Review Article

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Role and potential of artificial intelligence, robotics, and navigation-assisted technologies in the diagnosis, treatment, and prognosis of osteoporotic vertebral compression fractures

Wenlong Zhang, MS, Qinghong Ma, PhD, Jue Zhang, PhD*, Chao Sun, PhD*

Abstract

In recent years, there has been a rise in fractures caused by osteoporosis. Such fractures significantly contribute to bone morbidity and place an increasing strain on global healthcare systems. Among them, osteoporotic vertebral compression fractures (OVCFs) have shown a steady upward trend. There is an annual growth of roughly 4–5%, with age-adjusted incidence rates exceeding 850 per 100 000 individuals over 5 years. This trend portrays the necessity for improvement in OVCF diagnosis, treatment, and prognosis. Accordingly, there has been a recent surge in research, resulting in innovative technologies aimed at enhancing patient outcomes by improving diagnostic accuracy, reducing intraoperative radiation exposure, minimizing cement leakage, and optimizing postoperative recovery. These innovations span several areas, such as sophisticated imaging and navigation systems, virtual reality technology, 3D printing and robotic surgery techniques, and artificial intelligence-aided diagnostic, therapeutic, and prognostic tools. In this review, we summarize the status of knowledge regarding the role and potential of these digital orthopedic technologies involved in the diagnosis, treatment, and prognosis of OVCFs in detail. Moreover, we highlight some of the current limitations, challenges, and future directions that help develop new assistant techniques for these areas.

Keywords: artificial intelligence, digital technology, osteoporotic vertebral compression fractures, robotics

Introduction

The prevalence of osteoporotic vertebral compression fractures (OVCFs) has been increasingly rising, particularly among older patients[1]. The primary cause of this fracture is osteoporosis, which lowers the strength of the bones and makes the spine vulnerable to fractures with mechanical stress. In some cases, the fractures may involve compromises of the spinal cord or nerve roots and result in neurological damage. Clinically, individuals experience pain in the thoracic or lumbar regions, spinal deformities, and limited movement, all of which severely impact their quality of life[2].

Percutaneous vertebroplasty (PVP) and percutaneous kyphoplasty (PKP) are acknowledged as treatment options for these fractures due to their minimally invasive nature, effective pain relief, and quick recovery period[3]. However, with the increasing use of these procedures, side effects such as bone cement leakage and vertebral refracture have frequently been reported[4,5]. Currently, both PVP and PKP rely significantly on repeated intraoperative C-arm fluoroscopy, with continuous needle placement adjustments to ensure precise puncture and minimize surgical complications, significantly increasing the risk of radiation exposure for doctors and patients. Moreover, due to the differences in patient conditions, fracture types, and degrees of osteoporosis, personalized diagnosis and treatment are also important[6]. These are the existing problems in clinical treatment.

Recent advancements have led to the creation of sophisticated technologies like AI, robotic systems, and navigation-assisted tools, which have introduced more accurate and intelligent methods for diagnosing and treating OVCFs (Fig. 1). Although several studies have examined these technologies in OVCFs, few have comprehensively analyzed how AI, robotic systems, and navigation-assisted

HIGHLIGHTS

- The frequency of OVCFs has been rising, particularly among older individuals, putting more pressure on worldwide healthcare systems.
- The development of intelligent precision technologies such as artificial intelligence, 3D printing, and robotic assistance has resulted in more precise and intelligent approaches for the diagnosis, treatment, and prognosis prediction of OVCF.

Department of Spine Surgery, The Affiliated Jiangning Hospital of Nanjing Medical University, Nanjing, Jiangsu, China

Wenlong Zhang and Qinghong Ma contributed equally to this paper.

*Corresponding authors. Address: Department of Spine Surgery, The Affiliated Jiangning Hospital of Nanjing Medical University, Nanjing, Jiangsu 211100, China. Tel.: +86 13905198789. E-mail: zhangjue1027@163.com (J. Zhang); Department of Spine Surgery, The Affiliated Jiangning Hospital of Nanjing Medical University, Nanjing, Jiangsu 211100, China. Tel.: +86 15005183384. E-mail: drsunchao@163.com; drnjjyyy@stu.njmu.edu.cn (C. Sun).

