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Artificial Intelligence Surgery

Review

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Artificial intelligence in spinal imaging - a narrative review

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Abstract

Clinical integration of artificial intelligence (AI) in spinal surgery is still in its early stages, with spinal imaging being the most prominent. We present a review of recent literature on the topic. The reporting of traditional spinal imaging has been slow due to overburdened staff and unreliable in some patients. AI applications have shown promising results in improving the speed and quality of imaging while reducing costs and radiation exposure. Specific examples of clinical implementation include osteoporosis screening, diagnosing degenerative spine diseases and differentiating tuberculous and pyogenic spondylitis, helping in preoperative measurements and surgical planning. Other tools have demonstrated the ability to help clinicians in real time to reduce rates of missed fractures and to rule out cord impingement in emergency settings. Novel variants of magnetic resonance imaging (MRI) and synthetic computed tomography (sCT) scans, without ionizing radiation, have been successful in reducing the resource burden and scan time, while maintaining clinical utility. At its current stage, AI has the potential to improve significantly and is expected to tremendously enhance the efficiency and accuracy of radiologists and spine care providers. However, clinical validation studies are still required before the widespread integration of AI in direct patient care.

Keywords: Artificial intelligence, spinal imaging, spine, surgery, deep learning, machine learning, neural networks

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INTRODUCTION

The pioneering application of artificial intelligence (AI) can be traced back to the work of the English mathematician and computer scientist Alan Turning in the 1950s[1]. Since then, there has been a sustained interest in the field, and it has seen some real growth in the past two decades. Numerous industries have integrated experimental AI tools with iterative improvements in functionality and reliability. However, healthcare in general and spine surgery, in particular, have lagged in the AI race, primarily due to restrictive regulations and concerns over patient safety and data privacy[2]. Within spine surgery, however, there have been some interesting AI applications in spinal imaging[3]. One reason could be the flexibility available in imaging, which allows testing experimental technology with little to no direct harm to patients.

With the emergence of numerous AI tools in medical imaging and the media hype, there is a great interest among spine surgeons, trainees, hospital administrators, insurers, and regulators alike to stay up to date with the recent literature in the field. Therefore, we aimed to collate the recent literature on the developments in the use of AI in spinal imaging, focusing on its successes, challenges, and future opportunities. We begin with a brief description of the pre-AI landscape of traditional spinal imaging, followed by an introduction to the basics of AI and then literature on specific AI applications in spinal imaging.

Traditional spinal imaging

Imaging is essential in spine surgery, from initial diagnosis, preoperative planning, and intraoperative orientation to postoperative surveillance[4]. A lot of times, it also serves as crucial medicolegal evidence[5]. Despite this cornerstone importance, errors in spinal imaging and its interpretation and reporting are not uncommon. The case report by Herzog *et al.* underscores the gravity of the situation[6]. They obtained lumbar spine magnetic resonance (MR) images of 63-year-old patients from ten radiology centers within three weeks and found a global Fleiss' kappa statistic of 0.20, meaning none to slight interrater agreement[7].

This highlights the significant uncertainties that spine practitioners have to deal with daily in their clinics today. Although most practitioners know the error-prone nature of spinal imaging, it is impossible to reliably detect these for each patient. As a result, these suboptimal images form the basis of clinical decisions, possibly leading to suboptimal patient care.

Basics of AI

AI refers to computer systems mimicking human intelligence and cognitive functions[8]. It has broadly been classified as general-purpose AI and narrow AI[9]. General-purpose AI could perform any task that a human brain can do. However, no general-purpose AI tool has been developed yet. On the other hand, narrow AI can perform a specific task with a narrower focus. All AI tools available at the time of writing, such as natural language chatbots and computer vision used in self-driving cars, are examples of narrow AI[9].

Narrow AI uses machine learning (ML) algorithms to learn from the raw data without human input[10]. Deep learning (DL) is a more complex form of ML that forms multiple layers, mimicking the neural network of a human brain[11]. These multi-layered neural networks of DL are used for most AI applications today, such as language, image, and pattern recognition, classifications, and predictions. Convolutional neural networks (CNNs), a type of DL that helps with image recognition, have demonstrated successful application in spine surgery, for example, to enhance radiological images quantitatively and qualitatively, particularly helping with noise reduction[12]. A more in-depth discussion of the types of AI and their descriptions and workings are out of the scope of this review.

