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# Artificial intelligence in preoperative brain mapping for functional neurosurgery: A narrative review of current evidence and clinical limitations

**Kimia Kazemzadeh***

Network of Neurosurgery and Artificial Intelligence (NONAI), Universal Scientific Education and Research Network (USERN), Tehran, Iran

## Abstract

Preoperative brain mapping localizes eloquent regions before tumor surgery. The goal is to maximize resection while avoiding permanent deficits. Conventional techniques—navigated transcranial magnetic stimulation (nTMS), functional magnetic resonance imaging (fMRI), and magnetoencephalography (MEG)—have well-known limitations: patient cooperation requirements, acquisition variability, and interpretation challenges. nTMS combined with tractography predicts motor deficits better than fMRI in most comparative studies, because fMRI is prone to false signals from neurovascular uncoupling and co-activation of non-essential areas. MEG offers good spatial accuracy but is expensive and technically complex. Artificial intelligence (AI) can automate segmentation, integrate multimodal data, and improve functional localization. Early studies report increased mapping precision. Real-time AI-assisted neuronavigation, robotics integration, augmented/virtual reality, and explainable AI models are under development. But challenges remain: data heterogeneity, lack of external validation, and unresolved ethical and legal issues. Large-scale multicenter studies and prospective AI-driven trials are missing. Most published evidence is retrospective and single-center. This review synthesizes current AI applications in preoperative brain mapping, identifies what works and what does not, and argues that rigorous validation—not hype—will determine whether AI truly advances precision neurosurgery.

***Keywords:*** Brain mapping; Artificial intelligence; Neurosurgery; Deep learning; Preoperative planning; Navigated transcranial magnetic stimulation; Functional magnetic resonance imaging

***Corresponding author:**
Kimia Kazemzadeh
(kimia_kazemzadeh@yahoo.com)

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## 1. Introduction

Preoperative brain mapping identifies eloquent cortical and subcortical regions before tumor surgery. The goal is to maximize resection while avoiding permanent neurological deficits. fMRI is the most commonly used non-invasive modality for motor, sensory, and language mapping. Accurate localization reduces intraoperative mapping time and guides safer surgical approaches.[1-3] In epilepsy surgery and neuro-oncology, brain mapping also helps assess risks like memory impairment and motor deficits.[4]

Task-based functional magnetic resonance imaging (fMRI) needs patient cooperation. This limits its use in children, cognitively impaired patients, or sedated patients. [1] Other modalities— positron emission tomography (PET), magnetoencephalography (MEG), transcranial magnetic stimulation (TMS)—provide complementary information but vary in sensitivity, specificity, and accessibility.[2,4] Diffusion tensor imaging (DTI) gives white matter tract information but acquisition and interpretation vary across centers.[4] These limitations have pushed the field toward multimodal integration and artificial intelligence (AI). AI techniques (machine learning, deep learning) can automate image analysis, improve segmentation, and predict surgical outcomes.[3,5] AI also integrates multimodal imaging and clinical data, which may reduce operator dependency and enable personalized planning. However, most evidence comes from retrospective studies.

In this narrative review, we examine the role of AI in preoperative brain mapping: current modalities, AI-driven advances, and clinical evidence. We also identify challenges and future directions. The goal is a balanced view of what AI can and cannot do today.

## 2. Methods

This narrative review was conducted through a structured literature search of PubMed, Scopus, and Web of Science databases. The search period covered January 2015 to December 2025. Search terms included combinations of the following keywords: "artificial intelligence," "machine learning," "deep learning," "preoperative brain mapping," "functional neurosurgery," "navigated transcranial magnetic stimulation," "functional MRI," "magnetoencephalography," "brain shift," and "neuronavigation." Only peer-reviewed articles published in English were included. We prioritized original clinical studies with intraoperative validation (direct cortical stimulation as gold standard) and systematic reviews. Reference lists of retrieved articles were manually screened for additional relevant studies. Given the narrative design of this review, formal risk of bias assessment and quantitative synthesis were not performed. Instead, we critically appraised methodological quality and clinical validity of the included studies, with particular attention to sample sizes, external validation, and prospective versus retrospective design.

