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ORIGINAL RESEARCH ARTICLE

Time saving with artificial intelligence-assisted lumbar spine magnetic resonance imaging reporting: A preliminary study

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Abstract

Introduction: Lumbar spine magnetic resonance imaging (MRI) is a high-volume diagnostic examination, yet increasing caseloads and reporting complexity continue to strain radiology workflows. Emerging artificial intelligence (AI)-assisted reading tools may help streamline interpretation and reduce report turnaround times, but their real-world impact on efficiency remains insufficiently quantified.
Objective: To evaluate the impact of an AI-based reading tool on lumbar spine MRI interpretation and reporting time.
Methods: We randomly selected 236 lumbar spine MRI examinations performed between 2018 and 2023 in patients aged 18 and older. Cases with prior lumbar surgery or scoliosis were excluded. Digital imaging and communications in medicine (DICOM) data were processed using a commercial deep-learning software package, and outputs were reviewed in a standard DICOM viewer. Five radiologists participated. Studies 1 and 2 assessed the effect of AI on interpretation time using a within-reader design: radiologists interpreted each examination with AI support and then reinterpreted the same examinations 2 months later without AI, enabling direct comparison of interpretation times. Study 3 evaluated the effect of AI by comparing AI-assisted and unassisted interpretations in 146 randomly selected examinations.
Results: AI assistance significantly accelerated report generation. Across the full dataset, AI-supported interpretation reduced time by approximately 52% compared with unassisted reading. AI-assisted generation of preliminary reports reduced radiologists' overall time by nearly 30%. Linear mixed-effects modeling indicated that these reductions were statistically significant. The smaller reduction observed in Study 3 (9.21%) may reflect limited familiarity with the software's reporting style and occasional instances in which the AI outputs did not fully support the radiologists' findings.
Conclusion: AI assistance improves the efficiency of lumbar spine MRI reporting and shortens reporting time.

Keywords: Magnetic resonance imaging; Lumbar spine; Stenosis; Radiological report; Artificial intelligence; Time reduction

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1. Introduction

Artificial intelligence (AI) is rapidly integrating into diagnostic imaging, changing how medical images are interpreted and utilized in clinical practice. AI technologies can enhance efficiency and, in some applications, diagnostic accuracy across radiology workflows, primarily by automating a range of tasks.[1,2] These applications include image segmentation, abnormality detection, automated case triage, and assistive reporting.[2,3] By delegating routine processes, AI allows radiologists to focus on complex cases and critical decision-making, potentially reducing workload and interpretation time.[1] In high-volume modalities such as magnetic resonance imaging (MRI), AI-based reconstruction methods have been reported to shorten image acquisition or reconstruction time, and AI-supported workflows may reduce reporting delays in selected settings.[3] Furthermore, AI can serve as a "second pair of eyes" to support diagnostic performance in specific applications (e.g., prostate cancer detection on MRI), where convolutional neural network (CNN)-based approaches have shown strong performance in comparative studies.[4]

However, evidence specifically addressing reductions in diagnostic and reporting time for spine imaging remains limited, despite the high clinical volume of lumbar spine MRI.[1] Lumbar spine MRI is among the most commonly performed examinations, with millions of patients undergoing scans annually for conditions such as spinal stenosis.[5] Interpretation can be time-consuming and variable, which may delay diagnosis. Several factors contribute to difficulty in spine magnetic resonance interpretation, including the surrounding bony anatomy, motion of adjacent tissues, and the small cross-sectional size of relevant structures.[6] These challenges may be compounded by metallic implants in some patients. Progress in this area is also constrained by the limited availability of publicly accessible training datasets, which restricts the development and validation of imaging tools.

