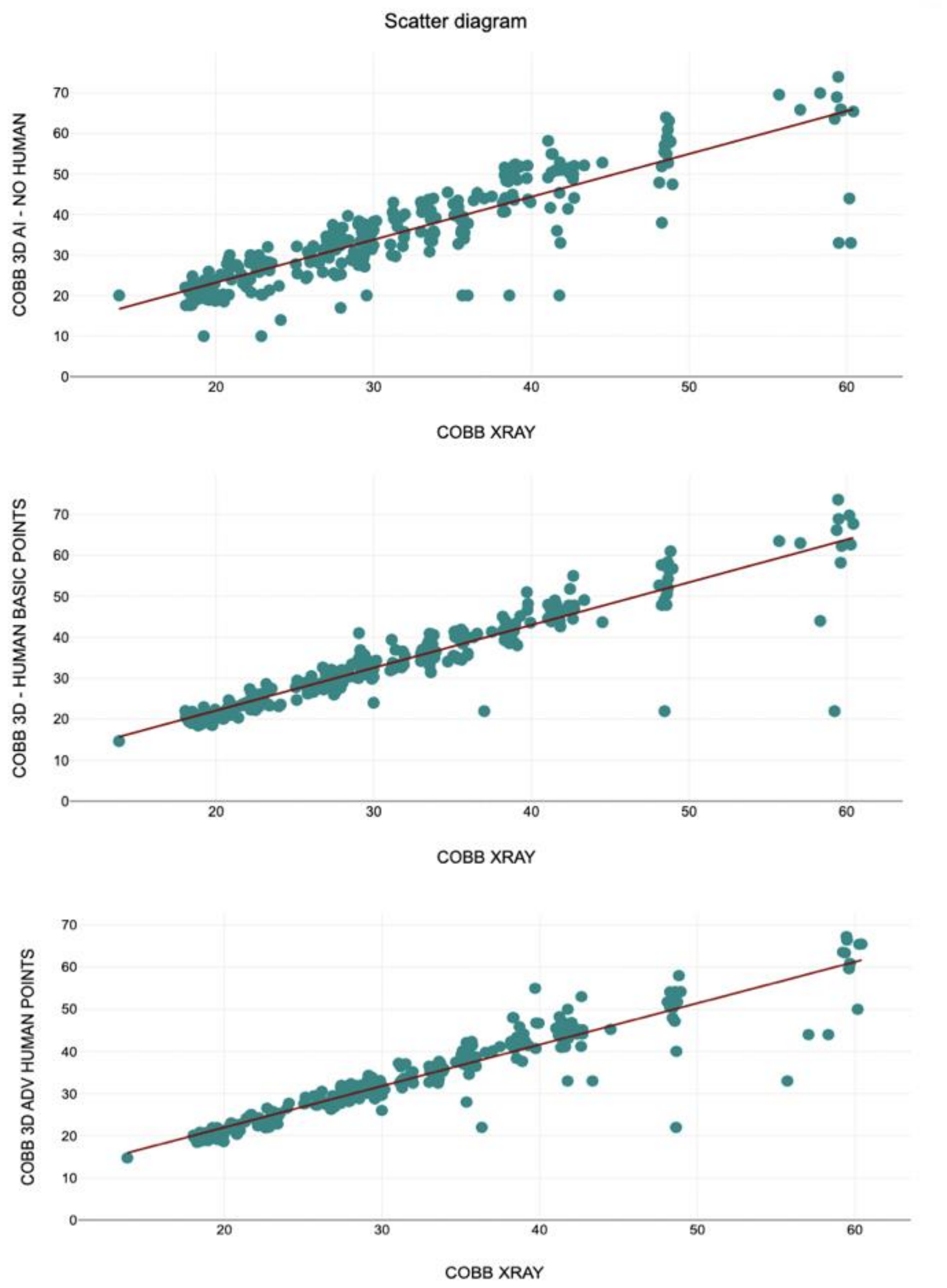


Figure 4.0 Scatter Diagrammes comparing Cobb angle on X-ray to the three variations of LiDAR assessment

Repeated measures ANOVA

Table 2.0 Repeated Measures ANOVA (Analysis of Variance) focusing on a specific treatment over the 4 time periods COBB XRAY, COBB 3D AI ONLY, COBB 3D - HUMAN BASIC POINTS and COBB 3D ADV HUMAN POINTS