## 3. Background: Preoperative brain mapping techniques

Preoperative brain mapping aims to identify eloquent cortex before tumor surgery. The goal is to maximize resection while avoiding permanent motor, language, or sensory deficits. Four techniques are commonly used: navigated transcranial magnetic stimulation (nTMS), fMRI, MEG, and direct cortical stimulation (DCS). DCS during awake craniotomy remains the gold standard, but it is invasive and limited to the intraoperative setting.[3]

nTMS uses magnetic pulses guided by individual MRI scans to stimulate cortical regions non-invasively. A systematic review of 48 studies found good concordance with DCS for motor mapping, with spatial errors typically under 10 mm.[3] Adding diffusion tensor imaging (DTI) tractography to nTMS helps visualize corticospinal tract integrity. For language mapping, repetitive nTMS has shown negative predictive value that helps decide between awake versus asleep surgery, though accuracy varies across centers.[3,6] fMRI measures blood oxygen level-dependent (BOLD) signals as an indirect marker of neural activity. Its main strength is whole-brain coverage. But the BOLD signal depends on neurovascular coupling, which is often disrupted in high-grade gliomas and vascular tumors. This can cause false negatives (missed eloquent areas) or false positives (overestimation of resection risk).[3,7] In a study of 62 patients with perirolandic tumors, fMRI had a false positive rate of 32% for motor cortex identification compared to DCS.[8] Despite this, fMRI remains widely used because it is non-invasive and available at most centers with 3T MRI.

MEG records magnetic fields from neuronal currents. It offers millisecond temporal resolution and good spatial accuracy, comparable to DCS in some series.[3] But MEG systems are expensive, require shielded rooms, and are available only at specialized centers. A 2017 survey of 45 European MEG centers found that routine clinical MEG for presurgical mapping was available only in a minority of sites outside major academic hubs.[9] DCS performed during awake craniotomy directly stimulates the cortical surface. It is the reference standard, but it requires patient cooperation, prolongs operative time, and only samples exposed cortex.[3]

All non-invasive methods share three problems. First, tumor-induced neurovascular uncoupling reduces fMRI accuracy.[7] Second, nTMS language mapping is operator-dependent.[6] Third, brain shift—the intraoperative deformation of brain tissue after dural opening and resection—changes the spatial relationship between preoperative maps and actual anatomy, sometimes by more than 10 mm.[4] The third problem is the reason why the majority of surgeons still rely heavily on intraoperative DCS rather than preoperative maps alone. AI has been tested to address these limitations. Machine learning (ML) models can denoise fMRI signals, automate nTMS target positioning, and compensate for brain shift using

deformable registration algorithms.[3] We review the evidence for these AI applications in the following sections.

## 4. Artificial intelligence technologies in brain mapping

Most AI applications in preoperative brain mapping fall into three categories: ML for classification and outcome prediction, deep learning (DL) for image segmentation and feature extraction, and hybrid models that combine both.[10] We briefly describe each, then focus on their clinical use.

ML algorithms (support vector machines, random forests, gradient boosting) have been used to classify tissue types, predict postoperative deficits, and identify imaging biomarkers from structural and functional MRI.[10] These methods work well with smaller datasets but require manual feature engineering. DL architectures, particularly convolutional neural networks (CNNs), learn features directly from raw images. CNNs now achieve expert-level segmentation of tumors and eloquent cortex on MRI.[11,12] Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks model time-series data from EEG and MEG for seizure focus localization and functional mapping.[12] Hybrid models combine CNNs for feature extraction with gradient boosting for decision-making; they have shown better generalizability across different scanner protocols.[10] Most published models remain at the proof-of-concept stage, with limited prospective validation. The data sources are multimodal: structural MRI, fMRI, DTI, MEG/EEG, and clinical records. The evidence for specific AI-enhanced mapping modalities is reviewed in the next section. Table 1 summarizes the main AI algorithm types, their clinical applications in brain mapping, and key limitations.

In addition, Table 2 compares AI-enhanced mapping techniques with traditional methods.

**Table 1. Summary of AI algorithm types used in preoperative brain mapping, with clinical applications and limitations,**

| Algorithm | Type | Pre-neurosurgical brain mapping application | Key features & benefits | Limitations | Clinical impact / performance | Reference(s) |
|---|---|---|---|---|---|---|
| Convolutional neural networks (CNNs) | Deep learning | Automated segmentation of brain tumors and eloquent cortex regions on MRI/ fMRI; identification of critical functional areas | High accuracy in image segmentation; learns spatial features; reduces manual annotation time | Needs large labeled datasets; black box (limited interpretability); risk of overfitting | Improved delineation of tumor margins and functional areas, aiding surgical planning and minimizing healthy tissue damage | 11,12 |
| Support vector machines (SVM) | Supervised machine learning | Classification of brain tissue types and prediction of tumor infiltration zones using multimodal imaging data (MRI, DTI) | Effective with small datasets; robust classification in complex imaging modalities | Performance drops with very high-dimensional data without feature selection; kernel selection is empirical | Enhanced differentiation between tumor and normal tissue, supporting surgical margin decisions | 12 |
| Random forest (RF) | Ensemble learning | Identification and classification of neurovascular structures and lesions in preoperative imaging | Handles heterogeneous data; interpretable feature importance; reduces overfitting | Can be slow with many trees; less accurate than deep learning on very large datasets | Accurate vascular mapping critical for avoiding intraoperative hemorrhage | 5 |

