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DIGITAL TRANSFORMATION OF NEUROSURGERY: AI, TELEMEDICINE AND VIRTUAL REALITY

Rafał Kobylański *(Corresponding Author, Email: rafalkobylanski01@gmail.com)*
Faculty of Medical Sciences in Katowice, Medical University of Silesia, Katowice, Poland
ORCID ID: 0009-0005-9221-1247

Olha Levchenko
Faculty of Medical Sciences in Katowice, Medical University of Silesia, Katowice, Poland
ORCID ID: 0009-0006-8743-3598

Katarzyna Nycz
Students' Scientific Club, Department of Neurosurgery, Faculty of Medical Sciences in Katowice, Medical University of Silesia, Katowice, Poland
ORCID ID: 0009-0001-0897-6855

ABSTRACT

Neurosurgery is a specialty that requires extensive knowledge, as well as comprehensive training and technical skills. Recent advances in the development of artificial intelligence (AI) demonstrate significant potential for improving the quality of both interventional and non-interventional neurosurgical treatment. One of the advantages of integrating artificial intelligence into everyday clinical practice is the acceleration and increased efficiency of neurosurgeons' work, allowing more patients to be treated within a shorter period of time. In the future, this may help healthcare systems provide more efficient patient care in modern clinical settings. At present, telemedicine can be predicted to become one of the key tools in neurosurgical practice, as it has the potential to help surgeons provide care to a greater number of patients, while augmented reality may support the extensive process of neurosurgical training. These technologies have demonstrated promising utility over recent decades and have the potential to transform aspects of neurosurgical practice in areas such as diagnosis, clinical decision-making, prognostic assessment, and data acquisition. It is important to note that, despite the advantages of artificial intelligence, several important limitations and challenges associated with its integration into routine medical practice remain. This review aims to summarize both the progress achieved in the application of these new digital technologies and the potential challenges and limitations associated with their use.

KEYWORDS

Artificial Intelligence, Neurosurgery, Telemedicine, Virtual Reality, Machine Learning

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1. Introduction

In the past decade, Artificial Intelligence has become widely recognized as an integral part of our lives. Medicine has proven to be no exception. The usage of Artificial Intelligence has become a part of diagnosis or treatment across nearly all medical specialties. Neurosurgery is an especially demanding profession, not only in required knowledge but also in psychomotor skills like dexterity, great hand-eye coordination and stamina required for long surgeries. Working with other doctors such as anesthesiologists, neurologists, radiologists as well as nurses also requires a great deal of teamwork and communication skills [1]. Despite these qualifications, a quarter of medical errors in neurosurgery are technical errors during surgical procedures [2]. It is safe to assume a significant portion of these mistakes and their harmful consequences could be avoided with the usage of new digital technologies such as Artificial Intelligence, telemedicine and augmented reality. The interest in these technologies, especially Artificial Intelligence, can be tracked by comparing the numbers of studies published in recent years about the usage of AI in different medical specialties. In this ranking, neurosurgery is ranked 11th, with 3.1% of studies written about this specialty. It places it in the first half, however significantly behind the first two – radiology (18.2% of studies) and pathology (16.4% of studies). The majority of studies written on the usage of AI in neurosurgery were written in the last two years, showing exponential growth in interest in this topic in recent years [3].

Since the first neurosurgical (and at the same time first surgical in general) procedure using a robot (computerized tomography (CT)-guided stereotactic brain surgery) was performed in 1988 [4], the usage of AI in neurosurgery has steadily increased. However, it remains more common in fields with relatively fewer anatomical space constraints such as urology, gynecology, and orthopedics. In the United States, only 40 out of 100 neurosurgical departments have robotic spinal programs and 30 out of 100 departments have robotic cranial programs [5].

Every year, 13.8 million neurosurgical procedures are performed worldwide [6], while an upward trend is likely to continue over the next century along with increased standards of quality and life expectancy [7]. It is one of the reasons for the "crisis in human resources" in the health sector, which has been described as one of the most pressing global health issues of our time. The World Health Organization (WHO) estimates that the world faces a global shortage of almost 4.3 million doctors [8]. In neurosurgery, despite approximately 50,000 doctors worldwide [9], there remains a profound deficit of at least 23,000 specialists, especially in low-income countries [10]. This worldwide deficit is in part due to rigorous, lengthy and expensive training and limited access to advanced surgical equipment [6]. New digital technologies have the potential to improve this situation by increasing the efficiency of neurosurgeons' work in order to provide the best possible care for the greatest number of patients, which facilitates access to safe, equitable, and high-quality medical care worldwide.

2. Methodology

A literature review was performed in PubMed, Embase and Scopus databases and several others. Articles published in English between 2021 and 2026 were taken into account. The keywords included, among others, "artificial intelligence", "machine learning", "deep learning", and "neurosurgery". Studies were screened by title and abstract. Full-text studies were screened for inclusion in the review based on prespecified inclusion and exclusion criteria. Relevant data from these chosen studies was used.