	Type III Sum of Squares	df	Mean Square	F	p	η2
Treatment	2228.4	3	742.8	41.09	<.001	0.13
Error	14861.13	822	18.08			

Lordosis and Kyphosis Results

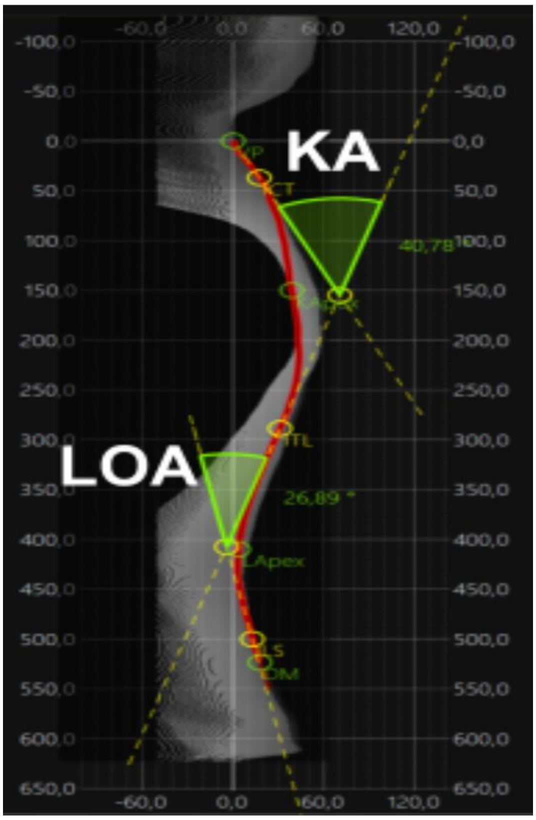


Figure 5.0 Spine3D LiDAR by Sensor Medica Lumbar Lordosis and Thoracic Kyphosis angle visualisation

Lumbar Lordosis angle results - Descriptive Statistics

TABLE 3.0 Descriptive statistics and Pearson correlation coefficients comparing X-ray measurements of Lumbar Lordosis to the LiDAR AI only and LiDAR with human intervention

	LORDOSIS XRAY	LiDAR AI Only	LiDAR AI with human
Mean	49.64	49.06	47.98
Median	46.01	45.41	47.41
Mode	44	55	33
Std. Deviation	20.03	20.63	19.97
Minimum	16	7	10.6
Maximum	93.75	100.14	92.84
95% Confidence interval for mean	47.25 - 52.03	46.6 - 51.53	45.6 - 50.37
Mean ± Std.	49.64 ± 20.03	49.06 ± 20.63	47.98 ± 19.97
Pearson Correlation p <.001	-	0.91	0.95

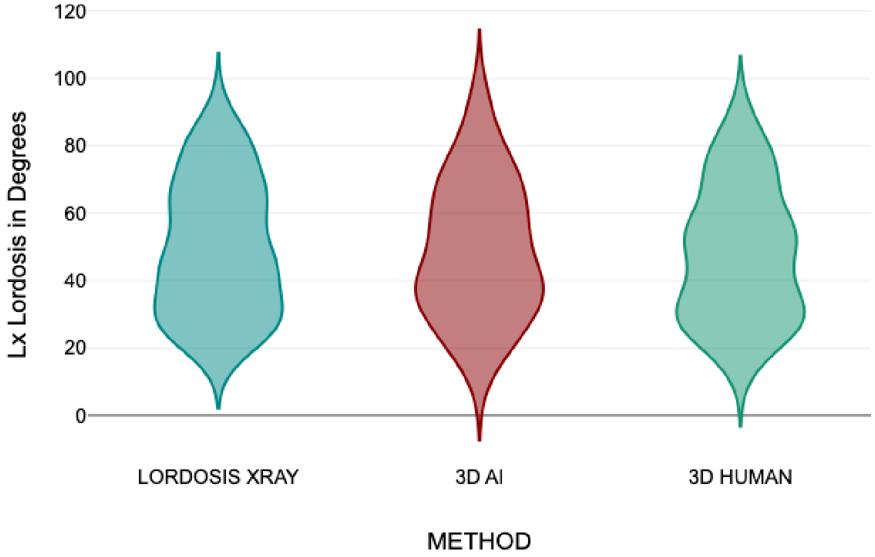


FIGURE 6.0. Violin plot comparing the Lumbar lordosis measurements from X-ray, LiDAR AI only and LiDAR with human intervention