(*Cont'd...*)

**Table 1. (*Continued*)**

| Algorithm | Type | Pre-neurosurgical brain mapping application | Key features & benefits | Limitations | Clinical impact / performance | Reference(s) |
|---|---|---|---|---|---|---|
| Deep neural networks (DNNs) | Deep learning | Modeling brain connectivity and predicting functional reorganization post-surgery using fMRI and DTI data | Captures nonlinear relationships; models complex brain networks | Prone to overfitting with small sample sizes; computationally expensive | Predicts potential functional deficits, improving risk assessment and patient counseling | 12 |
| Explainable AI (XAI) methods | Interpretability techniques | Providing transparent explanations for AI-driven brain segmentation and functional mapping results | Techniques like Grad-CAM and SHAP highlight important imaging regions influencing model decisions | Adds computational overhead; explanations may not fully capture model behavior; still under development | Builds neurosurgeon trust in AI outputs; facilitates clinical validation of AI-assisted surgical plans | 11,12 |
| Active learning algorithms | Hybrid human-AI | Interactive neuron tracing and anatomical segmentation in intraoperative imaging and preoperative scans | Combines AI automation with expert corrections; reduces annotation burden | Requires expert input; performance depends on quality of human feedback; not fully automated | Accelerates generation of accurate brain maps; supports intraoperative decision-making | 11 |
| Reinforcement learning (RL) | Machine learning | Optimization of robotic-assisted neurosurgical tool trajectories based on preoperative brain maps | Learns optimal surgical paths minimizing damage to critical brain areas | Needs careful reward function design; training can be unstable; limited neurosurgical validation | Enhances precision and safety in minimally invasive neurosurgery | 5 |
| Graph neural networks (GNNs) | Deep learning on graph data | Modeling and analysis of brain connectivity networks derived from DTI and fMRI for pre-surgical functional mapping | Captures complex network topology; models interactions between brain regions | Computationally intensive; requires large datasets; limited clinical validation in neurosurgery | Improves identification of critical white matter tracts to preserve during surgery | 12 |

Abbreviations: AI: Artificial intelligence; DTI: Diffusion tensor imaging; fMRI: Functional magnetic resonance imaging; Grad-CAM: Gradient-weighted class activation mapping; MRI: Magnetic resonance imaging; SHAP: SHapley Additive exPlanations.

**Table 2. Comparison of AI-enhanced mapping techniques vs. traditional methods.**

| Feature | Traditional Mapping Methods | AI-Enhanced Mapping Techniques | Key Advantages of AI-Enhanced Methods | Reference(s) |
|---|---|---|---|---|
| Imaging modalities | Task-based fMRI, resting-state fMRI, PET, MEG, DTI | AI-augmented fMRI, AI-driven multimodal integration (fMRI + DTI + MEG) | Higher spatial resolution and sensitivity, improved denoising, artifact removal, super-resolution image generation | 2,13 |
| Spatial resolution | Limited by scanner field strength (1.5T–3T), partial volume effects | Enhanced spatial resolution at submillimeter scale via AI super-resolution processing of UHF fMRI data | Significantly improved detection of brain activations and eloquent cortex localization | 13 |

(*Cont'd...*)

**Table 2. (*Continued*)**

| Feature | Traditional Mapping Methods | AI-Enhanced Mapping Techniques | Key Advantages of AI-Enhanced Methods | Reference(s) |
|---|---|---|---|---|
| Patient cooperation requirement | Requires active task performance (tb-fMRI), limiting use in pediatric or sedated patients | AI enables reliable resting-state and naturalistic paradigms (*e.g.*, passive movie viewing) with automated analysis | Allows mapping in non-cooperative or sedated patients, reducing motion artifacts and improving tolerability | 1 |
| Data processing and analysis | Manual or semi-automated analysis, prone to inter-operator variability | Automated AI algorithms for segmentation, network identification, and multimodal data fusion | Increased reproducibility, reduced human error, faster processing, and improved accuracy | 10,11 |
| Functional localization accuracy | Good but limited by noise, task compliance, and neurovascular uncoupling | AI improves signal-to-noise ratio, compensates for artifacts, and integrates multimodal data for precise mapping | Enhanced sensitivity and specificity; better prediction of eloquent areas and postoperative deficits | 2,13 |
| Integration with surgical tools | Limited integration with neuronavigation and robotic systems | AI-augmented imaging provides high-quality input for robotic neurosurgery and real-time neuronavigation | Enables safer surgical trajectories, dynamic intraoperative updates, and improved surgical precision | 5,14 |
| Clinical outcomes | Established but with variable morbidity and functional deficits | Early evidence suggests AI-assisted mapping reduces morbidity, improves extent of resection, and preserves function | Potential to decrease postoperative neurological deficits and improve long-term functional outcomes | 15 |
| Workflow efficiency | Time-consuming image processing and interpretation | AI accelerates image analysis and provides user-friendly interfaces | Shorter preoperative planning times and enhanced surgeon confidence | 10,11 |

