AI and machine learning in paediatric spine deformity surgery

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Paediatric spine deformity surgery is a high-stakes procedure. It demands the surgeon to have exceptional anatomical knowledge and precise visuospatial awareness. There is increasing demand for precision medicine, which rapid advancements in computational technologies have made possible with the recent explosion of AI and machine learning (ML). We present the surgical and ethical applications of AI and ML in diagnosis, prognosis, image processing, and outcomes in the field of paediatric spine deformity.

Take home message

- The role of AI and machine learning in paediatric spine deformity surgery remains in its infancy, but has the potential to revolutionize the delivery of individualized surgical healthcare with superior diagnostic accuracy and surgical precision.

Introduction

Clinical medicine is on the precipice of embracing a new era in healthcare delivery. Rapid advancements in computational technologies have enabled and created a demand for precision medicine. Acquisition of data in digital format has become routine, driving the recent explosion in AI and machine learning (ML)-based healthcare applications. The potential use of AI and ML in spine deformity surgery includes diagnostics, prognostics, image processing, and outcomes with the capability to offer patient-specific treatment, transforming our approach to surgical decision-making and practice.

Concepts and definitions

AI is an umbrella term encompassing numerous disciplines including logic, statistics, cognitive psychology, decision theory, neuroscience, linguistics, cybernetics, and computer engineering (Figure 1).[1-3] It can be defined as using computational methods to replicate human intelligence.[4] The term was first coined in 1956 as part of a proposal at Dartmouth College research workshop in New Hampshire.[5] The Turing Test, developed by Alan Turing in 1950, is an assessment method currently used to determine the computational intelligence of machines.[6] To satisfy the Total Turing Test (TTT), a machine must exhibit intelligence equivalent to or indistinguishable from human intelligence across six domains (Table I).[4,7-10] Machine competence can be subdivided into strong AI (actual thinking) or weak AI (simulated thinking), which is the current form of AI today.[4]

The role of AI in surgery was first explored in 1976 by Gunn,[11] who attempted to diagnose acute abdominal pain using computer analysis. Advances in computer technologies have not only supported the successes of modern medicine, but also unveiled deficiencies in our ability to tackle the rising number of increasingly complex clinical problems. AI is superior to current computational methods in the acquisition and analysis of large-volume, highly complex datasets. It has received global attention for its ability to rapidly generate accurate and reliable predictive models. As a result, the potential applications of AI in spine deformity surgery have sparked academic curiosity among surgeons and healthcare professionals.

ML is a branch of AI that utilizes computer algorithms to examine data for patterns and construct intelligent predictive models.[1,2,4,12,13] The resulting output represents the algorithm's understanding of complex relationships, which are presented in either linear or non-linear format.[14] The algorithm is graded according to its ability to discriminate (prediction accuracy) and calibrate (margin of error) as a measure of

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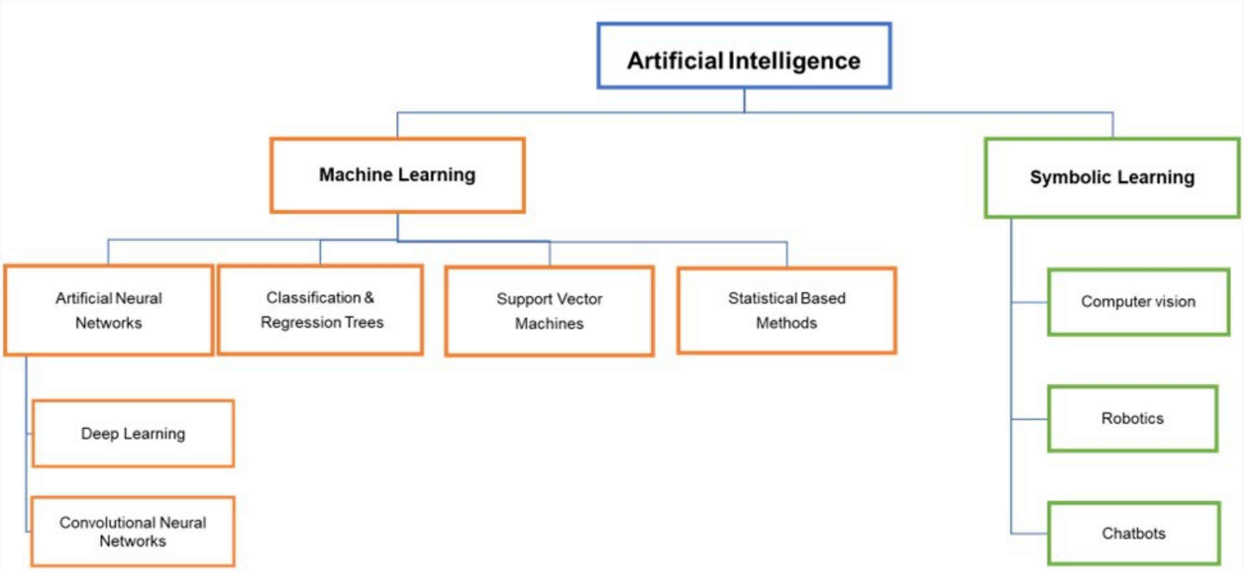

Fig. 1
Schematic overview illustrating the major branches of AI and machine learning.[3]

Table I. The machine is examined across six domains to satisfy the Total Turing Test.