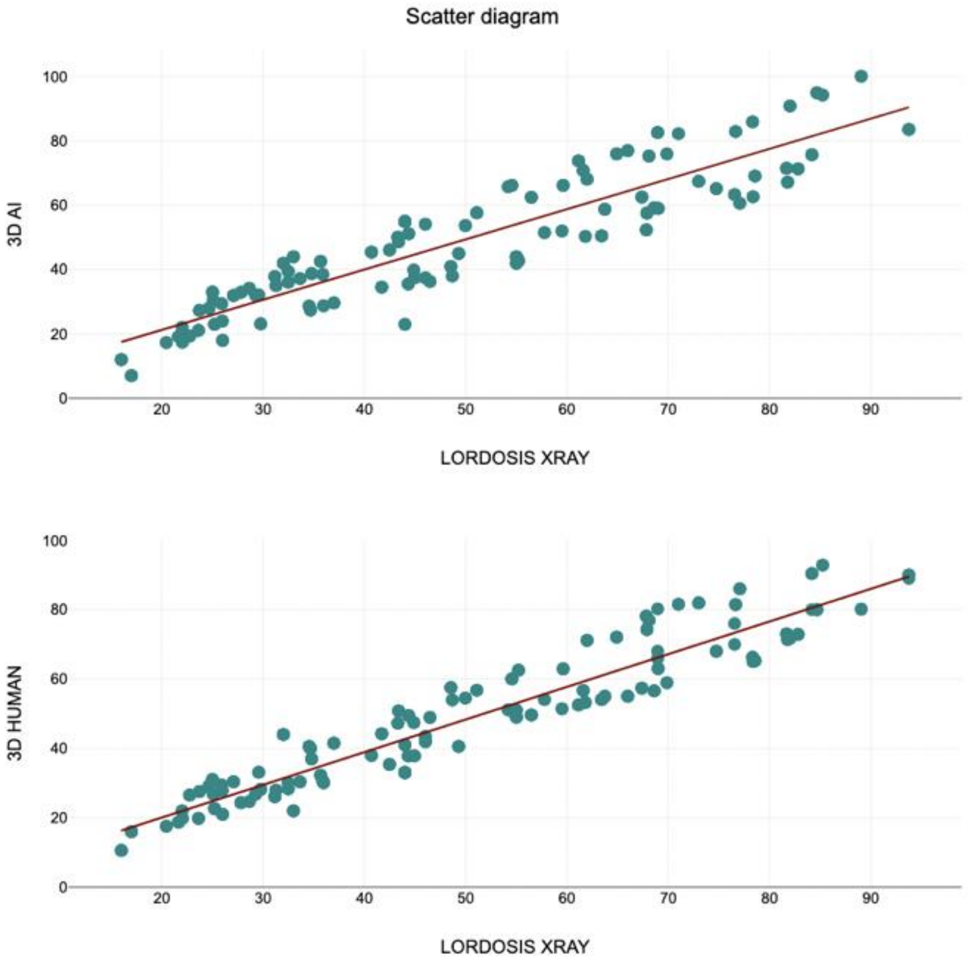


Figure 7.0 Scatter Diagramme comparing Lumbar Lordosis angle on X-ray to AI LiDAR and LiDAR with human intervention

Linear Regression for measurements of Lumbar Lordosis comparing X-ray to LiDAR

Table 4.0 Linear regression examining the influence of 3D AI LiDAR only and AI with human intervention results on X-ray

	R	R2	Adjusted R2	Standard error of the estimate
AI Only	0.91	0.83	0.83	8.26
AI with human intervention	0.95	0.89	0.89	6.56

Thoracic Kyphosis angle results - Descriptive Statistics

TABLE 5.0 Descriptive statistics and Pearson correlation coefficients comparing X-ray measurements of Thoracic Kyphosis to LiDAR AI only and LiDAR with human intervention

	X-ray Tx Kyphosis	AI ONLY	Human Basic Point Check
Mean	48.05	45.41	49.26
Median	48	42	48
Mode	71	33	11
Std. Deviation	26.57	25.27	26.14
Minimum	3	2.8	2
Maximum	93	111.73	106
95% Confidence interval for mean	44.88 - 51.22	42.39 - 48.42	46.14 - 52.39
Mean ± Std.	48.05 ± 26.57	45.41 ± 25.27	49.26 ± 26.14
Pearson Correlation p <.001	-	0.87	0.95