Abbreviations: AI: Artificial intelligence; DTI: Diffusion tensor imaging; fMRI: Functional magnetic resonance imaging; MEG: Magnetoencephalography; PET: Positron emission tomography; UHF: Ultra-high field.

## 5. AI-enhanced functional mapping modalities

### 5.1. AI in navigated transcranial magnetic stimulation

Navigated transcranial magnetic stimulation (nTMS) combines TMS with real-time neuronavigation using individual MRI data. The stimulating coil position is correlated with underlying brain anatomy, which solves the spatial inaccuracy problem of older TMS methods that relied on external scalp landmarks.[16-18]

Studies comparing nTMS with intraoperative DCS (gold standard) show good spatial agreement. In a prospective study of 30 patients with tumors near the precentral gyrus, the mean distance between nTMS and DCS motor sites was 4.85 mm, with a strong correlation ($r = 0.901$, $p < 0.001$).[19] Another series of low-grade glioma patients reported an average discrepancy of 4.16 ± 1.02 mm.[16] For language mapping, repetitive nTMS combined with AI algorithms improves signal detection and reduces operator dependency, but variability remains higher than for motor mapping.[20] Clinically, this means nTMS is reliable for motor cortex localization but should be used with caution for language areas, especially in centers without dedicated expertise.

Adding DTI-based tractography to nTMS visualizes the corticospinal tract and other white matter pathways. AI-driven algorithms fuse cortical motor maps with tractography data, giving surgeons a combined functional-structural view of what is at risk during tumor resection.[20,21] Electric field modeling and AI-based coil positioning further improve stimulation precision.[21] Preoperative nTMS mapping helps decide awake versus asleep craniotomy, guides resection extent, and predicts postoperative deficits. In two clinical series, incorporating nTMS into neuronavigation reduced operative time and improved motor outcomes.[16,19] The ability to see both cortical and subcortical anatomy preoperatively supports tailored surgical strategies. nTMS performs poorly when tumors cause severe peritumoral edema or lie deep (>3 cm from cortex) because the magnetic field attenuates exponentially with distance. Most published accuracy data come from patients with superficial, low-grade tumors. This selection bias should be kept in mind when applying nTMS to high-grade gliomas or deeply seated lesions.

### 5.2. AI in functional MRI

Traditional fMRI analysis needs manual or semi-automated processing. It takes time and varies between operators. AI, especially CNNs, now automates the identification of motor, language, and sensory areas. CNN-based segmentation achieves spatial agreement with intraoperative DCS within 5 mm in most published series. This improves reproducibility and reduces subjective thresholding.[22,23]

Functional MRI false positives happen because of neurovascular uncoupling (common in high-grade gliomas), patient motion, and low signal-to-noise ratio. Several studies have applied ML classifiers (support vector machines, random forests) and DL models to denoise BOLD signals and separate true activation from noise. AI-based preprocessing has been shown to reduce false-positive clusters compared to conventional analysis methods, though the reported effect size varies by tumor type, field strength, and the specific AI architecture used.[7,22] Functional organization changes with tumors due to cortical reorganization. AI models integrate structural MRI, fMRI, and clinical data to create patient-specific activation maps that account for neuroplasticity and tumor effects. ML models predicting postoperative language deficits from preoperative activation patterns have been tested in small cohorts, showing promising but not yet validated results.[22-24] Most fMRI-AI studies exclude patients with severe motion artifacts, aphasia, or cognitive impairment—exactly the patients in whom fMRI is most needed. Reported accuracy figures likely overestimate real-world performance.