3. Results

3.1. Artificial Intelligence in Neurosurgical Diagnostics

3.1.1 Overview

Artificial intelligence allows computers to perform work that traditionally required human cognition. The application of AI, ML, and DL could significantly advance neurosurgery, each in specific ways. For better understanding, it is important to differentiate between these acronyms. AI is the broadest term, referring to the usage of computers to mimic biological intelligence. Machine Learning is a subset of AI that aims to use computers to learn from previous data to make accurate predictions about new data by improving algorithms over time. The main difference between ML and other forms of AI is that while other forms of AI try to replicate decisions made by human physicians without actually mirroring human cognitive processes, ML achieves its purposes by using learning algorithms in a way that mirrors these cognitive processes. The desired processes are achieved by giving the AI access to enormous quantities of data about patient histories, results of tests, scans and other findings. The AI then analyzes this data and, by processes not directly controlled by its creators, finds patterns in the data and then uses these newfound patterns to make predictions in newly presented cases. Thus, ML, in a way, mimics human mental processes to achieve desired results. Deep learning, on the other hand, is a specialized subset of Machine Learning which uses multi-layered artificial neural networks to analyze complex, unstructured data [11]. All of these subtypes offer distinct and useful advantages and can prove highly useful in many different aspects of neurosurgery.

With radiology being the specialization where AI has proven by far the most useful, it should come as no surprise that in neurosurgical diagnostics, AI models are most useful in analyzing radiological images and detecting neurosurgical conditions. A large number of studies have attempted to measure the models' sensitivity and specificity, and the results seem promising across a wide variety of neurosurgical subspecialties. Apart from finding pathological changes, studies also show AI finding use in classifying and grading diseases, thus helping in outcome and risk prediction. AI's usage for non-diagnostic purposes has also increased in recent years, but research studying these other potential applications remains limited across a variety of neurosurgical specializations, while most of the research is focused on AI's application for diagnostic purposes.

One of the most significant advantages of AI over human physicians is its ability to analyze large sets of data quickly and accurately, including complex disorders. One study that can serve as an example aimed to quantify the abilities of the Viz LVO algorithm in ischemic stroke patients and found that the algorithm led to quicker reperfusion, quicker door-to-neurovascular team notification times, and improved clinical results [12]. Similarly promising results were shown by another study focusing on intracranial aneurysms, where it was concluded that AI can diagnose patients more quickly than human doctors while preserving a high degree of precision.

3.1.2 Neuro-oncology

In the case of using AI for diagnostic purposes, neuro-oncology is the subspecialty of neurosurgery where the most studies have been conducted (52.69% as demonstrated in one review study, with 19.89% in vascular neurosurgery, 16.67% in functional neurosurgery and 11.83% in spinal neurosurgery) [13].

In cases where the AI's task was to differentiate between normal and abnormal tissue, such as diagnosing low-grade gliomas in pediatric patients and differentiating normal brain tissue from low-grade gliomas intra-operatively, the results of some studies were promising, however others showed less promise. Other applications include differentiating true progression from radionecrosis in brain metastases and distinguishing true progression from pseudoprogression in GBMs. In these cases the median accuracy was 85%, specificity 83%, sensitivity 78.3% and AUC 77%, but the values varied between different studies [13].

The highest degree of median accuracy in neuro-oncology was achieved in the identification and diagnosis of tumors, with 114 AI models used in one review. The median accuracy was 91%, specificity 91%, sensitivity 89%, and AUC 91% [13]. Among these tumors were metastatic spinal cord tumors, different brain tumors, pituitary adenomas and pediatric tumor types (e.g., embryonal tumors vs. ependymomas), among others.

In tumor subtyping and grading the results are also promising. When classifying tumors by grade and differentiating between high-grade and low-grade classifications using both radiological imaging (mainly MRI) and histograms, one study found that 65 commonly used AI models had a median accuracy of 88%, specificity 88%, sensitivity 90%, and AUC 90% [13]. Among diseases most commonly assessed by AI in that study were gliomas, meningiomas, medulloblastomas, differentiating between benign and malignant vertebral lesions, as well as differentiating primary, secondary, and lymphoma lesions of the temporal bone skull base [13].

Some papers also investigated segmentation of craniopharyngiomas and their subtypes, intra-operative brain tumor boundary detection to maximize resection, and segmentation of lumbar spine stenosis; however, studies show less consistency [13].

Thanks to a reasonably large amount of research conducted on the subject of AI as a diagnostic tool in neuro-oncology, it can be concluded that the potential utility of AI models appears to be quite high. Across many different studies, AI could reliably distinguish between normal and abnormal tissue and diagnose specific neuro-oncological diseases, as well as distinguish tumor grades. In the case of segmentation and delineation tasks the results appear less consistent, highlighting a need for further research in this direction.