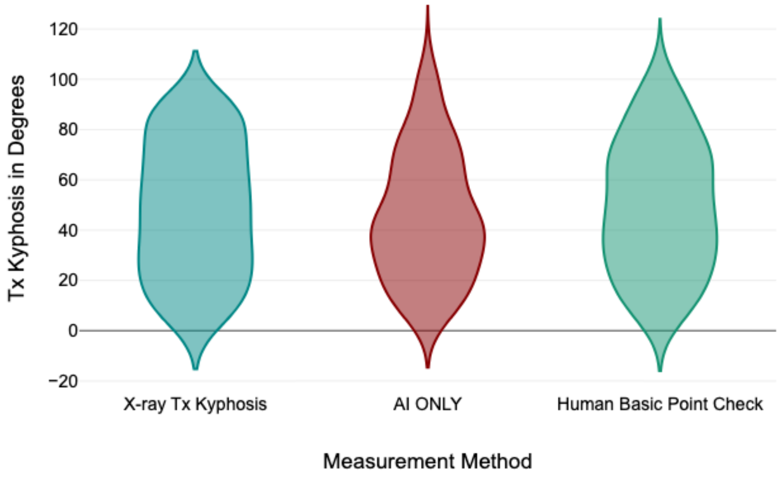


Figure 8. Violin plot comparing the Thoracic Kyphosis measurements from X-ray, LiDAR AI only and LiDAR with human intervention.

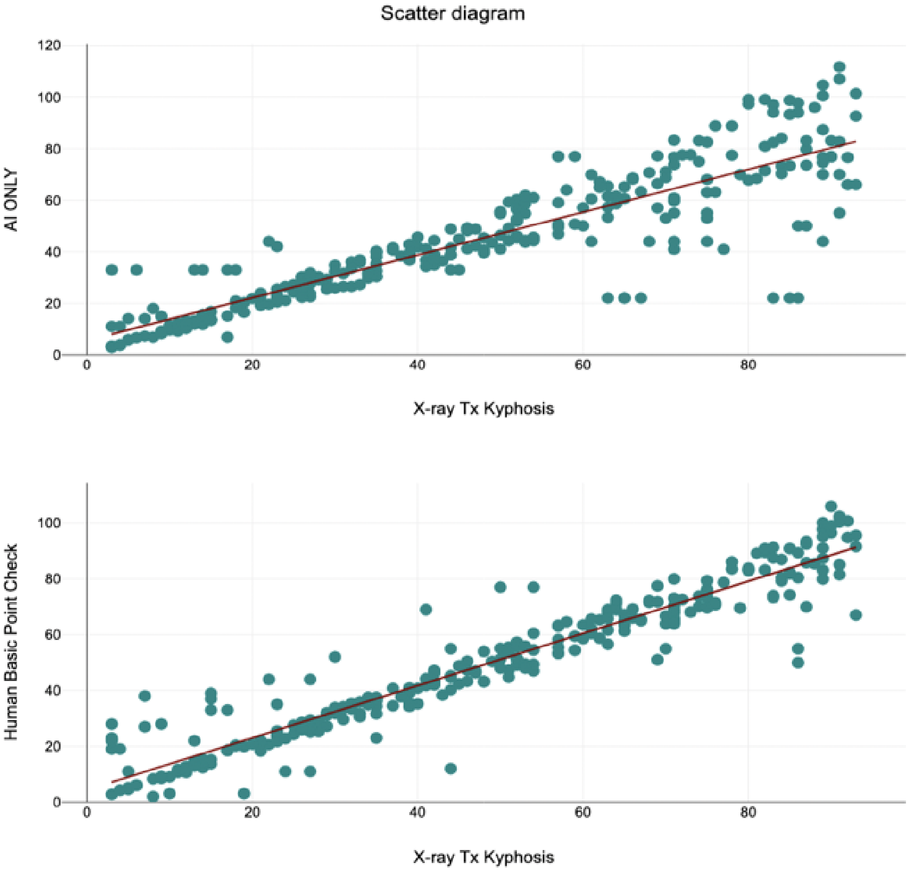


Figure 9.0 Scatter diagramme comparing X-ray to AI only and AI with human basic check points