Total Turing Test
1. Language processing (ability to understand speech)
2. Knowledge representation (ability to store information it knows or hears)
3. Automated reasoning (ability to recall stored information to answer questions)
4. Machine learning (pattern recognition and ability to adapt to dynamic environments)
5. Computer vision (derive information and understanding from images and video)
6. Physical interaction (interpretation of human senses with appropriate or adaptive responses)

performance.[15] The two main types of ML are supervised learning (SL) and unsupervised learning (UL) (Figure 2).

SL: the ML algorithm is trained on a subset of data with known labels predetermined by a human expert.[14,16] For example, a specific number of coronal spine radiographs selected from a database are prelabelled as having either 'scoliosis' or 'no scoliosis'. Machine analysis is performed on this training dataset to evaluate the relationship between independent variables (i.e. image pixel) and dependent variables (e.g. presence or absence of 'scoliosis') to build a predictive algorithmic model. The unlabelled or untrained dataset can then be studied to assess the machine's ability to predict outcomes (e.g. presence or absence of 'scoliosis'), which is graded based on accuracy and reliability.

SL is best suited to linear classification (LC)- or linear regression (LR)-based tasks, and commonly utilizes classification and regression tree (CART) and support vector machine (SVM) models. A potential disadvantage of SL is that larger-volume datasets would require more time and resources to ensure accurate labelling for machine training.[17]

CART: CART is an umbrella term encompassing decision trees (DTs) and random forests (RFs) used to describe a SL technique which provides a visual assessment of potential decisions at each stage in the form of a flowchart representing branches of a tree.[14,18,19] Multiple pathways that are non-critical or redundant are removed or 'pruned' to reduce overall DT complexity, which is termed 'over-learning' (Figure 3).[20] A RF is an ensemble of many DTs which help improve predictive accuracy. CART can be used to predict classification and regression problems, for example readmission rates, patient-reported outcomes, and surgical complications. Most recently, Dandurand et al[21] reported 82% accuracy of a CART model in appropriately recommending surgery in thoracolumbar burst fractures.

Supervised vector machines (SVMs): SVM is a SL algorithm used for classification and regression tasks.[14] They are most frequently used for text classification, pattern recognition, image analysis, and language processing tasks.[3,14] It works on the principle of separating data points into two groups, which are separated by a boundary called the hyperplane. Simplified, SVM is a predictive algorithm used to generate information on new data points depending on which side of the hyperplane they exist, without requiring the use of expensive computational calculations.[14]

UL: a training dataset primed by a human expert is not required for UL, which is a major advantage of this method but is potentially more vulnerable to inaccuracies. The algorithm attempts to elucidate patterns without any guidance by clustering unlabelled datasets based on their similarities or differences. This is based on the Hebbian theory of neuroplasticity, which stipulates the synaptic pathways between two neurones are strengthened with increasing stimulation, allowing humans and animals to learn relationships by association.[22-24] The UL algorithm can be used to construct artificial neural networks (ANNs) and represents the future of ML in surgery.[3,14,17,25]

ANN: ANN is an adaptive system comprising multiple layers of interconnected nodes modelled on the intricate

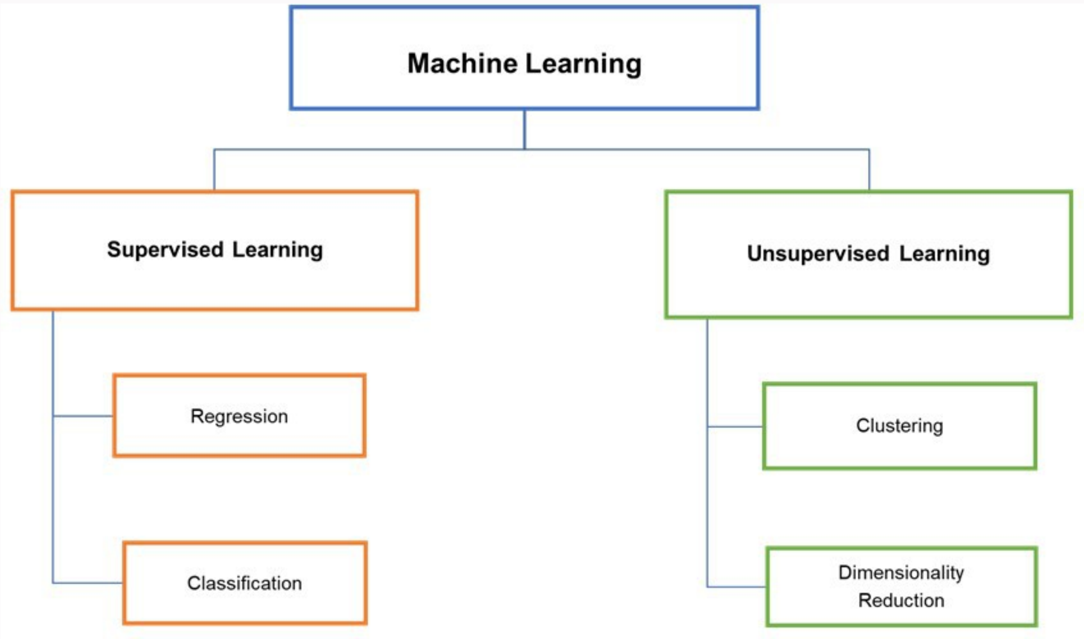

Fig. 2
Hierarchy of machine learning methods.[16]