APPLICATIONS IN SPINAL IMAGING

Spinal imaging has shown much greater enthusiasm for AI applications than the broader field of spine surgery, which has been traditionally slow. One reason is that researchers have the luxury to experiment with real-patient imaging in lab settings without impacting patient care. These experiments help to refine the model and generate evidence for its efficiency, effectiveness, and safety before implementing these in patient care settings. Most AI applications developed thus far in spinal imaging are focused on image processing and analysis, reporting, and clinical decision making, as illustrated in Figure 1. Next, we explore specific cases of AI being used in spinal imaging.

Osteoporosis detection

Osteoporosis is an important clinical consideration that would be responsible for 3 million fractures per year and $25.3 billion in medical costs by 2025[13]. In spine surgery, it is associated with higher postoperative odds of implant failure, pseudoarthrosis, vertebral fractures, and revision surgery[14]. Despite adverse consequences, less than a quarter of the at-risk population and less than a third of hospitalized spine fracture patients undergo a dual-energy X-ray absorptiometry (DXA) scan for osteoporosis screening[15,16]. Moreover, even though anti-osteoporotic medications reduce the risk of subsequent fragility fracture by 73%, only 28.8% get a prescription[16]. The reasons for these low screening and treatment rates include time constraints, cost concerns, lack of priority or awareness among providers, and fragmented care. Solutions that opportunistically detect bone mineral density in imaging done for any reason and identify patients at risk can dramatically improve the detection and treatment of osteoporosis.

Researchers have attempted to fill this gap in the clinical care of osteoporotic patients by using AI. Ordering DXA specifically for osteoporosis screening requires extra administrative work for the providers and additional costs, inconvenience, and radiation for the patients. Ferizi *et al.* used ML to predict the risk of fragility fracture based on magnetic resonance imaging (MRI) findings and fracture risk assessment (FRAX) metric without using a dual-energy X-ray absorptiometry (DEXA) scan[17]. They used MRI-derived bone microstructure parameters to identify features that can predict a patient's risk of fracture. Since MRI is part of the routine diagnostic workup for most spine patients, this study highlights an important opportunity to reduce the chance of missing osteoporosis by integrating AI in MRI reporting to include the fracture risk in reporting.

Other researchers have employed AI to diagnose osteoporosis using computed tomography (CT) scans ordered for purposes other than DXA. Kathirvelu *et al.* tested a computer-aided diagnosis model to use dental panoramic radiographs to calculate bone mineral density and compared the results to the gold standard - hip DXA scan[18]. They found a strong correlation between the gold standard and their model (Pearson coefficient = 0.96; $P < 0.01$). Pan *et al.* used the same idea and employed DL on low-dose chest CT done for lung cancer screening to detect osteoporosis[19]. Their model correctly detected osteoporosis in almost 93% of the patients.

These studies report very promising results and potentially a new paradigm in the osteoporosis world. Integrating these AI tools in radiology reporting systems could dramatically improve the diagnosis and treatment rates of undetected osteoporosis. The best part is that these benefits come at no additional cost, extra radiation, or inconvenience to either patients or providers. Even a modest reduction in the 3 million fragility fractures or $25.3 billion in healthcare costs could result in a significant return on investment and a notable improvement in patient care.