### 5.3. AI in magnetoencephalography

Magnetoencephalography (MEG) measures magnetic fields from neuronal currents. Its temporal resolution is milliseconds, better than fMRI. Spatial resolution is also good, though inferior to fMRI for deep sources.[25,26] For motor and language mapping, MEG provides direct measurement of cortical function without the neurovascular uncoupling problem that affects fMRI.[25]

MEG source localization is an inverse problem; many possible neural generator configurations can produce the same external magnetic field. Traditional methods (beamformers, minimum-norm estimates) make simplifying assumptions that may fail in tumor patients where normal anatomy is distorted. AI, particularly deep learning, has been applied to learn spatiotemporal patterns directly from MEG data. One example is DeepReducer, a linear transformer-based model trained to denoise event-related fields; it reduced source localization errors and improved signal-to-noise ratio compared to conventional trial averaging.[27] Other AI algorithms have been used to classify functional brain states and reconstruct neural sources with improved spatial precision for identifying eloquent cortex and epileptogenic zones.[25,28]

MEG systems still need superconducting sensors (SQUIDs) operating at cryogenic temperatures inside magnetically shielded rooms. Acquisition and maintenance costs are high. A 2025 systematic review noted that only one MEG system was available in South Korea (introduced in 2023), and a European survey found routine clinical MEG limited to major academic centers.[28,29] The complexity of MEG analysis also requires specialized neurophysiology and AI expertise.[27] Wearable optically pumped magnetometers (OPMs) are being developed and may lower costs and increase access, but clinical validation is ongoing.[30]

## 6. Machine learning for image analysis and brain modeling

Machine learning (ML) is now used in neurosurgery for image analysis and brain modeling. The main applications are automated segmentation, brain shift prediction, and integration with augmented reality (AR). Brain shift—tissue deformation during surgery—renders preoperative images inaccurate. Shimamoto *et al.*[31] trained a CNN on paired preoperative and intraoperative MRI from 248 patients. Their model predicted brain shift and generated updated images using only preoperative scans. The positional error was under 0.5 mm in validation, though this comes from a single center.[10,12] Boaro *et al.*[32] used a 3D CNN trained on 10,099 healthy brain MRIs and fine-tuned on 806 expert-labeled meningioma cases. The Dice similarity coefficient was 88.2%, matching human raters. This reduces inter-operator variability and speeds up planning. Other models integrate structural MRI, fMRI, and DTI to classify functional regions and white matter tracts.[10,11,33] AR overlays functional and anatomical information onto the surgeon's view. When combined with ML-based brain models, AR can show tumor margins, eloquent cortex, and predicted brain shift in real time. Early clinical reports suggest better spatial orientation and resection accuracy, though controlled trials are missing.[12,33] However, no prospective multicenter study has validated any of these models. Most published results come from single institutions using their own imaging protocols. Whether the Dice score of 88% holds across different scanner types and tumor grades is unknown. Table 3 summarizes the key ML models discussed in this section, their applications, datasets, and reported performance.

## 7. Outcome prediction and surgical planning

Deep learning has been tested for predicting surgical

**Table 3. Summary of machine learning models for image analysis and brain modeling in preoperative neurosurgery.**

| Application | Model | Dataset size | Key finding | Reference(s) |
|---|---|---|---|---|
| Brain shift prediction | CNN (W-Net) | *n* = 248 patients (paired preoperative and intraoperative MRI) | Positional error <0.5 mm | 31 |
| Meningioma segmentation | 3D CNN | Pre-trained on 10,099 healthy MRIs; fine-tuned on 806 expert-labeled meningiomas | Dice similarity coefficient = 88.2% (expert-level) | 32 |
| Multimodal functional mapping | ML models (integration of MRI, fMRI, DTI) | Various (review of multiple studies) | Improved classification of eloquent cortex and white matter tracts | 10 |
| AR integration with ML-based brain models | ML-driven AR systems | Various (early clinical reports) | Better spatial orientation and resection accuracy (controlled trials missing) | 11,12,33 |

Abbreviations: 3D: Three-dimensional; AR: Augmented reality; CNN: Convolutional neural network; DTI: Diffusion tensor imaging; fMRI: Functional magnetic resonance imaging; ML: Machine learning; MRI: Magnetic resonance imaging.

outcomes. Most models combine imaging, clinical records, or operative notes. The evidence is mostly retrospective. Several DL models (CNNs and RNNs) use preoperative MRI and intraoperative data to estimate likelihood of functional improvement or neurological deficits after tumor resection. One study reported area under the curve (AUC) of 0.82 for motor deficit prediction. DL-based survival models that combine imaging with genomic data have also been reported, with AUCs ranging from 0.75 to 0.88 across different tumor types.[12,33]