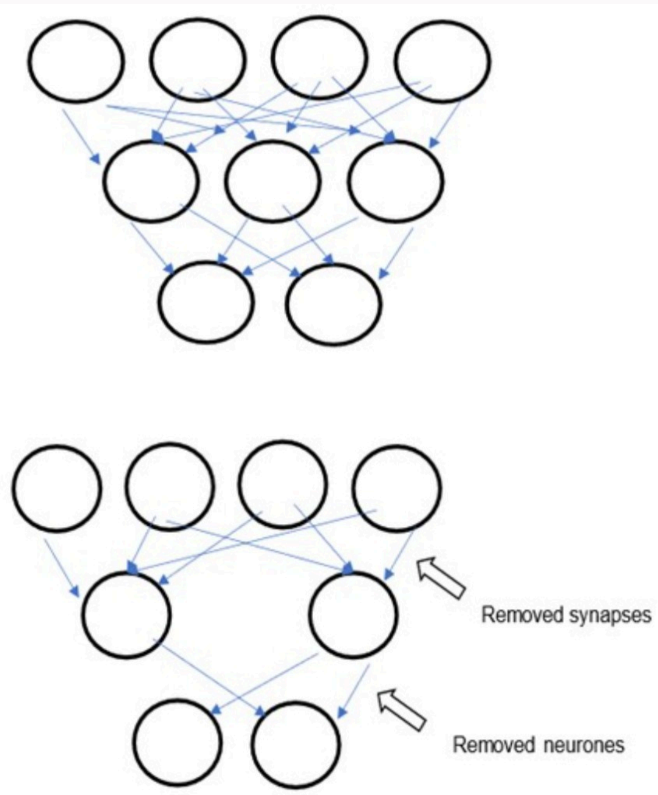

Fig. 3
Before pruning and after pruning used in classification and regression tree (CART).

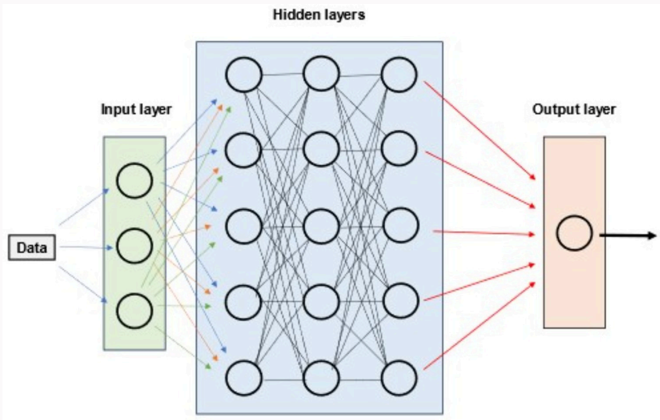

Fig. 4
A schematic illustration of a neural network with multiple hidden layers.

structure of the human brain.[3,26] Each node or 'computer neurone' learns from data by mathematically adjusting the probability weights between nodes. The directional flow of information travels from a starting input layer to a final output layer through a hidden layer in a simple ANN (Figure 4).[17,25,26]

ANNs with multiple hidden layers are termed 'deep learning neural networks'.

Convolutional neural networks (CNN): CNNs are a multilayered subtype of ANNs that are best suited for image, voice, and audio recognition algorithms.[26] They have been designed based on sensory neurones found in the visual cortex of animals, which are adept at successively processing tiny bits of information to construct an overall impression.[14,26] CNNs with multiple hidden layers are particularly adept at computer vision tasks, classically illustrated by the ability to identify a dog in a photograph.[14] Computationally, this is challenging as machines can only interpret pixels in an image, unlike humans, who have the ability to recognize an object regardless of orientation, environment, and variations in pose. Computer vision has vast potential in the future of spine surgical assistance, but the technology required to accurately interpret and reconstruct the spine, including deformities in 3D, is in its infancy.[27-29]

Natural language processing and large language models

Natural language processing (NLP) is a branch of generative AI that uses deep learning algorithms to interpret, analyze, and translate human language.[30,31] The algorithm is trained on large labelled datasets and is used to produce summaries, classifications, and translations. The applications of NLP in healthcare include aggregation and analysis of large patient databases such as clinical medical records.[31] This would significantly reduce time devoted to non-clinical workload as well as permit efficient extraction of clinical data useful for classification systems and diagnostic scoring tools.[31-34]

Large language models (LLMs) are a subset of NLP which specifically focuses on language comprehension and generating human-like content. They have the ability to deliver comprehensible and medically accurate information to patients and their families tailoring their response to users' knowledge base and emotional state.[35] This would provide crucial education for patients and families and, as a result, improve treatment compliance.