Thoracic Kyphosis linear regression analysis

Table 6.0 linear regression analysis comparing X-ray measurements of Thoracic Kyphosis to LiDAR utilising LiDAR AI only and LiDAR AI with human intervention

	R	R2	Adjusted R2	Standard error of the estimate
AI only	0.87	0.76	0.76	12.95
AI with human intervention	0.95	0.91	0.91	8.18

Discussion

COBB DATA ANALYSIS

The assessment of Cobb angles, crucial for scoliosis diagnosis and management, was performed using four different methods: traditional X-ray, LiDAR with AI-only, AI with basic human intervention, and AI with advanced human input. The results provide important insights into the accuracy, variability, and correlation of these methods with the gold standard, X-ray measurements.

OVERVIEW OF MEAN, VARIABILITY, AND SENSITIVITY

From the data, we observe some notable differences across the methods:

- **X-ray measurements:** The mean Cobb angle for X-rays is 31.64° (SD = 10.05), which serves as the baseline for comparison with the other methods.
- **AI-only method:** The LiDAR AI method without human intervention yields the highest mean

(35.56°) and standard deviation (SD = 12.3), indicating that this method produces slightly more varied results. The minimum value (10°) and the maximum value (74°) suggest that AI without human oversight may be more sensitive to outliers or extreme values.

- **AI with basic human input**: The basic human intervention method has a mean of 34.27° (SD = 11.34), with a range (14.65° to 73.61°) close to that of the AI-only method. This suggests that human input slightly moderates the extreme measurements, though the difference is not substantial.
- **AI with advanced human intervention**: The advanced human input method provides a mean of 33.4° (SD = 10.61), with a narrower range (14.76° to 67.23°). The reduced variability in this method indicates a higher degree of control and precision, likely due to the more meticulous human involvement.

The data reveal that while all methods provide relatively consistent mean Cobb angle measurements, the AI-only method has the highest mean and standard deviation, suggesting it may produce more varied results. This could be explained by the sensitivity of AI to outliers or subtle anatomical variations in the absence of human intervention.

CONFIDENCE INTERVALS AND VARIABILITY

The confidence intervals for the four methods (X-ray: 30.44°–32.84°, AI-only: 34.09°–37.02°, human-basic: 32.91°–35.62°, human-advanced: 32.14°–34.67°) overlap significantly. This suggests that while there are some differences in mean values across the methods, these differences may not be statistically significant. The overlap implies that, on average, the different methods are comparable when estimating the Cobb angle.

However, it is important to note that the **AI-only method** has the widest confidence interval and range, further reinforcing the point that it may be prone to variability, particularly in extreme cases. This could either be a reflection of the method's sensitivity or indicate potential outliers in the dataset.

CORRELATION COEFFICIENTS AND ACCURACY

One of the key elements in the analysis is the correlation between Cobb X-ray measurements and the LiDAR methods (AI-only, AI-human basic, and AI-human advanced). Pearson correlation coefficients provide insight into the strength of the relationship between these methods:

- **AI-only method**: The Pearson correlation between Cobb X-ray and Cobb AI-only is 0.86, indicating a very high positive correlation. This suggests that despite the slightly higher variability, the AI-only method aligns closely with the X-ray measurements.
- **AI with basic human intervention**: The correlation coefficient here is 0.92, an improvement over the AI-only method. The inclusion of basic human input enhances the reliability of the measurements by reducing extreme values and improving consistency.
- **AI with advanced human intervention**: The strongest correlation is observed between Cobb X-ray and Cobb AI with advanced human intervention, with a coefficient of 0.93. This suggests that the advanced human intervention method is the most reliable and accurate predictor of the Cobb angle compared to the other methods, potentially due to the higher level of scrutiny and control in this method.

In summary, all three AI methods show strong positive correlations with the X-ray measurements, indicating that they are all effective tools for estimating Cobb angles. However, the **AI with advanced human intervention method** is the most accurate predictor, as demonstrated by the highest correlation coefficient ($r = 0.93$). Whether the slight improvement in accuracy justifies the additional time and effort required for advanced human intervention remains a clinical decision.