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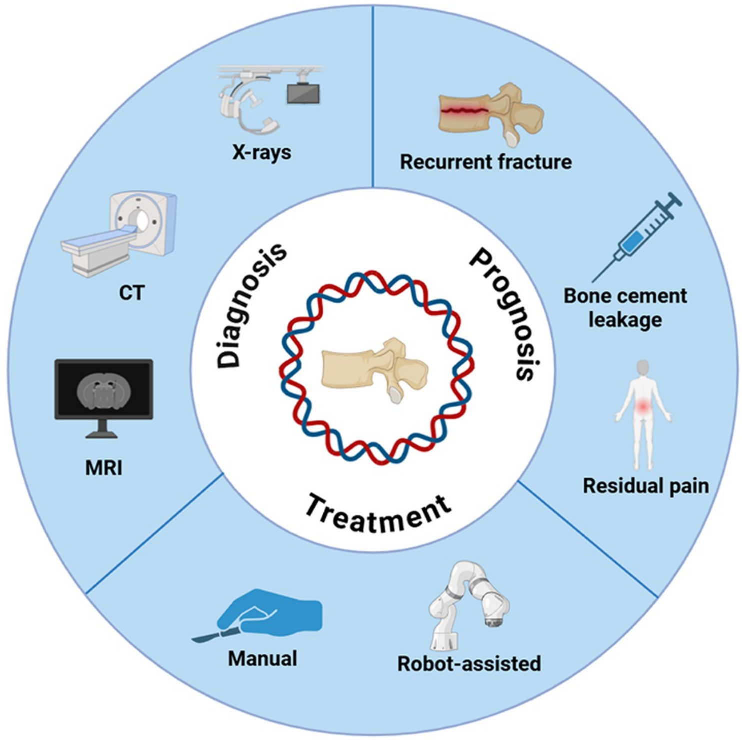

Figure 1. Diagram depicting the primary focus of this review in OVCF. Three main components about OVCF are explored: diagnosis, treatment, and prognosis. In terms of diagnosis, it focuses on the integration of deep learning technology with clinical imaging techniques. Regarding treatment, it emphasizes the role of various auxiliary tools, which can assist surgeons during the operation, as well as the application of robotic-assisted technology. In the aspects of prognosis, it summarizes that the use of deep learning technology can accurately predict recurrent fractures, bone cement leakage, and residual pain after the surgery.

tools work together to improve clinical care. This review addresses the gap by presenting an integrated overview of current innovations in OVCFs, which highlights AI algorithms for imaging-based diagnosis, the application of robotic and navigation systems in operation, and machine learning models for predicting postoperative outcomes. Given its focus on AI and other intelligent technologies, this review adheres to the TITAN 2025 guideline, and no AI tools were used in this review[7]. Overall, this paper aims to enhance clinicians' understanding of intelligent technologies and provide novel insights for clinical practice.

Diagnosis

OVCFs are the most common fragility fracture and the primary source of morbidity in older individuals[8]. These fractures tend to lead to serious complications such as persistent pain, kyphosis, and an increased risk of future fractures, which can significantly impair quality of life[9]. Prompt and accurate diagnosis not only facilitates the relief of immediate symptoms but also prevents further complications and reduces the long-term implications of these fractures.

Traditionally, the diagnosis of OVCFs relies on plain radiographs and tools like the Genant classification[10]. However, these assessments are often subjective and limited by inter-observer variability and imaging quality. With the help of a range of advanced imaging methods, such as computed tomography (CT), and magnetic resonance imaging (MRI), it makes the discovery and evaluation of OVCFs more comprehensive. Furthermore, AI-powered technologies have recently made it possible to accurately identify fractures, assess their severity, and plan treatments[11].

AI-assisted imaging diagnosis

AI-driven technologies have been used to enhance image interpretation and improve diagnostic accuracy. In the context of X-ray, CT, and MRI imaging, diagnostic procedures have become more automated and standardized. AI models can accurately detect subtle fractures and classify their severity, which improves diagnostic efficiency[11]. AI also has the potential to lessen the workload of doctors, but there are still challenges, such as inconsistent data quality, lack of algorithm transparency, and privacy concerns[12].

X-ray imaging, known for its convenience, speed, and cost-effectiveness, is deemed as the first-line imaging modality[13]. However, its utility is limited in detecting subtle fractures, particularly in patients with osteoporosis. Accurate assessment of vertebral compression height is vital for both the diagnosis and treatment of OVCF[14]. Traditional manual measurement methods are susceptible to observer variability. The accuracy is constrained by image quality and the technical expertise of the observer, often leading to inconsistencies in clinical decision-making. As a result, a convolutional neural network (CNN) model has been designed to automatically identify vertebral images on X-ray films and measure changes in vertebral height. It is demonstrated that deep learning models can reduce the human error inherent in manual assessments. In particular, when confronted with challenging or low-quality X-ray images, automated algorithms can extract key information more accurately than human observers[15]. For example, based on five-fold cross-validation using the Osteoporotic Fractures in Men Study (MrOS) dataset, a deep learning model demonstrated an accuracy of 89.1%[16]. These models can greatly improve the diagnostic process, allowing for quick fracture detection, which is beneficial in primary care practices and remote areas[17].

Additionally, anteroposterior (AP) X-rays are the most common imaging modality in clinical practice. Using the AP X-ray images for AI-driven analysis can effectively detect potential spinal compression fractures without adding extra diagnostic procedures[18]. Furthermore, the diagnostic performance of deep learning models in detecting OVCF is found to be comparable between AP and lateral X-ray images (Table1). Lateral images have slightly higher accuracy than AP images. However, the differences between the two views are not statistically significant (P = 0.6035), indicating similar discriminative capabilities for OVCF classification[19].