Modern chatbots are an example of generative AI language models. Zaidat et al[36] validated the use of popular LLM ChatGPT-4 in predicting codes of medical procedures undertaken from operation notes, thereby reducing coding errors. Similarly, Fabijan et al[37] demonstrated LLMs could be used to classify single-curve scoliosis based on radiological descriptions with high precision and consistent inter-rater agreement. Generative AI algorithms also have the capability to simultaneously analyze both textual and imaging data referred to as contrastive language-image pretraining (CLIP).[38,39] Fabijan et al[37] demonstrated that their CLIP model could perform a basic assessment of spinal radiographs showing severe scoliosis with high sensitivity.[40]

Traditional statistics compared with AI and ML

With increasing use, it is imperative surgeons become familiar with the nuances of AI technology and ML techniques. Statistics emerged from the field of mathematics, whereas ML methods emerged from computer science. Classical statistics essentially infers relationships between variables. It relies on a top-down approach to determine correlations where the hypothetical relationship between input variables, and output is assumed and often simplified.[41] This works well for specific hypothetical questions and a finite number of variables; a growing multivariate analysis reduces statistical power.[42] Furthermore, an optimal statistical model must be selected to ensure predictive accuracy.

In contrast, ML models essentially aim to predict the relationships between variables by forecasting outcomes without interrogating the potential existence of relationships. They are well suited to determine associations and correlations that may remain hidden due to their complexities and multifaceted origin. They are a bottom-up approach, purely data-driven rather than user-chosen, primarily focused on producing a predictive algorithm.[41] This avoids selecting and applying the wrong statistical model. Some of the limitations of ML are the clinical interpretability, utility, and applicability of such models, as they are prediction-focused, rather than relationship-focused.[41]

The main advantage of ML methods in data analysis is that the results can be applied prospectively during clinical practice and tailored specifically to individual patient needs rather than reporting generalized population estimates.[1,2] Paediatric spine deformity surgery is a prime example where surgical decision-making and patient outcomes are influenced by several factors including disease pathophysiology, imaging, and data published from heterogenous populations.

Paediatric spine deformity surgery applications

There has been a recent surge in the volume of research undertaken focusing on the potential applications of AI and ML to enhance preoperative planning, intraoperative guidance, and postoperative care in spine deformity surgery. However, studies in the paediatric population remain sparse.

Imaging segmentation, recognition, and analysis

Assessment of spinal imaging is critical to define patient-specific anatomy and complete quantitative measurements (e.g. Cobb angle), both of which underpin operative planning and treatment selection. Manual image analysis can be a time-consuming process prone to human inaccuracies. ML algorithms can automate these measurements, which can be used to triage patient suitability for surgery,[43-47] operative decision-making,[48,49] predicting blood transfusions,[47,50] and postoperative outcomes,[51-60] as well as to guide pedicle screw placement.[55,61] Algorithmic applications of frequently obtained radiological spinal imaging may provide additional information on bone quality and mineral density which may prove to critical to surgical planning.[62,63]

Screening: The ability of AI and ML algorithms to extract key information quickly makes them an invaluable screening tool, facilitating prompt diagnoses and early intervention across a wide spectrum of spine deformities.[64-66] Topographical assessment of unclothed backs for spine deformity diagnosis or scoliosis progression is one application as a screening tool which would reduce referral burden, economic costs, and radiation exposure.[67,68] A SVM displayed an accuracy of 69% to 85% in predicting the severity of idiopathic scoliosis based on surface topography from imaging of 111 human backs.[67] A deep learning algorithm was superior to a human expert in detecting scoliotic curves ≥ 20° and classifying their severity.[68] A CNN screening program demonstrated superiority in predicting the anatomical position, vertebral rotation angle, and Cobb angle from the interpretation of Moiré topography (3D surface description of the trunk with band patterns) in comparison to measurements performed by doctors.[69] More recently, a neural network analysis of ultrasound images has been used as a scoliosis screening tool with promising results.[65]

Automatic evaluation of spine deformity parameters: Radiographs remain the gold standard in the investigation to primarily quantify the magnitude of curve deformity as well as exclude any obvious congenital vertebral anomalies. Automated algorithms have been created to determine landmarks for the acquisition of coronal and sagittal parameter measurements. Initial studies demonstrate excellent intra and inter-measure reliability in angular and linear measurements using novel semiautomated measurement software in adult scoliosis patients.[70] A pre-trained CNN algorithm evaluating 990 standing lateral radiographs (542 on individuals aged < 18 years) reported a detection rate of 97% and 87% within 5 mm of the cervical (C)7 vertebral body and sacrum, respectively.[71] This program (ResU-net) also demonstrated excellent consistency in the automatic measurement estimates of the sagittal vertical axis (SVA) compared to physician measurements with an intraclass correlation coefficient (ICC) ranging from 0.946 to 0.993.[71]

Two methods are employed for automated quantitative analysis of spinal curvatures.[72-75] Segmentation-based methods extract anatomical information from imaging by assessing pixels region by region and then undertaking the relevant parameter measurements.[76-79] Advancement in deep learning algorithms, such as various U-net models, have seen significant improvement in segmentation accuracy and measurement precision.[80-82] Direct estimation-based methods rely on the identification of major landmarks on spinal imaging to measure deformity parameters without the need for segmentation. Models such as ResU-Net, BoostNet, MVC-Net, and MVE-Net utilize this methodology and have demonstrated high reliability in quantifying spinal deformity indices.[71-7375,,83] A 5° variation in Cobb angle measurements has been universally defined as the limit of acceptability.[84,85] Despite this, the mean errors in Cobb angle measurements have been reported to be as high as 11.8° for congenital scoliosis.[86] The sources of error may be attributed to imaging hardware, software measurement tools, and subjective human error in selecting upper and lower vertebral endplates.[75]