STATISTICAL SIGNIFICANCE AND REPEATED MEASURES ANOVA

A Repeated Measures ANOVA was performed to assess the differences between the four methods. The null hypothesis posited that there were no significant differences between the X-ray, AI-only, human-basic, and human-advanced methods. However, the analysis revealed a significant difference between the methods ($F = 41.09$, $p < .001$). This p-value indicates that the results are highly statistically significant, and the null hypothesis is rejected.

The finding confirms that the method used to estimate the Cobb angle has a statistically significant impact on the results. Specifically, the ANOVA suggests that while all methods are effective, there are meaningful differences in their accuracy and variability, as discussed above.

CLINICAL IMPLICATIONS

The use of AI-based methods in clinical practice offers clear advantages in terms of speed and automation. The data suggest that the AI-only method can produce accurate results, but the greater variability and sensitivity to extreme values may be a cause for concern in certain cases. In contrast, the AI methods that incorporate human intervention — particularly advanced human input — demonstrate more consistent results with fewer outliers, making them potentially more reliable in clinical settings.

However, the clinician must weigh the benefits of **accuracy vs. time**. While the advanced human intervention method yields the highest correlation with X-ray measurements, the improvement over basic human input ($r = 0.93$ vs. $r = 0.92$) is minimal. For many cases, the slight increase in accuracy may not justify the added time and resources needed for advanced human input, particularly in routine clinical practice.

In conclusion, **AI-based methods**, especially those incorporating human oversight, show great promise in estimating Cobb angles for scoliosis assessment. Clinicians must decide whether the slight increase in accuracy with advanced human intervention justifies the additional effort, or whether the AI-only method can provide sufficient precision for most cases. **Human involvement**, particularly in complex or borderline cases, remains essential to ensuring that outliers and extreme values are correctly interpreted and managed.

Inter and intra tester variability measuring Cobb angle has been found in the literature to be up to 8 degrees using the Cobb method on X-ray[29-30]. For more serious cases such as in patients at high risk of progression, the clinician may wish to check the basic anatomical points before AI processing for a more accurate assessment. However the benefit to checking every single spinal triangulation point is perhaps not necessary considering the Pearson correlation coefficient only increases by 0.01 over the basic data point check.

LUMBAR LORDOSIS DATA ANALYSIS.

The second focus of this study was to compare the accuracy of lumbar lordosis measurements obtained through X-ray, AI-only, and AI with human intervention (AI+Human), using 3D LiDAR technology. The results demonstrate a strong correlation between these methods, with AI-only and AI+Human closely aligning with the X-ray measurements. While both AI-based methods performed well, several key findings emerge that inform how these technologies can be applied in clinical practice.

The AI-only method demonstrated a mean deviation from X-ray measurements of just 0.58 degrees, outperforming the AI+Human group, which deviated by 1.66 degrees. This finding is somewhat unexpected, as human intervention is generally presumed to enhance accuracy by correcting potential algorithmic errors. However, the AI+Human group had a slightly better Pearson correlation coefficient (0.95) compared to AI-only (0.91), indicating a marginally stronger linear relationship between X-ray and AI+Human measurements. This higher correlation for AI+Human suggests a more consistent performance, even if the overall error in terms of mean deviation was slightly higher. Notably, AI-only showed higher variance at both extreme low and high values of lordosis, implying that AI may struggle with outlier cases without human oversight.

The comparison of standard deviations further supports this observation. The AI-only method had the highest standard deviation, suggesting greater variability in the results, particularly in atypical or extreme cases. This is reflected by the fact that the AI-only method produced both the lowest minimum and the highest maximum values among the methods, which could indicate either increased sensitivity to outliers or an inherent limitation in AI's ability to consistently handle cases at the extreme ends of the measurement spectrum. In contrast, the AI+Human method showed the highest median and the lowest mode, implying more consistent results in typical clinical scenarios.

Despite these differences, the overlapping confidence intervals across all methods indicate that no single method is statistically superior in terms of mean accuracy. This suggests that AI-only and AI+Human measurements are similarly effective for routine lumbar lordosis assessment when compared to X-ray. However, for cases where extreme values are anticipated, such as markedly increased or reduced lumbar lordosis, clinician oversight remains important. The recommendation that clinicians perform a rapid review of anatomical landmarks, taking less than 30 seconds, is a pragmatic step to ensure accuracy in such outlier cases.