In CT imaging, which offers superior bone detail and sensitivity to occult fractures[20]. AI applications have shown remarkable diagnostic value. AI-enhanced CT models not only achieve accuracy comparable to radiologists but also outperform them in detecting unreported fractures. Briefly, an AI model achieved a sensitivity of 85.2%, a specificity of 92.3%, and an overall accuracy of 88.9% for detecting Genant grade 2–3 vertebral compression fractures. Notably, only 30% of these fractures were reported by radiologists on routine CT scans, indicating that the AI system performs better than radiologists in routine practice[21]. Furthermore, a new deep-learning model capable of automatically localizing and segmenting vertebrae on CT scans and detecting osteoporotic compression fractures has been developed. The sensitivity and accuracy surpass those of the current deep-learning models used for OVCF detection[22]. Besides, using AI for CT-based classification of spinal diseases can identify four specific conditions—OVCF, old fractures (OFs), Kummel disease (KD), and post-surgical changes (PS), highlighting its significant potential for accurate and rapid diagnosis of spinal disorders[23]. The applications of AI are typically retrospective, as it involves analyzing CT images that are originally acquired for other purposes, such as abdominal or trauma evaluation. This approach avoids additional radiation exposure[21]. Due to the widespread application of CT in clinical practice and the rapid development of AI, CT has vast potential to be discovered.

MRI is widely regarded as the gold standard for diagnosing spinal compression fractures[24], particularly in cases requiring an assessment of bone marrow edema or soft tissue involvement. By exploiting the resonance of hydrogen ions within the body, MRI offers superior imaging of soft tissues compared to hard tissues[25]. In differentiating OVCFs and malignant vertebral compression fractures (MVFs), CNN models that utilize short-TI inversion recovery (STIR) and T1-weighted images (T1WI) can achieve accuracies of 93.8% and 96.4%, which is statistically higher than that of spine surgeons[26]. In addition, MRI is better at distinguishing acute fractures. CNN trained on T1-weighted MR images demonstrated comparable diagnostic performance to surgeons in identifying fresh OVCFs, with an accuracy of 88.0%[27]. In addition to conventional T1-weighted MRI sequences, advanced imaging techniques such as diffusion-weighted imaging (DWI) and dynamic contrast-enhanced MRI (DCE-MRI) play a critical role in differentiating acute from chronic VCRs. DWI helps detect bone marrow edema by measuring changes in water molecule movement, which is increased in acute fractures. DCE-MRI further assists in evaluating the blood flow and activity of the affected bone, which tends to be higher in recent fractures[28]. Although MRI provides high-resolution images of both soft tissue and bone structures, its relatively high cost and prolonged scan times limit its practicality in certain clinical settings.

Currently, CNN is the most commonly used AI-assisted imaging model. Despite the promising diagnostic performance, CNNs still have several limitations. In detail, these models are designed to detect image-based features. They do not incorporate patient history, clinical symptoms, or comorbidities—all of which are essential for comprehensive fracture assessment and treatment planning. Furthermore, CNNs are highly dependent on the quality and diversity of training data. Their performance may degrade when applied to ambiguous cases and poor-quality images. In addition, the "black box" nature of deep learning makes it difficult to interpret the internal decision-making processes, which presents a barrier to clinical trust and adoption[29].

Treatment

Both PKP and PVP are now common surgeries in minimally invasive OVCF management due to their minimally invasive nature, brief recovery times, and satisfactory pain relief[30]. The success of the procedure depends on proper vertebral localization, which itself is dependent on advanced imaging modalities[31]. Computer-assisted navigation is incorporated in this process through the utilization of digital scanning to transmit imaging information to a computer workstation where high-

Table 1

Performance comparison of deep learning models for predicting the OVCFs using anteroposterior and lateral X-ray images on internal and external test datasets

	Internal test data (N = 708)		External test data (N = 104)		
	AP (N = 354)	Lateral (N = 354)	AP (N = 52)	Lateral (N = 52)	P-value
F1 score	0.849	0.898	0.935	0.944	
Accuracy	0.847	0.896	0.932	0.941	
AUROC	0.915	0.953	0.982	0.979	0.6035*

AP, anteroposterior, AUROC, area under receiver operating characteristic.

*P-value for the AUROC comparison using the DeLong test. Reproduced with permission[18]. Copyright ©, 2024, Kim C et al.

The frequency of OVCFs has been rising, particularly among older individuals, putting more pressure on worldwide healthcare systems.

The development of intelligent precision technologies such as artificial intelligence, 3D printing, and robotic assistance has resulted in more precise and intelligent approaches for the diagnosis, treatment, and prognosis prediction of OVCF.

speed three-dimensional vertebral model reconstruction enables planning and simulation intraoperatively. Recently, many navigation assistance systems have emerged. Among them, C-arm fluoroscopy-based optical navigation and O-arm 3D navigation are the most common, each specifically developed to address some clinical requirements. In addition, this technology has also made it possible to produce specific 3D-printed drill guides for preoperative localization, further enhancing the accuracy of surgery[32]. The current navigation technology is summarized as follows.