Computer-assisted algorithms are considered superior to manual methods as they remove subjective errors, thereby enhancing reliability.[75,87-91] Both automated image segmentation and direct estimation algorithms provide high accuracy without time-resource constraints.[73-75,91] However, both methods described above face challenges posed by poor-quality imaging and are inadequate in the assessment of spine deformity in three dimensions. The creation of novel preprocessing algorithms and use of imaging captured in multiple planes appear to have solved this problem.[75,92,93] Despite this, the clinical application of automated qualitative estimation obtained from 3D cross-sectional imaging is lacking and will remain dependent on user bias.[73,75] Current studies have not evaluated comparative performance between segmentation and direct estimation-based methods, and future improvements will likely require AI integration of both systems.

Intraoperative guidance

Navigation: Accurate implant positioning is a vital component of paediatric spine deformity correction and CT navigation is recommended.[94] Pedicle screw malposition can potentially lead to disastrous complications including neurological injury, vessel penetration, fracture, and inadequate biomechanical stability. Despite advancement in navigational technology, freehand pedicle screw fixation remains common surgical practice due to being a familiar cost-effective technique requiring minimal hardware, resources, and training time. Consequentially, more emphasis has been placed on obtaining intraoperative confirmation of satisfactory implant position. This can become monumentally difficult to achieve in spines with rotational deformity.

Cadaveric studies report a 73% to 83% accuracy rate in confirming satisfactory pedicle screw position using radiographs with unacceptably high false-positive and false-negative rates, attributable to the lack of 3D capabilities.[95-97] Interestingly, these studies failed to describe criteria standardized to evaluate radiological screw position with an aim to improve interpretation.[98] Intraoperative CT scanning or 3D fluoroscopy has demonstrated improved accuracy, but at the expense of greater exposure to ionizing radiation, time-consuming setup, and extremely sensitive calibration.[99-105]

To compensate for these limitations, there has been an increased focus on segmentation-based ML methods designed to virtually construct the spine in 3D and guide implant placement.[106-108] These ML algorithms have been applied to images generated from 2D intraoperative fluoroscopy with substantially improved precision and reproducibility.[109-111] Burstrom et al[112] developed a system for automatic segmentation of the spine using a ML algorithm trained on cone-beam CT (CBCT) imaging of 21 cadaveric specimens. Compared to manual segmentation methods, their ML algorithm demonstrated 95% accuracy (86% if severe spinal deformities were included) with a mean time of 11 seconds for automatic segmentation and screw planning.

Robotics: The emergence of robotic-assisted surgery (RAS) is a relatively new technological concept, advertised as significantly boosting the accuracy rates of pedicle screw placement while reducing radiation exposure, operating time, and blood loss.[113-127] Two major advantages of RAS over current navigation techniques include the theoretical elimination of human error caused by uncontrolled hand tremors and reduced equipment assembly time.[113-115,122]

However, robotic assistance is ultimately controlled by the surgeon and heavily influenced by a time-dependent learning curve.[121] Integration of AI into robotic spinal surgery would mitigate such challenges, with the aim of eventually becoming an automated service.[128] Robotic autonomy is a spectrum ranging across five levels in order of decreasing human input from zero automation to complete automation.[128] The workflow of RAS incorporates multiple stages, and presently there is active research on integrating AI at each one of these stages.[114,115] This includes enhanced surgical field visibility, native tissue recognition with instrument delineation, and tactile sensation.[128]

Robotic assistance permits deep anatomical access via a small incision, and adjunctive AI algorithms have been used to enhance real-time intraoperatiove visualization by elimating blur, correcting colour, and removing ligation-assocatied smoke.[129,130] Native tissue recognition is a broad category where AI is being evaluated in better delineating safe dissection planes,[131] optimal oncological margins to prevent cancer recurrence,[132-134] and accurate detection and differentiation of instruments in robotic-assisted surgery (RAS).[135,136] The majority of these advancements are dependent on the robots' ability to translate haptic feedback into tactile sensation to appreciate subtle changes in native tissue or synthetic material resistance.[137-139]

Research into RAS is progressing in a stepwise manner, with a focus on using AI to undertake certain tasks automatically to reduce the physical and mental workload associated with complex surgery.[128] Currently, autonomous robotic surgery remains a concept of the future.