The clinical implications of this research are significant. AI-based methods, especially when combined with human review, could offer an efficient and accurate alternative to traditional radiographic methods for measuring lumbar lordosis. The benefits of AI include speed, consistency, and reduced radiation exposure, as AI may eventually eliminate the need for repeated X-rays in some cases. However, caution is warranted when relying on AI alone, especially for patients with atypical anatomy or extreme spinal curvature. In such cases, human oversight can help mitigate the risk of errors due to algorithmic misjudgment.

Moreover, while the data shows that AI-only is slightly less reliable at the extremes, its overall performance is robust enough to be considered for integration into clinical workflows, particularly for routine cases. The relatively high correlation (r = 0.91) and statistically significant p-value (<0.001) provide confidence that AI-based measurements are generally accurate and not a product of chance. Nevertheless, for optimal reliability and to account for edge cases, a hybrid approach involving both AI and clinician review appears to be the most balanced solution.

AI holds great promise for the future of spinal assessments, offering a scalable and efficient tool for lumbar lordosis measurement. However, the data suggest that a combined AI-human approach may offer the most reliable results, particularly for complex or extreme cases. While AI can handle the majority of cases independently, ensuring a clinician's review of anatomical landmarks will likely remain essential for ensuring accuracy in all clinical scenarios. As AI technology continues to advance, further research will be needed to refine its application and understand the contexts in which human oversight is necessary.

THORACIC KYPHOSIS DATA ANALYSIS.

Below is a detailed breakdown of the results, focusing on the performance of the AI-based methods relative to the X-ray gold standard.

DESCRIPTIVE STATISTICS AND DISTRIBUTION OF MEASUREMENTS

The data suggests the following:

1. AI ONLY METHOD:
    - **Mean**: The AI-only method shows a lower average kyphosis angle (45.41°) compared to X-ray.
    - **Mode**: The mode of 33° suggests that AI-only produces measurements more frequently around this lower value.
    - **Range**: The AI-only method has a minimum value of 2.8°, with a maximum value of **111.73°**.

The standard deviation (25.27) is slightly lower than the X-ray, indicating lower variability.

- **Confidence Interval**: The confidence interval for the AI ONLY method (42.39°–48.42°) is entirely below that of the X-ray, indicating that it consistently underestimates the kyphosis angle.

- **Human Basic Point Check Method**:

- **Mean**: This method shows the highest average kyphosis angle (49.26°), slightly higher than X-ray and AI ONLY.
- **Mode**: The mode of 11° is the lowest among the three methods, indicating that it might frequently capture smaller kyphosis angles.
- **Range**: Measurements ranged from a **minimum of 2° to a maximum of 106°**, with a standard deviation of 26.14, close to the X-ray's variability.
- **Confidence Interval**: The 95% confidence interval (46.14°–52.39°) is slightly higher than both the X-ray and AI ONLY methods, meaning this method may slightly overestimate kyphosis angles in some cases.

CONFIDENCE INTERVALS AND INTERPRETATION

The **overlapping confidence intervals** (X-ray: 44.88°–51.22°, AI-only: 42.39°–48.42°, Human Basic Point Check: 46.14°–52.39°) suggest that while there are some differences in the mean kyphosis angle measured by each method, none are likely to be statistically significant.

However, it's important to note that the **AI ONLY method**'s confidence interval is entirely below those of the other two methods. This suggests that, on average, the AI-only method produces slightly lower measurements of the kyphosis angle.

PEARSON CORRELATION COEFFICIENT

1. **AI ONLY vs X-RAY:**

- The Pearson correlation coefficient of 0.87 indicates a **strong, positive relationship** between the X-ray and AI ONLY methods. This suggests that the AI-only method, while underestimating the kyphosis angle slightly, tracks closely with the X-ray measurements.
- The p-value of <.001 is statistically significant, suggesting the correlation is not due to random chance, and the AI ONLY method can be considered a valid predictor of X-ray kyphosis.

- **Human Basic Point Check vs X-ray:**

- The Pearson correlation coefficient of 0.95 is even higher, indicating an **extremely strong correlation** between the Human Basic Point Check method and X-ray measurements. This method provides results more closely aligned with the X-ray.
- The p-value of <.001 confirms that this correlation is statistically significant, further establishing the reliability of the Human Basic Point Check method.

LINEAR REGRESSION ANALYSIS

AI ONLY METHOD:

- **R value (0.87)**: The correlation is strong, and the AI-only method explains **76.33% of the variance** in X-ray measurements ($R^2 = 0.76$). This means the AI-only method is quite effective at predicting X-ray results.