C-arm navigation

C-arm fluoroscopy represents a critical tool in modern-day orthopedic surgery, furthering significantly operating accuracy and lessening patient morbidity. The C-arm technology, featuring a C-shaped device with digital X-ray capabilities, combines its components to generate immediate, high-quality images of a patient's internal anatomy[33]. Providing constant dynamic visibility, C-arm navigation allows a surgeon to determine exactly where structures exist inside a patient at any time and, therefore, increase safety as well as precision. For minimally invasive procedures, this feature is highly beneficial, as precise guidance is essential for achieving optimal outcomes. In addition to minimally invasive spine surgery, C-arm fluoroscopy is also widely used in other orthopedic procedures, such as fracture fixation and joint replacement[34-36].

Clinicians depend on this technology to guide instrument positioning, monitor bone alignment, and determine surgical success in real time. For instance, in vertebral fracture management, C-arm fluoroscopy enables accurate navigation during vertebroplasty and kyphoplasty, with minimal risk of complications such as cement leakage or vertebral refracture[37]. However, repeated imaging during surgery is a concern for increased radiation exposure to the surgical team[38]. Long-term exposure to ionizing radiation has been associated with long-term health effects such as cataracts, skin damage, and increased risk of cancer[39]. Consequently, orthopedic practice has attempted to minimize exposure to radiation without compromising image quality and procedural integrity. One approach to maintaining that balance is the implementation of low-dose fluoroscopy[40]. In addition, technologies like intraoperative navigation systems, which integrate fluoroscopy with 3D imaging and robotic surgery, provide promising ways to improve surgical accuracy without increasing dependence on real-time fluoroscopic imaging[41]. Although C-arm navigation is widely used in clinical practice and this technology is very mature, it also has certain shortcomings, such as the inability to provide a comprehensive image, low image resolution, and low efficiency of intraoperative adjustment.

O-arm navigation

The O-arm navigation system is a more advanced imaging technology compared with C-arm navigation, delivering three-dimensional imaging and precise navigation to enhance surgical accuracy[42]. Unlike the C-arm, the O-arm possesses 360° rotational imaging around the patient, enabling full image capture and higher resolution visualization for 3D navigation[43].

O-arm navigation for the treatment of mid-thoracic (T6–T9) OVCFs has several advantages, which include more precise cement placement, greater cement injection volumes, less blood loss, and reduced occurrence of complications such as tissue damage and needle malposition[44]. For patients with spinal deformities, O-arm navigation was shown to increase intraoperative accuracy, minimize trocar misplacement, shorten the operative time, and lower the risk of bone cement extravasation, making it a safer option compared to standard C-arm guidance. Moreover, O-arm navigation reduces intraoperative radiation exposure when handling complex VCRs and spinal deformities, which is an essential factor in ensuring the safety of patients and surgeons[45].

The O-arm may also be coupled with patient-specific guiding tools, such as 3D-printed templates individualized to distinctive anatomical features, to further maximize treatment accuracy and safety[46]. As such, the use of O-arm navigation for bone cement injection has been demonstrated to elevate the effective dose, resulting in superior procedural control and outcomes when compared to C-arm[47]. Although the O-arm is much better than C-arm navigation, its use still faces several challenges, including the sizable footprint in the operating room, the complexity of system operation, and the difficulties in managing emergencies[48].

Mixed reality

Mixed reality (MR) technology is a novel form of digital holographic imaging[49] that emerged in the field of computer graphics following virtual reality (VR) and augmented reality (AR), effectively combining features of both[50]. By superimposing the real world and 3D virtual images in the same visual space in real-time, MR blends real and virtual environments, enables real-time interactivity, and ensures precise alignment[51,52], This technology can overlay holographic, real-time digital content onto the physical environment, thus providing visual navigation for the surgeon[53,54]. Integrating 3D reconstruction with MR enables precise replication of patient anatomy, ensuring proper spatial alignment between anatomical structures and surgical instruments[55,56].

Virtual reality technology, combined with 3D bone structure modeling, can visually simulate vertebral microstructural changes caused by osteoporosis. In particular, MR technology-aided PKP can accurately identify the intravertebral vacuum cleft (IVC) region in OVCF, allowing for balloon expansion there to better restore vertebral height, improve bone cement distribution, and alleviate pain[57]. Consequently, MR technology supports surgeons in achieving more precise navigation during spinal procedures[58,59].

3D printing technology

In recent years, the application of 3D printing technology in PVP and PKP has advanced considerably, particularly in OVCF[60]. 3D printing is an additive manufacturing technology that constructs three-dimensional objects by depositing materials layer by layer. It can utilize plastics, metals, ceramics, and biomaterials and is widely applied in fields such as industrial manufacturing, healthcare, aerospace, and consumer goods[61]. 3D printing technology is extensively applied in orthopedics for personalized implants, preoperative planning, and training to achieve surgical precision improvement and recovery rates of patients[62].