Surgical training and virtual operative assistance: The accepted definition of virtual reality (VR) is "a real or simulated

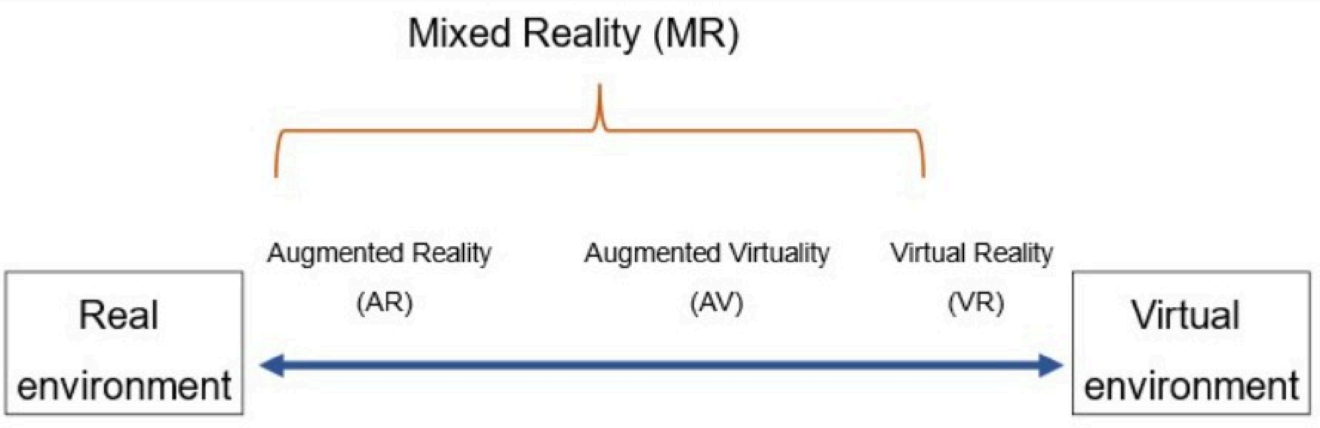

Fig. 5
The virtual continuum spectrum.[144]

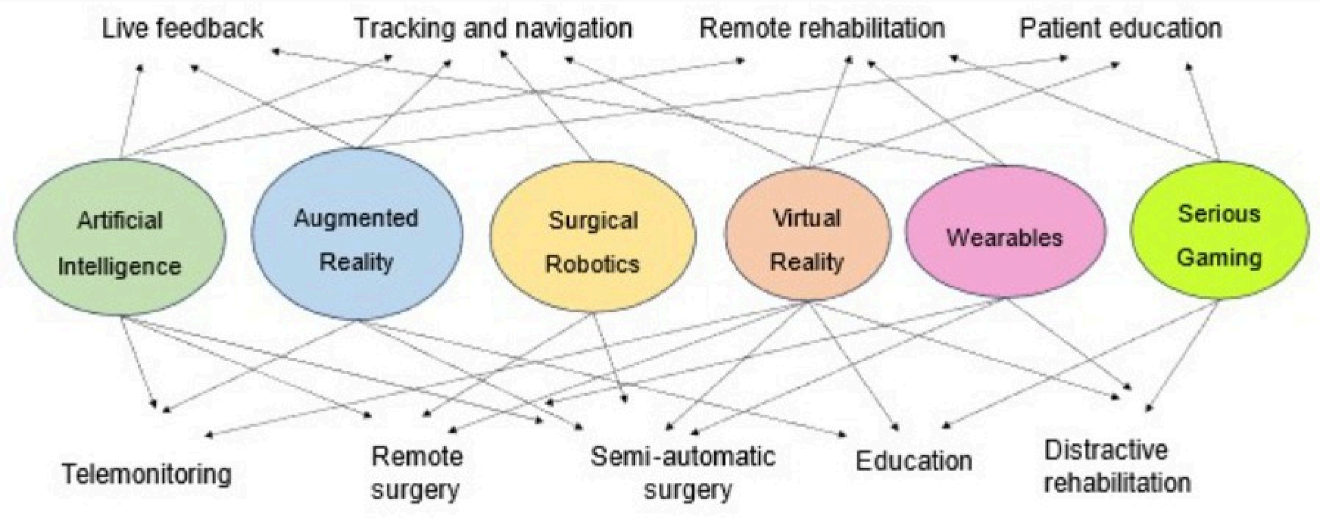

Fig. 6
Potential integrations and applications of virtual and augmented reality.

environment in which a perceiver experiences telepresence", which is essentially the subjective experience of being fully immersed in an interactive virtual environment.[140] Conversely, augmented reality (AR) describes technological integration of virtual reality with the user's environment to enhance the senses of sight, touch, hearing, and smell in real time (Figure 5).[141,142] We believe mixed reality (MR) represents the future of AI in healthcare, especially surgical training.[143]

Presently, achieving operative competence relies on repetition, pattern recognition, and successfully completing an apprenticeship-style training pathway.[31,143,145,146] Surgical simulation has become a useful adjunct for trainees to aquire specific operative skills in an era with reduced operative exposure and economic restrictions.[147] However, simulation remains slow to evolve, limited to based tasks, and unable to replicate the complexities of actual surgery.[128] A virtual operative assistant, which integrates AI and mixed reality, represents the evolution of simulation training providing surgeons and trainees with an accurately rendered layer of 3D anatomical information.[143,148,149] Siemionow et al[150] developed an AR-assisted ML system that faciliated accurate pedicle probe placement at all 24 vertebral levels by overlaying a 3D spinal image onto cadavers.