- **Standard Error**: The standard error of 12.95 suggests that on average, the AI-only method deviates from the X-ray measurement by approximately **±12.95 degrees**.

- **Human Basic Point Check:**

- **R value (0.95)**: This method has a stronger correlation with X-ray measurements. The R^2 value (0.91) means that **90.55% of the variance** in X-ray kyphosis is explained by the Human Basic Point Check.

- **Standard Error**: The standard error of 8.18 shows the Human Basic Point Check method has a tighter fit to the X-ray, with an average deviation of **±8.18 degrees**.

CLINICAL IMPLICATIONS

While both AI-based methods correlate well with X-ray measurements, the **Human Basic Point Check** provides a more accurate prediction, as evidenced by its higher correlation coefficient (0.95) and lower standard error (8.18 vs. 12.95). Clinically, this suggests that **Human Basic Point Check** may be more reliable, especially when precision is critical.

On the other hand, the **AI-only method** shows promise due to its strong correlation (0.87) and slightly lower variability (standard deviation of 25.27). However, its tendency to **underestimate kyphosis angles** and slightly larger standard error may require further adjustments or validation in clinical practice.

Overall, while both AI methods are effective, **Human Basic Point Check offers the most accurate and precise estimates.**

Conclusion

It is noted that on each of the assessment groups for Cobb, Lordosis and Kyphosis, the LiDAR does tend to have greater minimum and maximum values and so care must be taken with cases that have, or are expected to have very mild or very significant curvatures in the coronal and sagittal planes. Nonetheless, the AI only measurements for coronal and sagittal planes were statically significant in all cases. Clinics and hospitals should consider investigation and investment into the wide stream use of LiDAR as part of the spinal diagnostic and case management process.

It was noted in the introduction that at the time of this research the Spine3D LiDAR machine by Sensor Medica did not calculate cervical lordosis. The engineers stated that it was more complicated due to a number of factors namely the distribution of flexible skin, fat and hair on the cervical spine. However this is in development with an expected release in late 2024. The authors believe that this will be a welcome addition for both clinical practice and research.

It should also be noted that Sensor Medica have created a cloud learning system where each machine can pool data to improve machine learning. Therefore adding the human data check point to each scan as standard improves the accuracy of both local and global data generation.

In conclusion, the data presented in this study provides valuable insights into the potential of LiDAR technology in spinal screening, orthopaedic and neurological assessments, highlighting its strengths and areas for improvement.

The importance of these findings lies in the potential of LiDAR technology as a reliable accompaniment and at times an alternative to X-ray for the assessment of spinal conditions. The high correlation between the two methods suggests that LiDAR, can provide accurate assessments of the Cobb angle (presented as bending angle), lumbar lordosis, and thoracic kyphosis. This could have significant implications for the field of orthopaedics and neurology, potentially reducing the need for repeat X-ray exposure and offering a non-invasive, cost-effective, and efficient method for spinal assessment and monitoring.

It is the belief of the authors that X-ray should always be used as the initial diagnostic method for scoliosis and other spinal deformities such as Scheuermann's kyphosis, until the availability of upright MRI scanners allow for accurate weight-bearing assessments without the use of ionising radiation. However LiDAR technology is a fast, affordable and powerful tool for screening and repeat monitoring of patients which may reduce the lifetime radiation dose to the patient, invaluable to reduce the risk of cancer[31]. The data is also valuable for the treating clinician to be able to visualise a worsening or improvement of a condition at regular intervals and adapt their management accordingly rather than waiting for the next scheduled X-ray which may be many months time, where in rapidly progressing conditions such as Adolescent Idiopathic Scoliosis, early intervention is critical.

Rotational data in the transverse plane is also captured by the Spine3D LiDAR but this data was not assessed as it is not common practice to measure rotation by X-ray. A handheld scoliometer is often used in Adam's forward bending test[32] and cannot be directly compared to a LiDAR scan in an upright position. However as rotation is an important aspect of the diagnosis and management of scoliosis it is an area of research that would be worth exploring.

Conflict of interest statement

The author is the clinical director of the Dorsi Spinal Institute, Nottingham and a leading non-surgical scoliosis specialist. The authors have no conflict of interest to declare.

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