Recent studies have explored the use of personalized 3D-printed guide templates and navigation systems (Fig. 2) to enhance surgical precision, minimize fluoroscopy duration, and decrease radiation exposure for both patients and medical personnel[63]. 3D-printed templates also have the potential to

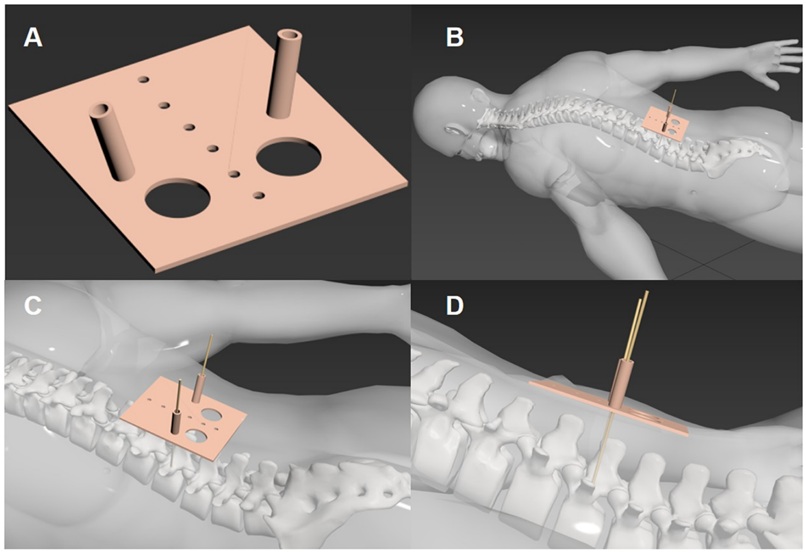

Figure 2. Model of 3D-printed guide plate. (A) The general appearance of the 3D-printed guide consists of a flat plate and several channels above the plate. There are holes in the plate to determine the position of puncturing, and the channel is used to guide the angle of needle insertion. (B) The position of the guide plate on patient's body. (C) The guide plate guides the insertion angle of the puncture needle. (D) Side view of the guide plate.

improve the accuracy of needle placement, particularly in patients with severe osteoporosis undergoing unilateral puncture techniques[64]. A study assessed the effectiveness of a 3D-printed surface puncture guide plate, revealing that it enhanced the accuracy of vertebroplasty substantially while reducing the application of repeated fluoroscopic imaging[60,65]. Also, using 3D printing technology can lead to a reduction in complications associated with vertebral punctures[66].

Overall, the research highlights the expanding use of 3D printing in aiding personalized medicine, as patient-specific surgical guides are printable based on preoperative imaging data. Given its potential for improving surgical accuracy and minimizing invasiveness, 3D printing holds considerable promise for significantly enhancing clinical outcomes in spinal procedures.

Electromagnetic navigation

MRI-based electromagnetic tracing, combined with standalone AR technology, can achieve high accuracy in treating thoracolumbar OVCFs and may serve as a supplemental guidance technique to conventional X-ray and CT-based approaches[67]. However, MRI is not the primary choice for spinal surgery because it provides limited visualization of bony structures, requires specialized imaging environments, and involves lengthy scan times. Nonetheless, it is demonstrated that CT-guided electromagnetic navigation is both feasible and effective for managing fractures and tumors involving the C1 and C2 vertebrae. Surgical interventions in the cervical region, particularly at C1–C2, are complex due to the unique local anatomy and the proximity of critical nerves and the spinal cord. Electromagnetic navigation, which excels at visualizing soft tissues, can enhance both the precision and overall effectiveness of these procedures[68].

Robot-Assisted technology

Surgical robots are intelligent medical systems that integrate robotics, AI, and computer vision, widely used in minimally invasive surgeries and precision procedures to enhance surgical accuracy and safety[69]. Robot-assisted techniques for treating OVCFs have gained prominence in recent years (Fig. 3) and offer several advantages over conventional fluoroscopy-guided methods[70]. For example, robot-assisted kyphoplasty (RA-PKP) has been shown to reduce radiation dose exposure to operating room staff and surgeons[71], with improved fracture correction compared with conventional fluoroscopy-assisted kyphoplasty (FA-PKP)[72]. Robot-assisted unilateral percutaneous kyphoplasty (RAUPK) is also superior to fluoroscopy-assisted unilateral percutaneous kyphoplasty (FAUPK) in long-term outcomes, such as increased clinical efficacy. In addition, it is also shown that patients who receive robot-assisted puncture experience more pain relief at 6 months post-surgery compared to those receiving standard fluoroscopy-guided therapy. In conclusion, robot-assisted PKP is more accurate in puncturing, exposes the surgeon to less radiation, and offers more comfort to the patient, and hence is an excellent choice for local anesthesia procedures[73].