By gathering data and providing personalized feedback, integrated AI software systems could be used to track skill improvements and compare these to predetermined benchmarks,[151] the main advantage being objective assessment and critique while negating patient risk and reliance on the traditional 'apprenticeship' training framework.[31,143] Evidence suggests that AR-based surgical navigation systems are superior to freehand, computer-aided, and robotic-assisted techniques.[139,152–159] Integration of AI into AR-based overlay technology has real-time operative applications in spine deformity surgery. It can significantly aid preoperative planning and intraoperative execution by highlighting anatomical landmarks, guiding osteotomy cuts, enhancing patient-specific rod-bending, and facilitating implant positioning compared to a predicted vision of final alignment.[160–162]

The lack of tactile feedback, restricted field of view, headaches, blurred vision, and dizziness are the main limitations of VR and AR technologies.[163] The costs of

Table II. Clinical Practice Integration of Artificial Intelligence (CPI-AI) framework, adapted from Farrow et al (2024).[189]

CPI-AI framework stage	Summary
0: Concept outline	• Conceptualization of the AI algorithm. • Include feasibility, literature review, safety profile, theoretical implementation, and data security. • Involve a team of AI experts, clinicians, patients, and policymakers.
1: Algorithm development	• Development of an AI algorithm to test proof of concept. • Typically involve a single/multicentre study to develop the AI tool in accordance with AI-reporting guidelines.
2a: External validation	• Testing the AI algorithm using an external dataset which is different to the training dataset. • Ensures AI algorithm is effective within different populations.
2b: Prospective assessment	• Prospective assessment on the feasibility of implementing the AI algorithm into clinical practice. • Enable testing, modification, and performance evaluation of the AI algorithm without impacting clinical decision-making in accordance with AI reporting guidelines.
3: Clinical impact assessment	• Formal assessment of the AI algorithm on clinical practice using standardized methodology on a large population such as multicentre randomized controlled trial. • This would be in accordance with AI reporting guidelines.
4: Implementation and model surveillance	• Implementation of the AI algorithm with assessment of its clinical effectiveness, economic viability, and widespread adoption.

CPI-AI, Clinical Practice Integration of Artificial Intelligence.

investment, mentorship, maintenance, and assimilation of these technologies into existing surgical workflow processes, including staff training, are additional obstacles to availability, even if long-term routine use potentially offsets initial economic burden by improved surgical outcomes.[149,160,164–166] The integration potential of VR and AR into newly emerging healthcare technologies is limitless (Figure 6).[163] Research studies focused on validating and improving this technology with an assessment of reproducibility and reliability are required.

Management guidance and predictive prognosis

AI and ML models can provide adjunctive aid in treatment planning, operative strategy, and predicting clinical challenges.

Classification systems: Incorporating AI and ML image recognition software, with scoliosis classification systems, from large datasets to prompt early diagnosis and treatment. The use of a decision tree for Lenke curve determination improved classification accuracy from 77.2% to 92.9% ($p = 0.005$) without requiring addition time.[167] A CNN has been developed and validated to automatically assess radiographs to classify scoliosis rapidly, accurately, and reliably.[168]

The rising demand for modernizing classification systems to incorporate the 3D spinal alignment has escalated as advanced imaging technology becomes more readily available. Pasha et al[169] showed that their novel 3D preoperative cluster classification was more accurate than the Lenke classification in predicting postoperative spinal shape.

Predicting curve progression: Appropriate management relies on accurately predicting the rate of curve progression which, in children, has an intimate relationship with remaining skeletal growth and peak height velocity. Yahara et al[170] have designed a deep learning CNN algorithm to predict the risk of adolescent idiopathic scoliosis (AIS) progression with an accuracy of 69% compared to diagnostic accuracy of 47% by five blinded spinal surgeons. The algorithm was trained on a population of 58 AIS patients divided into two groups. The progressive group (Cobb angle increase > 10° within two years) comprised 28 patients (23 females, five males; mean age 12.2 years (SD 1.6)). The non-progressive group (Cobb angle increase < 5° within two years) comprised 30 patients (26 females, four males; mean age 12.8 years (SD 1)). It was postulated that Cobb angle changes between 5° and 10° within two years were attributable to postural changes and therefore those patients were excluded from the study. The images were divided into six regions: the upper to middle thoracic spine; lower thoracic spine; lumbar spine; lung; abdomen; and iliac.

Wang et al[171] designed a deep learning CNN algorithm to differentiate between progressive (Cobb angle increase ≥ 6° or cobb angle ≥ 25° at skeletal maturity) and non-progressive (Cobb angle < 6° or < 25° at skeletal maturity) AIS curves at first clinic presentation. This retrospective cohort study evaluated 490 patients between October 2015 and April 2019 with mild AIS curves (11° to 30°) and Risser grade ≤ 2. Patients with non-progressive curves receiving brace treatment were excluded. They hypothesized that features identifying asymmetry from coronal posteroanterior (PA) radiographs, such as rotation, would suffice for prediction of progressive curves. The ML algorithm was trained on 328 radiographs obtained at initial clinic visit and at skeletal maturity or prior to surgery. The algorithm was scrutinized by trained assessors on an independent testing cohort (110 patients) and underwent cross-platform validation (52 patients). This algorithm was able to predict curve progression from a coronal radiograph obtained at first clinic visit with 76.6% accuracy, 75.2% sensitivity, and 80.2% specificity upon independent testing. Cross-platform performance on standard standing PA radiographs yielded an accuracy of 77.1%, a sensitivity of 73.5%, and a specificity of 81.0%.