Surgical phase recognition (SPR) uses video data to identify phases of surgery in real time. It is well studied in laparoscopic surgery but less so in neurosurgery. Khan *et al.*[34] trained a DL model on endoscopic pituitary surgery videos. Their model achieved 89% accuracy for phase recognition and 81% for step recognition in a single-center dataset.[12,35] SPR could eventually alert surgeons during high-risk phases or generate automated operative notes, but no prospective trial has tested whether this improves outcomes.[12,36] Danilov *et al.*[37] used RNNs to extract features from 101,654 narrative operative reports. Their model predicted prolonged hospital stay (>7 days) with AUC of 0.85. Whether this changes discharge planning in real-world settings is unknown.[12] Pangal *et al.*[38] trained SOCALNet, a CNN that analyzes 1 minute of surgical video during hemorrhage events. The model predicted successful hemostasis, slightly better than expert surgeons in a retrospective test. AI outcome prediction models are technically promising. But almost none have been tested prospectively. Whether they improve patient outcomes or just add to the surgeon's workload remains an open question.

## 8. Integration of multimodal data for enhanced mapping

Multimodal data integration means combining different types of information: imaging (MRI, fMRI, DTI, PET, MEG, EEG), clinical variables (genetics, behavior, neuropsychology), and sometimes genomic data. The idea is that each modality captures something the others miss. Advanced ML and DL methods—graph neural networks and transformers—can fuse these heterogeneous datasets. They extract biomarkers and functional maps that single modalities cannot provide.[39-41] Several studies report that multimodal AI models outperform unimodal ones for disease progression, functional localization, and treatment response. For example, integrating fMRI and DTI with clinical metadata using graph-based neural networks improved language and motor area localization compared to using either imaging modality alone. Combining MEG or EEG with imaging also improved identification of epileptogenic zones and eloquent cortex.[11,39-41] But most of these studies are retrospective and single-center. Imaging protocols vary by center. MEG systems differ. EEG recording montages are not standardized. Clinical data collection is even more heterogeneous. A model trained on one dataset often fails on data from another center. This is called domain shift.[40-42] Fixing it requires large, well-curated multimodal databases and standardized acquisition protocols—neither of which exists yet for most neurosurgical applications. Multimodal data often include genetic and neuropsychological information. Data sharing for AI development raises privacy concerns. Transparent and interpretable AI models are needed before clinical adoption.[41,42] Multimodal AI is theoretically powerful and the technical methods exist, but clinical translation is held back by data heterogeneity, lack of standardization, and privacy concerns.

The stepwise workflow of AI integration into preoperative brain mapping,[10-12] from data acquisition to intraoperative decision support, is illustrated in Table 4.

**Table 4. Workflow of AI integration in preoperative brain mapping.**

| Phase | Input/Data | AI processing | Output/Clinical application |
|---|---|---|---|
| 1. Data acquisition | Structural MRI (T1, T2), fMRI (task-based & resting-state), DTI (tractography), MEG, nTMS | DICOM images with high spatial resolution (including UHF MRI where available) | Raw multimodal data ready for preprocessing |
| 2. Preprocessing | Raw imaging data | Spatial normalization, skull stripping, motion correction, AI-enhanced denoising (improves SNR and image quality) | Cleaned, standardized images |
| 3. Segmentation & feature extraction | Preprocessed MRI/fMRI/DTI | Automated AI models (*e.g.*, 3D U-Net) segment tumors, edema, and normal brain structures; extraction of BOLD signals; AI identifies relevant time series and filters noise | Tumor boundaries, eloquent cortex candidates, white matter tracts |
| 4. Multimodal data fusion | Structural, functional, and diffusion data | AI integrates cortical activation maps with DTI tractography; deep learning builds functional connectivity graphs from resting-state fMRI; identifies eloquent cortex and network hubs (language, motor) | Comprehensive brain maps with cortical and subcortical functional anatomy |
| 5. Critical structure labeling | Segmented and fused data | AI-assisted annotation tools label eloquent areas and critical fiber tracts (corticospinal tract, arcuate fasciculus) | Color-coded maps of structures at risk |
| 6. Surgical path planning | Labeled brain maps | AI algorithms (*e.g.*, Q-learning) compute optimal trajectories that avoid eloquent cortex and critical tracts; penalty scores for intersecting critical structures; rewards for reaching tumor | Optimized surgical trajectory balancing maximal resection with functional preservation |
| 7. 3D visualization & validation | AI-generated maps | 3D rendering of multimodal maps; cross-validation with intraoperative DCS or nTMS where available; neurosurgeon review for clinical relevance | Interactive 3D maps integrated with neuronavigation or AR platforms |
| 8. Intraoperative integration | Preoperative maps + intraoperative imaging (iMRI, iUS) | Real-time updates compensating for brain shift; AI provides proximity alerts for eloquent areas | Dynamic neuronavigation with enhanced surgeon awareness and reduced risk of deficits |