As minimally invasive spine surgery becomes more common, surgeons have noticed an increase in radiation-related issues, including cataracts, skin erythema, and cancer, particularly during multi-level procedures[74,75]. Even though robot-assisted operations lessen radiation exposure for surgeons, they do not reduce it for patients. Thus, fluoroscopy-guided PKP with abbreviated operative time still remains an option for the management of single vertebral fractures[76]. However, in treating multi-level OVCFs, robot-assisted multi-level PKP shows obvious advantages by reducing both the frequency and dosage of radiation exposure and substantially mitigating associated risks. In detail, the robotic system, after intraoperative 3D scanning and reconstruction, can design multiple puncture routes for adjacent vertebrae at the same time, thus avoiding repeated fluoroscopy. Collectively, the robot-assisted interventions exhibit more pronounced benefits in multi-segment treatments compared to single-level kyphoplasty[77].

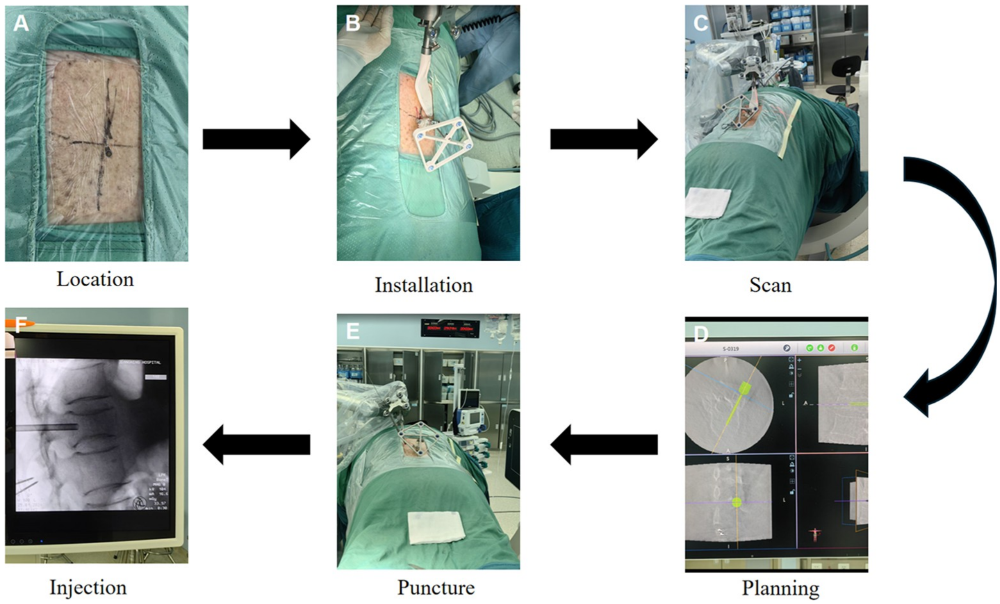

Figure 3. The surgical procedure of robot-assisted percutaneous kyphoplasty. (A)The puncture point is located according to the image data and body surface landmarks. (B) Installation of the robotic arm. (C) Intraoperative fluoroscopy provides positioning information for the robot. (D) Planning the depth and angle of needle insertion. (E) The robot guides the needle into the target position of vertebral body. (F) Set up the casing and create an annotation channel.

Cement leakage, a complication occurring in up to 20% of procedures, is a major concern due to its potential to cause issues like back pain or pulmonary embolism[78]. Robotic systems help minimize this risk through more controlled and accurate delivery of cement, further enhancing the safety of the procedure. Furthermore, they solve the issue of rapid curing of bone cement, which limits injection time and leads to a risk of non-homogeneous or partial cement distribution. With high-precision control, robotic systems enable cement to remain within the best range of viscosities for more homogeneous distribution[79]. Thus, it is believed that the future development of surgical robots will obviously ease the burden on doctors and provide patients with better surgical outcomes.

Prognosis

Prognosis assessment in OVCFs was traditionally based on clinician experience and limited statistical models, such as logistic regression, focusing on factors like age, fracture type, and low bone mineral density (BMD). Although these methods are widely used, they have difficulty in finding the interactions between various factors. AI, with its powerful data analysis capabilities, offers distinct advantages in predicting outcomes following vertebral augmentation procedures[80]. By compiling multidimensional patient data, such as pre and postoperative imaging, AI systems can determine bone healing status, the stability of reinforcement materials, and any structural changes at the augmentation site. Patient clinical information is also integrated for comprehensive assessment[81]. Subsequently, AI leverages deep learning models to process imaging data, automatically identifying and evaluating vertebral morphological changes, fracture healing progress, and any latent risk factors such as stress concentration around the reinforcing materials, microfractures, and the distribution of bone cement (Fig. 4). Recent studies have applied various machine learning algorithms to predict postoperative outcomes in patients undergoing percutaneous vertebral augmentation procedures.