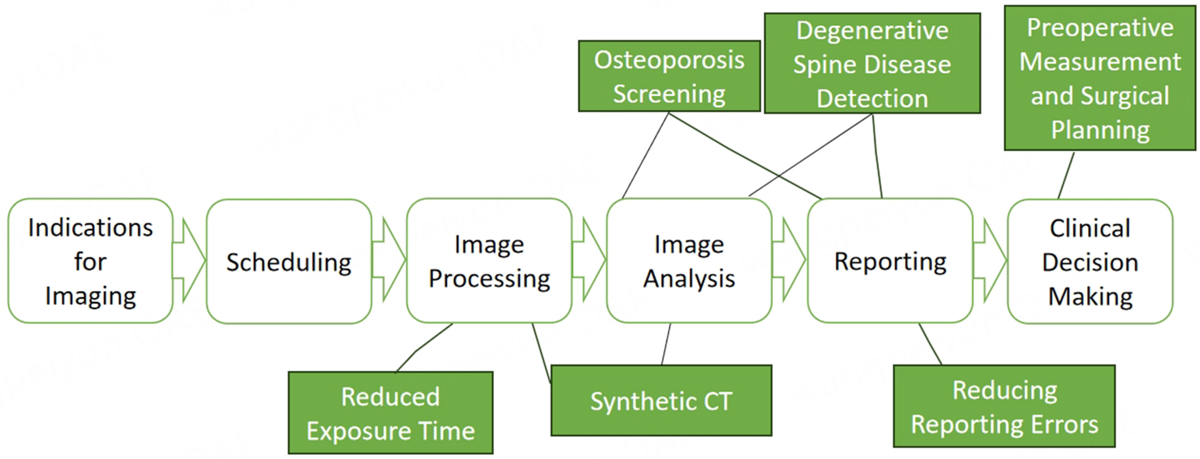

Figure 1. Summary of AI applications (green boxes) in spinal imaging clinical pathway. AI: Artificial intelligence.

Enhanced reporting

Spine surgery needs access to high-quality, reliable, and efficient radiology reporting to provide timely and optimal patient care. Current musculoskeletal radiology could benefit from AI integration for several reasons. Increased workload has led to a reported 3%-5% real-time error rate in radiologic examinations[20]. Intraoperative radiology reports often take up to two hours to be completed and are frequently finalized after the procedure has been completed[21]. This delay diminishes their value to the surgeon and adds unnecessary costs. Moreover, some studies report up to 33%-43% of missed diagnoses in spinal imaging reporting[6,22]. AI integration provides an opportunity to address these inefficiencies and provide better patient care.

Degenerative spine disease is one of the most common reasons for spine imaging. It affects up to 27.3% of the Medicare population[23]. Jamaludin *et al.* employed CNN to evaluate the key features of degenerative spine on MRI, such as disc narrowing, spondylolisthesis, and central canal stenosis[24]. Their AI model demonstrated a promising 95.6% accuracy compared to trained radiologists. It could label spinal structures and grade the pathologies with high precision.

Other researchers have shown similar results for other pathologies as well. A CNN model developed by Kim *et al.* successfully differentiated between tuberculous and pyogenic spondylitis on MRI with an 80.2% accuracy[25]. Pan *et al.* reported an 89.59% sensitivity and 70.37% specificity of their CNN model in diagnosing scoliosis on chest radiographs[26]. These initial results are very promising, and with continued training to improve these models, AI holds immense potential to enhance its diagnostic capabilities, reducing uncertainties and human errors found in the current radiology reports. This granularity can also help with the timely reporting of critical diagnoses that require urgent attention, for example, by sorting the patient lists based on the severity of findings so that critical images can be reviewed first. Moreover, with improved precision and reliability, automated real-time alerts can be set up for time-sensitive conditions by cord compression even before a radiologist reads the images.

AI has also shown the potential to assist clinicians with improved real-time imaging interpretation. Guermazi *et al.* experimented with an AI algorithm to reduce the chances of missing fractures on X-rays[27]. AI significantly improved the rate of fracture detection in both experts (70.7 ± 8.3 *vs.* 79.1 ± 5.5, $P = 0.006$) and non-experts (61.8 ± 8.6 *vs.* 73.3 ± 5.2, $P < 0.001$). Moreover, it also reduced the rate of false positives in the non-expert group (0.12 ± 0.11 *vs.* 0.05 ± 0.04, $P = 0.005$).

Voter *et al.* employed a similar AI tool to rule out spinal impingement in cervical spine fractures presenting at an emergency department and found sensitivity and specificity at 91.7% and 88.6%, respectively[28]. This can be a lifesaver, particularly in resource-limited settings and during nights and weekends when radiology reports may be delayed.

As we see the increasing literature with promising results of AI integration, we must be mindful of its infancy. After deployment, Voter *et al.* conducted an external validation of their tool as well and found the measures of diagnostic accuracy as follows: 54.9% sensitivity, 94.1% specificity, 38.7% positive predictive value, and 96.8% negative predictive value[28]. Therefore, although the tool was still good in ruling out, it may not be an ideal system for screening patients yet.