In addition to these challenges, delays in radiological reporting have been attributed to incomplete patient histories available to clinicians and the heavy workload faced by radiologists.[7] This also increases the potential for human error and fatigue during manual analysis. Radiological errors are more frequent during the latter hours of a shift than at the beginning. Extended work shifts in medical settings have also been linked to increased medical errors and occupational injuries.[8]

In the diagnosis of lumbar spinal stenosis, neural networks for automated MRI grading have already shown substantial potential to assist clinicians.[9] In our recent prospective study, we also successfully demonstrated and evaluated the safety of a deep learning-based application for assessing lumbar findings and for providing accurate segmentation and measurements.[10] While AI may enhance diagnostic accuracy by identifying complex patterns in MRI scans, its potential extends beyond precision alone. The integration of AI-driven tools also addresses the need for faster interpretation and radiological report preparation, which may accelerate diagnoses and treatment decisions and potentially reduce radiologists' workload. Several studies support this focus on reducing interpretation and reporting time. Rathmann *et al.*[11] reported a significant reduction in the time required to reach final decisions regarding lesion assessment on MRI in patients with multiple sclerosis when using the machine learning software mdbrain® (Mediaire GmbH, Germany; https://mediaire.ai/). Their study compared five experienced radiologists without AI with two less experienced radiologists using the tool, showing a reduction in average reading time of approximately 210 s per case and enabling automated report generation within 5 min, underscoring AI's potential to streamline complex assessments and radiological reporting. Similarly, Yang *et al.*[12] assessed a deep learning platform (CoLumbo) and reported that the average interpretation time per MRI examination was significantly lower with CoLumbo assistance than without. The interpretation time interquartile range was 5.29 min with AI assistance, compared with 56.46 min without assistance. However, the study was limited by the small sample sizes (51 MRI cases), reliance on less experienced users, and frequent workflow interruptions.

While limited evidence from studies such as Yang *et al.*[12] suggests AI can shorten lumbar spine interpretation time, further investigation is needed to validate and quantify any substantial reduction in final radiological reporting time for lumbar spine MRI examinations. The objective of the present study was therefore to address this gap by assessing the impact of AI assistance on reporting time for lumbar spine MRI examinations. Specifically, this study focused on quantifying efficiency improvements in a practical clinical setting rather than re-evaluating diagnostic performance.

2. Materials and methods

2.1. CoLumbo software

CoLumbo software (Smart Soft Healthcare, Bulgaria: https://columbo.me/) is designed to support the diagnosis of several common spinal pathologies, including disc herniation, disc bulging, stenosis, spondylolisthesis, and abnormal lordosis (hypo- and hyperlordosis), as well as other degenerative pathologies. It is based on an AI algorithm that performs tissue segmentations on magnetic resonance images and generates measurements (e.g., distances, areas, and angles) used for clinical assessment and automated reporting. CoLumbo is a *Conformité Européenne* (CE)-marked product for spine MRI and is Food and Drug Administration (FDA)-cleared for use in the USA.

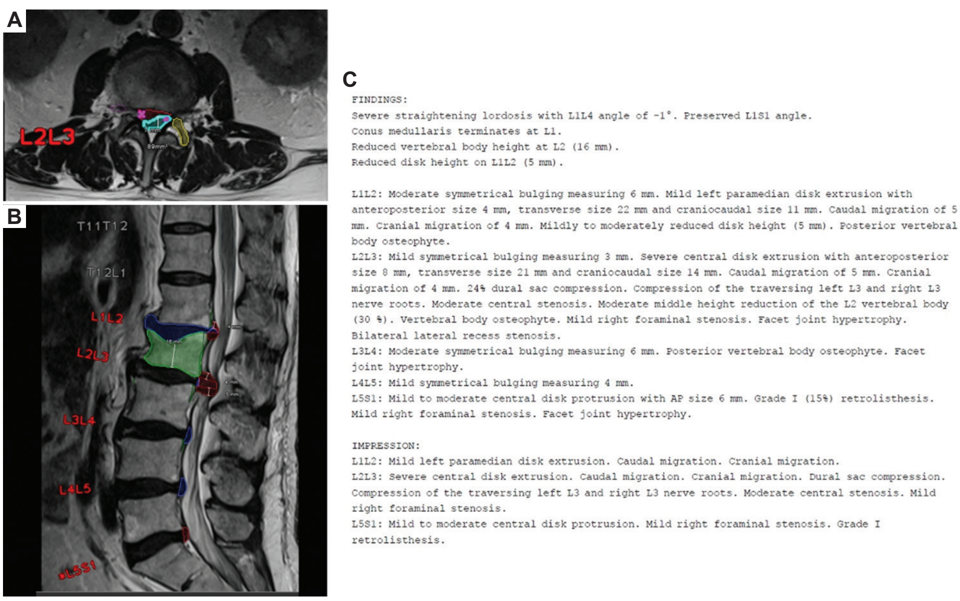
The CNN used is U-Net-based and was initially developed by Georgiev and Asenov[13] and presented during the IVDM3Seg challenge at the 2018 MICCAI conference (https://ivdm3seg.weebly.com/). This challenge established a dataset and framework for advancing automated segmentation and localization of intervertebral discs on MRI. Competing algorithms predominantly utilized deep neural networks, with U-Net variants and standard CNNs being common, alongside specialized models such as RIMNet. For example, the DeepSPINE algorithm[14] is an end-to-end deep learning pipeline that uses U-Net segmentation with a multi-input CNN to grade spinal stenosis; however, it currently remains a research tool without CE marking or FDA clearance. These models, enhanced by techniques such as data augmentation and multi-modality fusion, have enabled the development of clinical applications such as CoLumbo, which automates disc segmentation and pathology identification.