Refractures after vertebral augmentation

Vertebral fractures (VFs) account for approximately 50% of all osteoporotic fractures annually, making them the most prevalent complication of osteoporosis[82,83]. The incidence of new vertebral compression fractures (NVCFs) varies significantly over time. A multicenter study reported that 74% of NVCFs occurred within 6 months after surgery, with a median time to refracture of 70 days[84]. Another study found a cumulative refracture rate of 34.8% during an average follow-up of approximately 2 years. These results highlight the importance of timely follow-up and early prevention. Moreover, BMD, especially lumbar T-scores below –2.5, was consistently identified as a risk factor for new fractures in both univariate and multivariate analyses[85,86]. Thus, routine BMD monitoring after vertebral augmentation is essential for identifying high-risk patients. Importantly, the onset of NVFs highly correlates with increased morbidity and mortality rates[87].

Accurate prediction of the risk of recurrent postoperative fractures is important for clinical decision-making and treatment planning. It has been demonstrated that machine learning algorithms using radiomic features and clinical data can distinguish between osteoporosis, osteopenia, and normal BMD from CT imaging features. Such algorithms can also predict fragility-related vertebral fracture risk[88]. By detecting fractures early, this method allows for the timely initiation of anti-osteoporotic treatment, making it easier for clinicians to treat high-risk patients[89]. MRI-based radiomic features are also tasked with assessing the recurrent risk of OVCF. In combination with the Random Survival Forest (RSF) model (a complex machine learning model aimed at risk analysis), MRI imaging can accurately

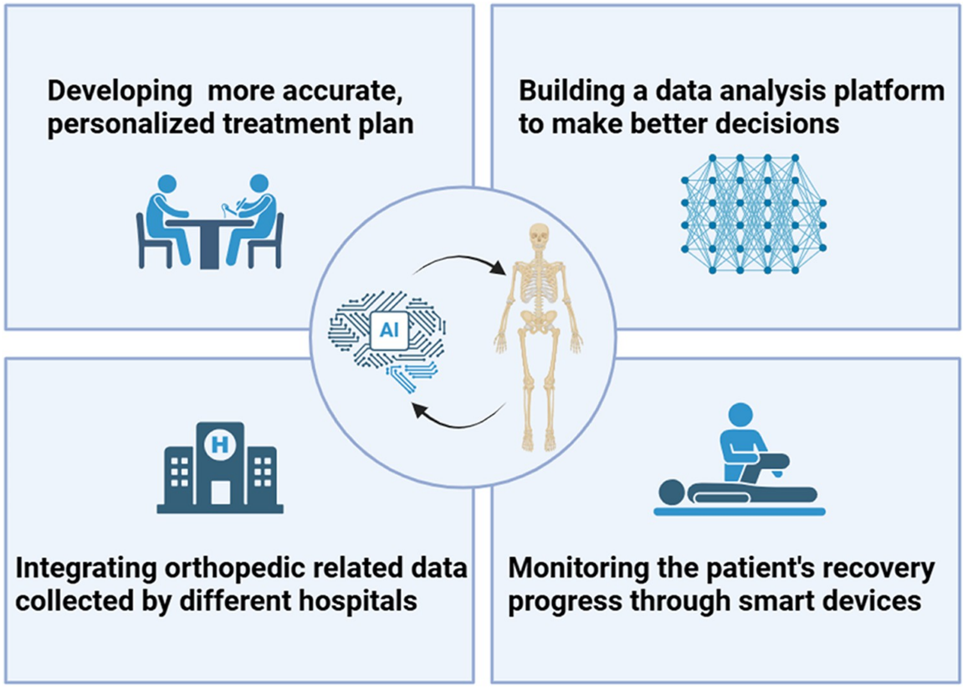

Figure 4. Diagram illustrating the AI technology in orthopedics. There are four key areas that summarize the potential of AI technology in orthopedics. First, AI can identify the most precise treatment plan based on personal physical condition. Second, with its powerful data collection and analytical capabilities, AI can establish a data analytics platform to guide clinical decision-making. Third, AI can integrate information from various hospitals to support relevant scientific research. Finally, AI can monitor patients' rehabilitation progress by using smart devices.

predict the risk of NVFs following vertebral augmentation[90]. Moreover, A recent study compared several machine learning models for predicting NVFs. The Random Forest (RF) model demonstrated the highest area under the curve (AUC) of 0.940. Neural networks followed with an AUC of 0.923, gradient boosting achieved 0.910, and regularized discriminant analysis reached 0.915. In contrast, logistic regression showed a lower AUC of 0.898. These findings suggest that the RF model, as a representative ensemble model, may offer superior prognostic performance in clinical applications[91].

Postoperative residual pain

The residual pain of post-VA refers to persistent back pain that continues after PVP[92]. Despite a high success rate of 78% to 95% for pain relief after PVP, a significant number of patients (1.8–15.6%) still experience ongoing back pain[93]. Potential causes include bone cement leakage, infection, or nerve compression[94,95]. Additionally, ongoing osteoporosis can predispose other vertebral segments to fractures or increased mechanical stress, thereby provoking further pain.