In a similar study, a RF algorithm was employed to general a model predicting temporal changes in spinal shape from first visit in 150 AIS patients.[172] Curve progression was learned using 3D spinal models generated from retrospective coronal and sagittal spine radiographs. The estimated change in shape differed from actual curvatures by Cobb angles of 1.8°, 5.2°, and 4.8° in the proximal thoracic, main thoracic, and thoracolumbar lumbar sections, respectively.

Predicting the rate and severity of scliotic curve progression accurately directly impacts management, decision-making, and prognosis. Current studies are promising, but solely concentrate on radiological assessment. Eventually, AI models will need to incorporate clinical parameters to generate powerful patient-specific predictions. A major application would be on the utility, timing, and effectiveness of brace treatment, which the literature lacks.

Fusion levels: Mezghani et al[173] investigated the relationship between Lenke classification and fusion regions using an ANN applied to a database of 1,776 surgically treated AIS patients. When reviewed retrospectively, overall agreement was 88%. This pretrained ANN was modified using self-organized maps to predict an individual surgeon's preferred fusion levels with extremely high accuracy (topological error 0.02).[174] It is critical to note that operative planning guidance is offered by several scoliosis classification systems, and their application is surgeon-specific and highly variable. Therefore, routine use of AI and ML technologies to select fusion levels is currently limited and must be approached with caution.

Predicting outcomes: AI and ML models have been designed to analyze vast datasets to build predictive models to assist surgical decision-making, set realistic expectations, and improve patient satisfaction. Traditional studies rely on multivariate linear regression statistical analysis to identify and evaluate specific clinical and radiological parameters.[175,176] This is subject to various inaccuracies, inconsistences, and is not patient-specific. Studies integrating statistical AI models will revolutionize data intrepretability and applicability, especially when counselling prospective patients on the likelihood of long-term complications. A major example is the ability to predict proximal junctional kyphosis (PJK) and failure risk, which is associated with pain and poor quality of life following scoliois surgery.

Peng et al[177] designed a RF alogorithm to predict the risk of PJK following surgery in 44 patients diagnosied with Lenke 5 AIS. They demonstrated an accuracy of 90.9% with area under the curve (AUC) of 0.944. The algorithm was trained using two validated oversampling statistical techniques to balance the inequality between the PJK group (ten patients) and the non-PJK group (34 patients). The random oversampling method duplicates some of the original samples in the minority group, whereas the synthetic minority oversampling techique (SMOTE) generates new samples by interpolation.

The use of predictive models can be expanded to simulate the possible improvements in minimal clinically significant differences in patient-reported outcome measures (PROMs) depending on the treatment. Ames et al[58] developed a model based on the Scoliosis Research Society-22R (SRS-22R)[178] questionnaire to forecast the scores at one and two years postoperatively in the ASD population. Predicting the degree of improvement in PROMS offers personalized preoperative counselling and treatment strategy, although this would be challenging to enrol in the paediatric population.[58,179]

Postoperative monitoring and rehabilitation

The integration of AI and smartphone technology has the potential to revolutionize postoperative care. This would enable collection and tracking of patient data such as vital observations, as well as engagement with prescribed therapies.[30,180] This would also allow clinicians to be alerted if certain thresholds were not being attained.[181] The aim of postoperative monitoring using AI would be to reduce readmission rates by designing individualized rehabilitation regimes and personalized educational modules.[31]

Genetic studies

Studies have identified scoliosis susceptibility genes and genes associated with promoting curve progression.[182] Recently, ML algorithms have been employed to analyze and validate a dysregulated key gene set in osteoarthritic cartilage that is capable of accurately diagnosing osteoarthritis.[183] There is huge scope for the use of AI and ML in future genetic studies in identifying individuals susceptible to scoliosis, as well as predicting severity of deformity progression.

Ethics, safety, and limitations

Advances in computational AI and their broad-ranging applications are evolving at rapid pace.[31] However, this technology in healthcare is in its infancy. Current limitations of AI and ML models include misdiagnoses and inaccuracy, lack of data collected from diverse clinical environments, limited generalization, and economic challenges.[31,73,184] Furthermore, we have grave concerns regarding the data biases inputted into AI algorithmic models and the lack of ethical frameworks guiding AI implementation in healthcare ensuring secure access to confidential patient data.[31,184–189] Finally, it is imperative that we investigate patients' and healthcare professionals' perception of AI-based clinical decision-making.[31,184,189,190] Farrow et al[189] have developed the five-stage Clinical Practice Integration of Artificial Intelligence (CPI-AI) framework to assist in merging AI and ML into clinical practice (Table II). This framework is based upon the IDEAL principles, which are used to govern the integration of surgical technologies, innovation, and safety.[191]

In concluson, paediatric spine deformity surgery is high-risk and demands the surgeon to have exceptional anatomical knowledge and precise visuospatial awareness, especially when instrumenting the spine. Despite our best intentions, challenges exist and complications occur. Therefore, there is a role for AI and ML as potential future partners in improving surgical outcomes and safety.

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