In this study, we used CoLumbo version 2.0, which was developed for the visualization and analysis of lumbar spine MRI scans. The software outputs annotated magnetic resonance images and an auto-generated report that can be edited by the radiologist, as shown in Figure 1. The software supports MRI field strengths of 1.5 T and 3 T, is compatible with major MRI vendors, and has been reported to significantly reduce lumbar spine MRI interpretation times.[12]

The effectiveness of the AI-based tool CoLumbo in assessing degenerative lumbar spine pathologies on MRI has been demonstrated in several recently published studies.[10,15,16]

2.2. Study design

The present study included randomly selected lumbar spine MRI examinations of patients with back pain, aged 18 and older, retrieved from the local hospital Picture Archiving and Communication System (PACS) and acquired between 2018 and 2023, as well as five radiologists, each with at least 8 years of specialized experience in MRI radiology. The dataset comprised 236 MRI examinations, with each examination yielding an average of 60–75 slices across the lumbar spinal region. These examinations were evaluated by radiologists for spinal stenosis. Cases with prior surgery or scoliosis were excluded. The software was installed at three European healthcare centers: University Hospital St. Marina – Varna (Bulgaria; retrospective study), Diagnostikum Linz (Austria; prospective study), and Unilabs (Spain; prospective study), allowing participating radiologists to use the software for a predetermined period before switching to a period without it. Radiologists received 5 h of training on the CoLumbo software before its use.



FINDINGS:
Severe straightening lordosis with L1L4 angle of -1°. Preserved L1S1 angle.
Conus medullaris terminates at L1.
Reduced vertebral body height at L2 (16 mm).
Reduced disk height on L1L2 (5 mm).

L1L2: Moderate symmetrical bulging measuring 6 mm. Mild left paramedian disk extrusion with anteroposterior size 4 mm, transverse size 22 mm and craniocaudal size 11 mm. Caudal migration of 5 mm. Cranial migration of 4 mm. Mildly to moderately reduced disk height (5 mm). Posterior vertebral body osteophyte.
L2L3: Mild symmetrical bulging measuring 3 mm. Severe central disk extrusion with anteroposterior size 8 mm, transverse size 21 mm and craniocaudal size 14 mm. Caudal migration of 5 mm. Cranial migration of 4 mm. 24% dural sac compression. Compression of the traversing left L3 and right L3 nerve roots. Moderate central stenosis. Moderate middle height reduction of the L2 vertebral body (30 %). Vertebral body osteophyte. Mild right foraminal stenosis. Facet joint hypertrophy. Bilateral lateral recess stenosis.
L3L4: Moderate symmetrical bulging measuring 6 mm. Posterior vertebral body osteophyte. Facet joint hypertrophy.
L4L5: Mild symmetrical bulging measuring 4 mm.
L5S1: Mild to moderate central disk protrusion with AP size 6 mm. Grade I (15%) retrolisthesis. Mild right foraminal stenosis. Facet joint hypertrophy.

IMPRESSION:
L1L2: Mild left paramedian disk extrusion. Caudal migration. Cranial migration.
L2L3: Severe central disk extrusion. Caudal migration. Cranial migration. Dural sac compression. Compression of the traversing left L3 and right L3 nerve roots. Moderate central stenosis. Mild right foraminal stenosis.
L5S1: Mild to moderate central disk protrusion. Mild right foraminal stenosis. Grade I retrolisthesis.