Historically, it has been reported that clinical prediction models, such as linear regression and generalized linear models, are employed to identify OVCF patients at risk of residual back pain before surgery[95-97]. Recently, machine learning (ML)—based predictive models, informed by large-scale retrospective analyses, can integrate factors such as comorbid conditions, preoperative imaging features, fracture type, patient age and sex, and intraoperative parameters (e.g. Cement volume and distribution) to accurately estimate the risk of postoperative back pain. Among numerous ML models, the Support Vector Machine (SVM) models have demonstrated superior performance over other predictive models in forecasting postoperative outcomes. As such, it is reported that this model achieved an AUC of 0.88, an accuracy of 91.5%, a sensitivity of 82.3%, and a specificity of 87.3%, followed by Light Gradient Boosting Machine (AUC 0.86) and Categorical Boosting (AUC 0.85). Logistic regression reached an AUC of 0.83, while RF performed slightly lower at 0.80. These results suggest that SVM may offer more accurate prognostic predictions compared to traditional methods[98].

Extent of bone cement leakage

Bone cement, primarily composed of synthetic materials like polymethylmethacrylate (PMMA)[99], is widely used in orthopedic surgeries. Its main function is to fill and reinforce bone defects or fragile bone tissue, providing mechanical support and promoting postoperative skeletal stability[100]. In the case of OVCFs, which often involve multiple vertebral fractures, bone cement penetrates the vertebrae in various directions. Leakage of bone cement into the epidural space or neural foramina can compress the spinal cord and nerve roots, increasing the risk of adjacent vertebral fractures and potentially leading to paralysis[101]. Moreover, if bone cement enters the paravertebral venous system, it may lead to serious issues like pulmonary embolism, cardiac perforation, cerebral embolism, and potentially death[102].

Therefore, predicting bone cement leakage is critical in clinical diagnosis and treatment. Among various ML algorithms, the RF algorithm has demonstrated strong performance as a tool for predicting postoperative bone cement leakage. In a previous study, the RF model achieved an AUC of 0.898 in predicting bone cement leakage, along with a precision of 93.6% and a recall of 85.0%.

Utilizing a web-based calculator with this algorithm can effectively prevent complications following PVP and assist surgeons in making informed decisions[103]. By employing AI, predictive models for bone cement leakage following single-level PVP can effectively handle clinical data, refining the model structure with intersection methods for greater conciseness. The ML process also identifies factors such as age, gender, and thoracolumbar kyphosis as risk factors for bone cement leakage[104]. Through deep learning, clinicians can detect patients with a high risk of cement leakage in advance and take corresponding measures in time, which has a great guiding role in clinical practice.

Conclusions and future directions

Intelligent and precise orthopedic technologies represent the future direction of modern orthopedics, driving the diagnosis and treatment of OVCFs toward increasingly personalized, minimally invasive, precise, and intelligent approaches. While current navigation systems are relatively advanced, each has its own limitations and challenges. In the years to come, research is expected to focus on developing minimally invasive, radiation-free, and multimodal navigation solutions, which will enhance both safety and efficiency. Meanwhile, 3D printing for making preoperative planning models and intraoperative navigation templates has demonstrated potential in enhancing clinical results and speeding up the move toward personalized medicine. Additionally, emerging from interdisciplinary cooperation, surgical robotics embodies the ideals of precision medicine and is poised to become a central focus in orthopedic advancements. Furthermore, the seamless integration of mixed reality technology with navigation and robotics is expected to enhance the capabilities of spinal surgery, providing more dynamic and interactive solutions. Moreover, it is recognized that cement viscosity plays a critical role in cement leakage. However, to date, no published research has applied AI to optimize cement viscosity in the context of OVCF. This remains a promising area for future research, particularly as AI continues to advance procedural precision. With the ongoing development of AI technologies, orthopedics will see increased advantages from AI's quick diagnostic and prognostic capabilities, which help in the early detection and long-term management of OVCFs. However, many of these technologies are still in the early stages and lack validation from large-scale clinical trials, which need further prospective studies to confirm their effectiveness. In the future, AI will not only help make more accurate, personalized treatment plans but also collect data from different hospitals. As scientific and technological innovations continue to evolve and as various digital applications become more deeply integrated into clinical practice, patients will experience significantly improved care. Ultimately, these innovations will drive progress in orthopedics and play a role in the overall transformation of healthcare.

Ethical approval

Not Applicable.

Consent

Written informed consent was obtained from the patient for publication and any accompanying images. A copy of the written consent is available for review by the Editor-in-Chief of this journal on request.

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Author contributions

W.Z. and Q.M.: wrote the manuscript; C.S. and J.Z.: supervised the study.

Conflicts of interest disclosure

The authors declare no conflicts of interest.

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