Radiation exposure

Balancing radiation exposure with the clinical utility of spinal imaging is a delicate balance. This is particularly crucial in an environment where failure to order radiological imaging may expose a practitioner to liability. On the other hand, the harms of excessive radiation exposure mostly remain a topic of academic and theoretical discussion. In this scenario, leveraging AI tools can be a powerful way to maximize the clinical utility of scans done while simultaneously reducing the cumulative radiation dose per spine patient.

CNNs have been employed to enhance the radiology images and reduce noise[29]. This improves the ability to retrieve clinically useful images from less optimal scans, reducing the need to repeat these studies[30]. Kaplan *et al.* used a DL model to produce full-dose equivalent positron emission tomography (PET) scans from low-dose PET images, lowering both the costs and radiation dose delivered to patients[31]. Similarly, Gong *et al.* reported their DL model that can produce at-par images with a 10-fold reduction in gadolinium contrast dose[32]. This can be tremendously helpful in patients with relative contraindications for gadolinium contrast.

Although most tools have only been tested in experimental settings, the reported results are very promising. We anticipate that these tools will soon be incorporated into real-life clinical pathways, reducing patients' radiation exposure.

MRI

MRI is extremely useful in spine surgery due to its superior performance in detecting soft tissue anatomy and pathologies. However, compared to a CT scan, MRI takes significantly longer to schedule and perform, making it time-intensive and costly[33]. Scheduling an MRI may take up to four weeks in the US[34], which worsens outcomes, particularly in time-sensitive life-threatening diseases[35]. Longer scan times also make patients anxious and claustrophobic during MRI[36]. This long scan time, anxiety, and the expectation to stay still during the scan increase the chances of artifacts due to patient motion requiring re-imaging.

AI integration in MRI can help reduce the scan time and re-imaging rates and, therefore, the scheduling time for MRIs. Suboptimal images or artifacts are a major reason for repeat scans. DL has been employed to successfully boost the signal-to-noise ratio[37] and "denoise" the image efficiently[38,39]. In one study, Bash *et al.* modified the conventional MRI protocol by "reducing excitations, raising bandwidth, and increasing parallel imaging factors at the cost of increasing image noise" and then used DL to de-noise the images[40]. They demonstrated up to 40% reduction in scan time[40]. In another study, Bash *et al.* demonstrated a 60% reduction in scan time for volumetric brain MRI by employing DL[41]. This sustained reduction in imaging time and improved processing motion artifacts in a variety of MRI scans demonstrate the potential to reduce the need, costs, and inconvenience of repeat scanning[40]. Other researchers have also published promising results with similar AI tools. One example is Zero echo-time (ZTE) MRI, a novel MRI sequence that uses ultrafast short-T2 tissue signals to reduce scan duration and increase the tolerance for artifacts[42]. Ensle *et al.* employed DL in ZTE MRI and reported a significant improvement in contrast-to-noise ratio and signal-to-noise ratio[43]. Although most of these models were tested in experimental settings as well, a multitude of successful demonstrations means that we can anticipate significant improvements in MRI experience and costs for real-world patients as these tools are integrated into the radiology departments.

Synthetic computed tomography scans

Most spine patients still undergo a CT scan since bones are poorly visualized on a traditional MRI. CT scans add significant radiation exposure and costs to the patients. Therefore, researchers have experimented with technologies to reduce, if not eliminate, the need for CT scans in spine patients. MRI uses super-short transverse relaxation times, which does not visualize bones well. ZTE MRI attempts to overcome this by using ultrashort echo time to improve bone visualization[44]. ZTE MRI can generate a synthetic CT (sCT) from the MRI images[45]. Therefore, ZTE MRI provides the clinical information found in a CT without incurring additional costs or radiation exposure[46]. It successfully visualizes a pars interarticularis fracture, which was not readily identifiable on a conventional MRI[44], and has superior detection of sacroiliitis as compared to traditional MRI[47]. Conventional MRI has a 20% sensitivity for sclerosis and 70% for ankylosis, whereas sCT improves this sensitivity to 94% and 93%, respectively[47]. Moreover, sCT also performs equivalent to preoperative spine measurements compared to a conventional CT[45,48]. This holds tremendous potential to minimize the side effects of a CT scan, particularly in patients with radiation contraindications, such as children and pregnant women[49]. Ensle *et al.* further enhanced the capabilities of sCT with a DL-based reconstruction algorithm (DLRecon)[43]. Leynes *et al.* applied a similar concept to a conventional PET scan and used deep CNN to improve the bone signal in a traditional PET scan, resulting in better identification of lesions[50]. Further studies report the use of sCT in therapeutic radiotherapy, using a type of AI called generative adversarial networks[46].