Figure 1. Screenshot from the Report module of the CoLumbo software: (A) axial and (B) sagittal planes from the scanned volume showing the dural sac (cyan), vertebral bodies (green), intervertebral discs (dark blue), herniations (red), and nerve roots (strong magenta); (C) text report generated by the software

Figure 2 outlines the studies conducted: (a) Studies 1 and 2, examining the temporal impact of CoLumbo assistance on radiological interpretation and routine or AI-assisted report preparation, and (b) Study 3, comparing CoLumbo-assisted and unassisted radiological interpretation and report preparation times.

In Study 1, following the 5-h training, radiologists interpreted up to 25 MRI cases using CoLumbo (with added visualizations and measurements) and reassessed the same cases after 2 months using their standard clinical reporting workflow. Interpretation time with and without software assistance was documented in minutes and seconds using data retrieved from radiology information system logs. In Study 2, the same procedure as in Study 1 was performed, but radiologists used the CoLumbo-generated radiological report, which differs from the standard clinical report routinely used. In Study 3, the impact of AI assistance was assessed by comparing reporting time for 146 randomly selected lumbar spine MRI examinations interpreted either with CoLumbo assistance or without it.

Total and average times were calculated across the studies. A linear mixed-effects model was used to estimate the average effect of AI, assess variability between radiologists, and compute *p*-values and confidence intervals (CIs). This model is appropriate for repeated measurements from the same radiologists, including unbalanced datasets. By treating the radiologist as a random effect, the model accounts for inter-reader variability and differences in the cases interpreted, enabling accurate estimation of the effect of AI-based software.

2.3. Inclusion and exclusion criteria

The inclusion and exclusion criteria followed CoLumbo regulatory clearance support and are summarized in Table 1.

3. Results and discussion

3.1. Study 1: Impact of AI assistance on interpretation/report preparation time for routine clinical reports: A 2-month retest analysis

In Study 1, four radiologists participated. One radiologist initially analyzed 10 lumbar spine MRI examinations with AI assistance and then re-evaluated the same examinations without AI after 2 months. The other three radiologists analyzed 5, 8, and 25 examinations, respectively, as specified in Figure 3. In total, 48 MRI examinations were evaluated, with each case interpreted both with and without CoLumbo assistance. The results are summarized in Figure 3A.

The overall time saved across all radiologists and cases was 52%, indicating that the AI-based software improves efficiency with respect to image interpretation. A detailed analysis of the average time saved per case for each radiologist is presented in Figure 3B, showing time saving for each radiologist; however, the magnitude of time saving varied considerably. Because the participating radiologists were experienced in evaluating spinal stenosis on MRI, differences in expertise are unlikely to explain this variability. Another possible contributor is case complexity. The MRI cases were either sourced retrospectively from the local PACS at the retrospective site (via script-based randomization) or selected prospectively based on patient presentation at the prospective sites, and therefore differed between radiologists. Herzog *et al.*[17] described factors contributing to variability in MRI interpretation, including radiologist specialization, equipment type, the number of MRI sequences, and the nomenclature employed to describe findings. Among the four radiologists, Radiologist 2 had the highest time saving (64.55%), which may reflect greater familiarity with the AI tool or differences in case mix. Radiologist 4 had the lowest time saving (13.31%), which may reflect less familiarity with the AI tool or a greater proportion of routine cases.