Abbreviations: AI: Artificial intelligence; AR: Augmented reality; BOLD: Blood oxygen level-dependent; DCS: Direct cortical stimulation; DICOM: Digital Imaging and Communications in Medicine; DTI: Diffusion tensor imaging; fMRI: Functional magnetic resonance imaging; iMRI: Intraoperative magnetic resonance imaging; iUS: Intraoperative ultrasound; MEG: Magnetoencephalography; MRI: Magnetic resonance imaging; nTMS: Navigated transcranial magnetic stimulation; SNR: Signal-to-noise ratio; UHF: Ultra-high field.

## 9. Clinical impact and utility of AI in preoperative brain mapping

A systematic review of 128 studies compared nTMS, MEG, and fMRI for preoperative mapping. nTMS plus DTI had the best evidence for motor mapping, with spatial agreement to DCS generally within 10 mm. This translates into safer resections of motor-eloquent tumors. MEG agreed well with fMRI and DCS but had a larger mean deviation (~12.5 mm) from DCS-identified motor hotspots, partly because MEG localizes somatosensory cortex while DCS maps motor cortex directly.[7] AI-driven segmentation models (mostly 3D CNNs) achieve Dice similarity coefficients around 0.88 for meningioma and glioma, matching expert human raters. Better segmentation means better tumor boundary identification, which helps maximal safe resection. One study linked higher Dice scores to increased extent of resection, though survival benefit data are indirect.[43,44] In pediatric neuro-oncology, DL models analyzing longitudinal MRI predicted glioma recurrence with up to 90% accuracy in a retrospective series.[43]

CNN models trained on paired preoperative and intraoperative MRI predict brain shift with reported positional errors under 0.2 mm. This allows dynamic navigation updates. But as noted in **section 5**, most of these results come from a single Japanese group.[43] Small clinical series report better spatial orientation when AI-driven models are integrated with AR systems. Whether this changes complication rates or extent of resection is not yet proven.[15] AI-enabled platforms are expensive. Acquisition and maintenance costs limit access, especially outside major academic centers.[43] Effective use needs multidisciplinary

**Table 5. Workflow of AI-driven brain shift compensation in intraoperative neuronavigation**

| Phase | Input/Data | AI processing | Output/Clinical Application |
|---|---|---|---|
| 1. Preoperative imaging & planning | High-resolution MRI and DTI scans | Baseline anatomical reference for tumor boundaries and eloquent areas (motor, language cortex, white matter tracts) | Surgical plan and initial neuronavigation registration |
| 2. Intraoperative imaging acquisition | iMRI or iUS | Captures real-time brain anatomy reflecting tissue deformation from CSF loss, gravity, and tumor resection | Raw intraoperative data for comparison with preoperative scans |
| 3. AI-based brain shift estimation | Paired preoperative MRI and intraoperative imaging (iMRI/iUS) | Deformable image registration; ML models estimate magnitude and spatial distribution of brain shift; FEM combined with AI optimization; generation of virtual updated images (*e.g.*, virtual iMRI) | Quantitative brain shift map; virtual iMRI aligning preoperative functional maps with current anatomy |
| 4. Updated neuronavigation & surgical guidance | AI-corrected images (virtual iMRI) | Dynamic update of neuronavigation system with real-time tumor and eloquent cortex localization despite brain deformation | Improved precision of surgical resection; reduced risk of damaging critical brain areas |
| 5. Clinical impact | AI-compensated navigation data | Enables more complete tumor resections with fewer neurological deficits; virtual iMRI accurately corrects fiber tractography distortion (correlates with intraoperative neuromonitoring); reduces reliance on repeated intraoperative imaging (saves time and resources) | Better patient outcomes; maintained surgical accuracy with less intraoperative imaging |

Abbreviations: AI: Artificial intelligence; CSF: Cerebrospinal fluid; DTI: Diffusion tensor imaging; iMRI: Intraoperative magnetic resonance imaging; iUS: Intraoperative ultrasound; MRI: Magnetic resonance imaging.

training. Some studies report that AI-assisted planning reduces operative time and complications, which could offset initial costs, but formal cost-effectiveness analyses are missing.[15,43,45] Almost all evidence comes from single centers. No prospective randomized trial has tested whether AI-enhanced mapping improves patient-reported outcomes or quality of life compared to standard mapping.