Although initial results are promising, sCT still requires further clinical validation to establish its utility. For instance, sCT has not been successful in patients with chronic bony injuries and complex anatomy[49]. Additionally, due to incomplete suppression of signals from tendons, ligaments, labra, and menisci, these soft tissues may appear diseased on sCT[44]. However, since sCT is based on MRI images, soft-tissue pathologies can be easily ruled out. With continued improvements, we can expect better clinical integration of sCT in the coming years.

Preoperative planning

In addition to diagnosis, imaging is a cornerstone in preoperative planning for spine surgery. The spine has a complex anatomy with proximity to numerous high-risk structures. Injury to any one of these structures has a detrimental effect. Therefore, meticulous imaging-based preoperative planning is paramount[51]. AI tools have been employed to assist in this step as well.

Pan *et al.* used CNN to measure the Cobb angles automatically on chest radiographs and found a high interobserver reliability of 0.887[26]. Wu *et al.* also tested an automated system to determine the Cobb angle and achieved a circular mean absolute error (CMAE) of 4.04°[52]; for reference, CMAE reported in previous literature ranges from 5.37° to 6.26°. Another example is the determination of the sagittal vertical axis (SVA), which is one of the few radiological parameters that coincides well with patient symptoms[53] but is highly cumbersome to obtain with manual measurements[54]. Weng *et al.* used CNN to determine SVA and found an excellent interclass correlation coefficient of 0.946 to 0.993[54]. Automating this burdensome but clinically important measurement enables easier preoperative surgical planning and, hence, better surgical outcomes. Incorporating robotic systems and navigation in traditional preoperative planning has also shown great potential[51]. Integrating robotics, navigation, and AI can spearhead operative planning and execution of those plans, reducing error rates and improving outcomes.

Wang *et al.* used CNN to localize pathologies on spinal CT scans with an accuracy ranging from 76.26% to 87.97%, with the highest accuracy in the lumbar spine and the lowest in the thoracic spine[55]. Suzani *et al.* employed another DL approach to localize pathologies on spinal CT and reported a much higher accuracy of 96% and results within three seconds[56]. Formally integrating these AI algorithms in clinical imaging and navigation tools can aid surgeons in accurately localizing the operative sites and reduce the risks of wrong-spinal-level surgery[57].

Present-day spinal imaging mostly consists of static radiographs. However, the spine is a dynamic structure, so the diagnosis and operative planning need to consider the spinal motion as well. Dynamic spinal imaging greatly enhances the understanding of individual patient's anatomy and pathology[58], providing better individualistic care. Currently, most surgeons have to infer the dynamics of spinal pathologies from static radiographs in different postures. This requires a surgeon with high analytic skills, knowledge, and experience. There is great potential in integrating AI with dynamic spinal imaging and biomechanics to enhance the information provided by simple static images and subjective inferences. The computational power of AI can outperform human deductions and lead to much better surgical outcomes.

CHALLENGES AND LIMITATIONS

Although most published literature and new headlines usually point toward the marvels and efficiencies of AI, it is important to be careful with the earlier-than-necessary implementation of these experimental tools in patient care areas. These tools have not been thoroughly tested for their failures and shortcomings. Moreover, although these deficiencies may be well tolerated in certain areas where they are used as suggestive tools, they may lead to actual patient harm if oversight is not maintained.