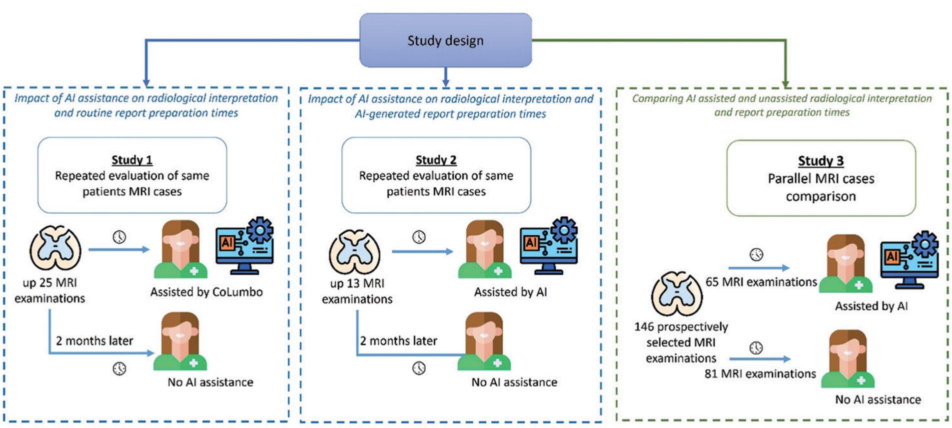


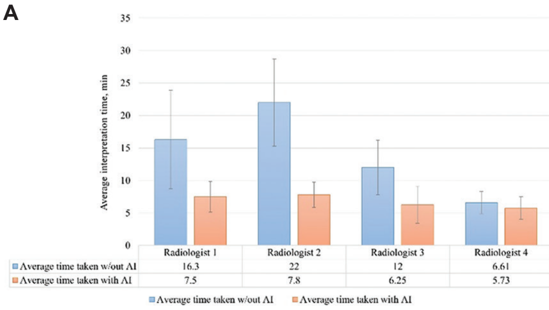
Figure 2. Study design for assessing time reduction in the magnetic resonance imaging interpretation

Table 1. Inclusion and exclusion criteria

Category	Inclusion criteria	Exclusion criteria
Study population	Patients aged 18 years and older at the time of the MRI scan.	Patients under 18 years of age.
Clinical indication	Patients undergoing MRI for evaluation of common lumbar spine degenerative pathologies, such as degenerative disc disease, disc herniation, or spinal stenosis.	Known history of specific spinal diseases that significantly alter anatomy (e.g., primary and metastatic tumors, active infection/osteomyelitis, acute spinal trauma, or fracture).
Anatomical region	MRI scan must fully encompass the entire lumbar spine (L1–S1 levels).	MRI examinations focused solely on other regions (e.g., thoracic spine, cervical spine, pelvis) or with incomplete lumbar spine coverage.
Prior surgery/hardware	No significant spinal surgical instrumentation (e.g., pedicle screws, rods, interbody devices, or fusion hardware).	Presence of metallic instrumentation or fixation hardware within the field of view causing significant susceptibility artifacts and obscuring anatomical detail.
Image quality/deformity	Images of diagnostic quality with minimal motion artifacts.	Severe spinal deformities, such as scoliosis with a Cobb angle>25° or severe kyphosis that significantly complicate anatomical plane definition.
Imaging modality	Lumbar spine MRI.	Any other imaging modality (CT, X-ray, or ultrasound).
Field strength	Magnetic field strength between 1.5 T and 3.0 T, inclusive.	Field strength outside the 1.5T–3.0T range.
Sequence requirements	At least one high-resolution axial and one sagittal T2-weighted sequence, with a minimum of five slices per sequence.	Missing or non-diagnostic required sequences (e.g., only T1-weighted images available or severe motion artifacts rendering required sequences unreadable).

Abbreviations: CT: Computed tomography; MRI: Magnetic resonance imaging.

A



B

	MRI examinations interpreted without/with CoLumbo	Time saved (min)	Time saved (%)
Physician 1	10/10	8.8±7.76	53.99%
Physician 2	5/5	14.2±7.92	64.55%
Physician 3	8/8	5.74±2.79	47.92
Physician 4	25/25	0.88±0.51	13.33%

Figure 3. Impact of artificial intelligence assistance on time for preparing radiological reports: (A) time spent on image interpretation per radiologist (minutes); (B) Radiologist workload and corresponding time savings
Abbreviations: AI: Artificial intelligence; MRI: Magnetic resonance imaging.

Lumbar spine MRI interpretation typically takes approximately 15–30 min, and final radiological reports are often delivered within 24 h, especially for complex cases such as spinal stenosis, tumors, or demyelinating disease that require detailed interpretation. In some settings, reporting may take longer due to a high workload. The time saved may allow radiologists to undertake additional activities, such as reading the latest research literature, allocating more time to complex cases, patient consultations, and clinical decision-making, and potentially reducing workload and burnout.[18-21]

Table 2 shows the average AI effect on interpretation time across all radiologists, based on the linear mixed-effects model.