The clinical workflow of AI-driven brain shift compensation integrated into intraoperative neuronavigation [31,46-49] is detailed in Table 5.

## 10. Limitations and challenges

AI in neurosurgery faces several real limitations that fall into two categories: data and generalization problems, as well as ethical and technical barriers. High-quality datasets are scarce. Neurosurgical data are often small, heterogeneous, and poorly annotated. Imaging protocols, scanner types, and acquisition parameters vary across centers, which degrades AI performance and reproducibility.[50] Rare conditions have almost no usable data. Bias in training data—underrepresenting certain demographic groups—leads to unequal performance across populations.[50,51] Beyond data quality, generalization failure (domain shift) is common: a model trained at one hospital often fails at another because radiomic features from MRI change with scanner hardware.[52] Most published AI studies skip external validation; only a minority test their models on independent cohorts.[50] GAN-based synthetic data augmentation helps but does not solve the problem.[52] A systematic multi-institutional validation and transparent reporting is needed and it has yet become a standard practice.

Ethical and legal issues add another layer of complexity. Patient privacy and data security are non-negotiable, and data breaches could expose sensitive health information.[32,51] Informed consent forms do not yet cover AI-specific risks, and liability for algorithmic errors or biases remains ambiguous.[51] The EU AI Act offers a framework, but global consensus is absent. Similarly, questions of data ownership, patient consent for AI model retraining, and accountability for automated decisions during surgery remain unresolved and require specialty-specific guidelines. Technical barriers also limit clinical adoption. Real-time AI processing is computationally heavy, and latency matters during surgery.[32] Brain shift—tissue deformation during resection—invalidates preoperative maps within minutes. Some CNN models predict brain shift with submillimeter accuracy, but integrating this into the surgical workflow in real time is technically difficult.[32,51] Black-box models also limit clinician trust; explainable AI is being developed but needs more validation in neurosurgery.[50,51] The missing piece across all these challenges is that no study has yet shown that AI-driven preoperative mapping improves long-term patient-reported outcomes in a randomized trial.

## 11. Future directions and opportunities

Recent work focuses on dynamic intraoperative guidance. Modern neuronavigation now combines preoperative imaging with real-time instrument tracking, plus AI for tumor segmentation, brain shift compensation, and registration updates. NeuroIGN, for example, uses DL for tumor segmentation on real-time ultrasound; early reports show high accuracy and usability even for novice users.[12] The goal is to help surgeons adapt to brain shift and other intraoperative changes. Faster computational hardware is making near-instantaneous processing possible, which is critical for clinical adoption. AR navigation overlays 3D anatomical and functional information onto the surgeon's field of view. Head-mounted displays like Microsoft HoloLens 2 have reduced operative times and improved screw placement accuracy in spinal surgery, though their value in cranial tumor surgery is less studied.[14] Robotics combined with AI can automate repetitive tasks, assist with instrument stabilization, and provide haptic feedback. The synergy of AI, robotics, and AR/VR may eventually enable safer minimally invasive approaches, but most applications remain in early development. Explainable AI (XAI) is also needed to make black-box models interpretable. NeuroIGN includes some explainability features; more work is required before surgeons trust AI outputs for high-risk decisions.[12]

Large-scale multicenter studies and prospective AI-driven trials are essential. Without them, generalizability and safety cannot be proven. The field also needs standardized datasets, harmonized protocols, and collaborative research networks. AI's ability to integrate multimodal data (imaging, electrophysiology, genomics, clinical variables) could enable truly personalized surgical planning. Deep learning models that predict functional recovery and complication risks are being tested, but none is ready for routine use. Real-time AI feedback during surgery remains a future goal, not a current reality.[5,12]

## 12. Conclusion

AI is changing preoperative brain mapping, but the shift is gradual, not revolutionary. Current evidence shows that AI-assisted techniques, particularly nTMS combined with tractography, predict motor deficits better than conventional methods in retrospective series. Multimodal AI integration improves tumor characterization and mapping accuracy in controlled research settings. Some studies report higher gross total resection rates and fewer neurological complications, but almost all evidence comes from single centers with no prospective validation. The real question is not whether AI works in principle—it does, for specific tasks like segmentation and brain shift prediction—but whether it improves patient-relevant outcomes in routine clinical practice; however, it remains unproven. Large multicenter studies, standardized datasets, and prospective trials are needed before AI can be integrated into everyday neurosurgical workflows. For now, AI is a useful adjunct, not a replacement for surgical judgment. Its clinical potential is real, but realizing it requires more rigorous validation and less hype.

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