It is critical to realize that any AI model is only as good and generalizable as the training dataset it uses. Current AI models are mostly trained and tested on limited datasets; therefore, generalizability and widespread implementation are a concern. For example, the dataset that Bash *et al.* used to train their DL to achieve a 40% reduction in MRI scan time[40] comprised primarily of only the common pathologies. Its performance in rarer diseases remains unchecked and ignoring this can lead to disastrous patient outcomes and potential liability. Similarly, Voter *et al.* reported poor diagnostic accuracy of AI tools in cervical spine fracture patients[28]. Hence, although these tools have immense potential, they may not be safe enough to aid in patient care yet. Moreover, AI can "hallucinate" at times, be more assertive than it should be, or produce outright false information[59]. There is a high chance that physicians may over-rely on the "magical" AI tools, without realizing the inherent limitations of these systems. It may also be difficult to challenge AI-produced reports, especially for relatively inexperienced and overburdened early-career practitioners.

A 2021 study on 100 commercially available medical AI products for radiology concluded that the industry is still in "the infancy"[60]. The authors reported that only 36% of products were supported by peer-reviewed evidence, and most of this evidence demonstrated a lower level of efficacy. Moreover, only 18% of these products had a potential clinical impact[60]; evidence derived from simulation or lab-based research studies may not always translate to improvement in real-world clinical outcomes.

Table 1. Review at a glance

Osteoporosis detection
● Low screening and treatment rates: less than 25% of at-risk individuals and 36.7% of spine fracture patients undergo osteoporosis screening; only 28.8% are treated. ● AI for osteoporosis detection: AI improved osteoporosis detection and fracture prevention.
Enhanced reporting
● Radiology efficiency issues: currently, there is a high error rate and delays in reporting. ● Diagnostic improvement: AI reduces missed diagnoses and improves diagnostic accuracy. ● Real-time detection and alerts: AI enables real-time interpretation with high accuracy and has the potential for automated alerts for critical conditions.
Radiation exposure
● Reducing radiation exposure: CNNs and DL models help enhance image quality and reduce noise, minimizing the need for repeat scans and lowering radiation doses. ● Low-dose imaging: AI models help to produce high-quality PET, CT, and MRI images with significantly reduced radiation and contrast doses, aiding in patient safety.
MRI and CT
● Challenges: conventional MRI is time-consuming and costly. CT has radiation exposure. ● AI enhancements: AI can reduce MRI scan times by up to 60%, improve image quality, and reduce the need for repeat scans due to motion artifacts by boosting signal-to-noise ratios. ● sCT: ZTE MRI can generate synthetic CT images without radiation.
Preoperative planning
● AI in preoperative planning: AI tools, like CNNs, help automate critical measurements. ● Pathology localization: CNN and DL improve spinal pathologies localization on imaging, with accuracy of up to 96%, significantly reducing the risk of wrong-level spine surgery. ● Dynamic imaging: AI integration provides more precise insights into spine motion, enhancing diagnostic accuracy and preoperative planning beyond static radiographs.
Challenges and limitations
● Limited generalizability: AI models have limited applicability in patients not represented in their dataset, which are often obscure. ● Lack of clinical validation: most AI tools lack real-world testing, risking patient harm, especially if providers over-rely on them without sufficient evidence and training.

AI: Artificial intelligence; CNNs: convolutional neural networks; DL: deep learning; PET: positron emission tomography; CT: computed tomography; MRI: magnetic resonance imaging; sCT: synthetic computed tomography; ZTE: Zero echo-time.

Another important consideration, particularly for enthusiastic clinicians who may not be well-versed with the nuances of medical research and AI, is to differentiate between initial proof-of-concept papers versus thoroughly vetted, externally validated, and real-world clinically tested AI technologies[61]. While a constant stream of literature discusses a promising future of AI integration in clinical medicine, there is a shortage of clinically validated AI tools ready to be employed, unrestricted, in daily clinical practices[62,63].

Table 1 summarizes the uses of AI in spinal imaging presented in this review.

CONCLUSION

At the current level of development and integration, AI is expected to tremendously enhance the efficiency and accuracy of radiologists and spine care providers. However, it appears less likely, if not impossible, to see AI replacing the role of any clinician soon.

DECLARATIONS

Authors' contributions

Conceived the idea: Ibrahim MT, Milliron E, Yu E
Wrote the first draft of the manuscript: Ibrahim MT
Critical revisions of the manuscript: Milliron E, Yu E

Critical revisions and complete responsibility for all aspects of the work: Ibrahim MT, Milliron E, Yu E

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All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate
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