The estimated mean interpretation time without CoLumbo was 12.75 min. A p-value of 1.9×10^{-11} indicates that this baseline time is statistically significant. Use of CoLumbo was associated with a reduction of 4.73 min in interpretation time. This reduction was statistically significant ($p=2.32 \times 10^{-7}$), with a 95% CI of 3.05–6.41 min. The model also indicated variability among radiologists, with a standard deviation of 3.08 for the random intercept (95% CI: [1.43, 6.61]).

3.2. Effect of AI assistance with AI-generated reports on radiologist reporting time: A 2-month retest analysis

Study 2 compared the time required for radiological report preparation under two conditions: Unassisted reporting (routine practice) and reporting with the aid of AI-generated preliminary reports. To ensure consistency, the same radiologists participated in both conditions, each completing distinct case sets, as specified in Figure 4. The results are summarized in Figure 4 and show that, on average, interpretation time decreased for all four radiologists when AI was utilized.

The overall time saved across all radiologists when using AI-generated reports was more than 30%, indicating improved time efficiency. Table 3 shows the average effects across radiologists, based on the linear mixed-effects model.

The estimated mean interpretation time without AI was 24.56 min. The *p*-value of 2×10^{-4} indicates that this baseline time is statistically significant. Use of AI was associated with a reduction of 7.61 min in interpretation time. This reduction was statistically significant (p=6.89 × 10^{-5}), with a CI of 3.99–11.23 min. The model also indicated variability in baseline performance among radiologists, with a standard deviation of 12.22 for the random intercept (95% CI: [6.03, 24.78]).

3.3. AI-assisted vs. unassisted radiological interpretations: Reporting time reduction in 146 randomized cases

This prospective study investigated the effect of CoLumbo assistance on reporting time by comparing the time required to complete radiological reports for 146 randomly selected MRI examinations interpreted with and without AI support. Of these 146 images, 81 were interpreted with CoLumbo assistance and 65 without CoLumbo, assessed by a radiologist over a 3-month period.

As shown in Figure 5, reporting time decreased when an AI-assisted report was prepared. Mean reporting time without AI was 27.69 min, compared with 25.14 min with AI, corresponding to an average reduction of 9.21%. The median reporting time reduction was 13.02%. In many cases, AI reduced reporting time substantially, whereas in others the reduction was smaller, resulting in a lower overall average. Limited familiarity with the CoLumbo reporting style and instances in which findings were not supported by the software may also have delayed AI-assisted evaluation.

Overall, these studies suggest that AI support may enable faster reporting and may facilitate more timely clinical decision-making. Time savings may allow radiologists to review more cases or allocate additional time to challenging cases and continuing professional development. Potential benefits at the institutional level (e.g., more efficient resource utilization) require further evaluation.

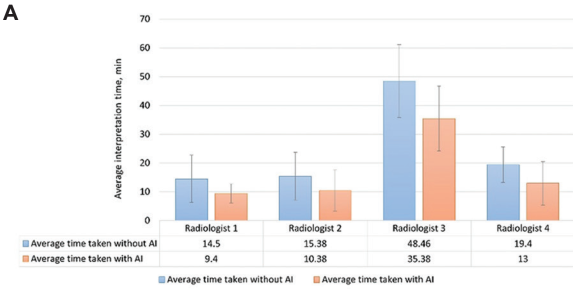
This preliminary study has several limitations. First, the sample size was limited, primarily due to time constraints related to radiologists' workload, which limits generalizability. Future work is planned to validate these findings with a larger and more diverse group of radiologists and to assess whether the impact of AI varies by experience level, specialization, or familiarity with the software. Second, the number of participating MRI radiologists was small, partly due to reluctance to participate in such research, which further limits generalization. For instance, a recent diploma thesis[22] suggested that this reluctance may be related to concerns

Table 2. Impact of AI on radiologist interpretation time based on linear mixed-effects model results (Study 1)

Parameter	Estimate	SE	tStat	DF	*p*-value	95% CI (Lower)	95% CI (Upper)
(Intercept)	12. 75	1.67	7.63	94	$1.9\times10-^{11}$	9.43	16.07
AI effect	−4.73	0.85	−5.58	94	$2.32\times10-^{7}$	−6.41	−3.05

Abbreviations: AI: Artificial intelligence; CI: Confidence interval; DF: Degrees of freedom; SE: Standard error; tStat: *t*-statistic.

A



B

	MRI examinations interpreted without/with CoLumbo	Time saved (min)	Time saved (%)
Radiologist 1	10/10	5.1±5.47	35.17%
Radiologist 2	13/13	5±3.54	32.51%
Radiologist 3	13/13	13.08±3.25	26.99%
Radiologist 4	10/10	6.4±5.66	32.99%

Figure 4. Effect of AI assistance with AI-generated reports on radiologist reporting time: A two-month retest analysis: (A) Average time spent (minutes) per case per radiologist with and without CoLumbo assistance when using AI-generated reports; (B) Radiologist workload and corresponding time savings Abbreviations: AI: Artificial intelligence; MRI: Magnetic resonance imaging.

Table 3. Impact of AI on radiologist interpretation time based on linear mixed-effects model results (Study 2)

Parameter	Estimate	SE	tStat	DF	*p*-value	95% CI (Lower)	95% CI (Upper)
(Intercept)	24.56	6.24	3.93	90	2×10^{-4}	12.16	36.97
AI effect	−7.61	1.82	−4.17	90	6.89×10^{-5}	−11.23	−3.99

Abbreviations: AI: Artificial intelligence; CI: Confidence interval; DF: Degrees of freedom; SE: Standard error; tStat: *t*-statistic.

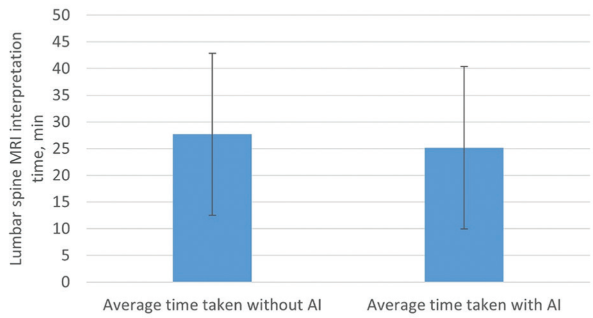


Figure 5. CoLumbo-assisted versus unassisted radiological interpretations of 146 randomly selected cases

Abbreviations: AI: Artificial intelligence; MRI: Magnetic resonance imaging.

about AI reliability or fear of job displacement; it also reported that only one of four large Bulgarian hospitals used AI for bone fracture recognition. Third, differences in case complexity across radiologists' assignments likely contributed to variability in individual time reductions. Nevertheless, the consistent reduction in reporting time observed in this investigation supports the potential efficiency benefit of AI assistance.

Despite concerns regarding AI errors and limited transparency of AI decision-making (often described as "black box" behavior),[1,2] the reduction in reporting times observed in this study supports the potential utility of AI assistance for report drafting and image analysis in clinical workflow. The observed benefits—reduced workload, time savings, and support for report drafting and image analysis—support human–AI collaboration and may facilitate broader acceptance of this technology in routine practice.

4. Conclusion

The AI-based CoLumbo software demonstrated significant potential to improve time efficiency in lumbar spine MRI interpretation and reporting. Our analysis suggests that AI use could yield average time savings of 30–60% in preparing final radiological text reports. However, variability in radiologist performance indicates that tailored implementation strategies may be required to maximize benefits in clinical practice. These results support the integration of AI-assisted tools in radiology departments to enhance efficiency, especially in high-volume or time-intensive workflows. Future research with larger datasets and diverse cases is warranted to confirm these findings and to identify factors that influence AI-associated time savings.

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Conflict of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization: Kristina Bliznakova
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Investigation: Kristina Bliznakova, Radoslav Georgiev
Methodology: Kristina Bliznakova
Writing–original draft: Kristina Bliznakova
Writing–review & editing: All authors

Ethics approval and consent to participate

The study "Clinical Trial with CoLumbo software" received ethics approval from the Ethical Committee for Clinical Trials of the Ministry of Healthcare of Bulgaria with a protocol ЕККИ/СГ-0687 from August 06, 2020.

Consent for publication

The authors declare that they have obtained the verbal informed consent of the human patients for releasing their data or images in this paper.

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Further disclosure

During the preparation of this work, Gemini was used by the author to improve the readability and language of several paragraphs in this article.

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