3.1.3 Vascular Neurosurgery

According to research, AI shows great promise in its diagnostic capabilities when it comes to vascular diseases, mainly stroke lesions, classifying strokes, triaging major ischemic strokes, using CT imaging for acute cerebral infarction, detection of large vessel occlusions and cerebral venous thrombosis. The median accuracy in the aforementioned review was 89%, while specificity was 88%, sensitivity 84%, and AUC 88% [13].

Another group of diseases where AI has proven useful were intracranial hemorrhages. Different models scored a median of 91% accuracy, specificity 94%, sensitivity 90%, and AUC 97%. In different papers, AI was used in detecting ICHs, nontraumatic subarachnoid hemorrhages, the segmentation of aneurysmal subarachnoid hemorrhages, detection of intracranial hematomas, cerebral microbleeds and the occlusions of intracranial arteries, with promising results [13].

AI has also proven useful in the case of diagnosing aneurysms. Studies have described AI reliably diagnosing ICAs, such as saccular, ruptured, and unruptured aneurysms. Some studies also explored the segmentation of ICAs and intracranial hemorrhages. The median accuracy in detecting all of these conditions was 88%, specificity 92%, sensitivity 88%, and AUC 85% [13].

Overall, trends in the diagnostic usage of AI in vascular neurosurgery are promising. AI shows a high degree of specificity in diagnosing the most common vascular neurosurgical diseases, especially strokes, intracranial hemorrhages and aneurysms; however, studies measuring the direct impact these new AI models have on real-life healthcare systems remain a possible area for future research.

3.1.4 Functional Neurosurgery

AI models are also used in diagnosing functional neurological disorders, such as Parkinson's disease (PD) and identifying associated axial postural abnormalities, including Pisa Syndrome and thoracic and lumbar Camptocormia. AI has also been utilized in differentiating PD from other conditions such as dementia with Lewy bodies, cerebellar ataxia, multiple system atrophy, spinocerebellar degeneration, and progressive supranuclear palsy Richardson syndrome. The median accuracy in an aforementioned study was 94%, specificity 94%, sensitivity 84%, and AUC 97% [13].

Another common functional neurological disorder where AI was utilized for diagnostic purposes was Mild Cognitive Impairment (MCI), dementia, as well as dementia with Lewy bodies. The median accuracy in the case of these diseases was 92%, specificity 85%, sensitivity 95%, and AUC 86% [13].

Some studies also focused on diagnosing epilepsy, determining seizure onset lateralization, and distinguishing between temporal-plus and temporal lobe epilepsy. Other studies differentiated generalized tonic-clonic, focal to bilateral tonic-clonic, and nonconvulsive seizures. Some studies also identified epilepsy types in specific regions, such as the temporal lobe, frontal lobe, and perirolandic areas. Studies also examined temporal lobe epilepsy subtypes, including focal awareness seizures, focal impaired awareness seizures, and focal to bilateral tonic-clonic seizures. Here, the median accuracy was 91%, specificity 94%, sensitivity 93%, and AUC 94% [13].

In diagnosing Multiple Sclerosis (MS), studies assessed AI's performance in delineating white matter lesions, as well as in differentiating between MS and cerebral small vessel disease. The median accuracy here was lower, at 77%, while specificity was 89% and sensitivity was 87% (AUC not reported in this case) [13].

Other studies showed promising results using ML in categorizing seizure types based on scalp electroencephalography (EEG), achieving F1 scores of 97.4% and 97.2% of correctly identified seizure types in two datasets with 8 and 4 distinct seizure classes, respectively [14]. Research has also shown that AI models can successfully be used for diagnosing epilepsy using EEG. In other studies, AI has been demonstrated to be a useful tool in localizing the seizure onset zone (SOZ) using data from intracranial electroencephalography (iEEG).

AI also shows some promise in diagnosing and classifying epilepsy based on symptoms; however, studies show an accuracy of 60%, significantly less than in other aforementioned applications [15].

In functional neurosurgery, AI has found most diagnostic success in Parkinson's disease, dementia and seizures. Research has proven it to be a valuable and precise tool; however, more studies on larger groups of patients are required to confirm the findings.

3.1.5 Spinal Neurosurgery

In the case of spinal neurosurgery, AI has been used in diagnosing patients with central lumbar stenosis, disc herniation, lumbar spondylolisthesis, lumbar disc herniation with L5 and S1 radiculopathy, as well as detection of cervical spine fractures. The median accuracy was 91%, with specificity 97%, sensitivity 89%, and AUC 89% [13].

AI models were also utilized in diagnosing segmentation of spinal stenosis and intervertebral disc herniation, disc segmentation and measuring full alignment parameters in whole-spine lateral radiographs. Here, the median accuracy was 90%, while other metrics were not reported [13].

In other studies, AI was shown to diagnose compressions and lesions in the spinal cord using radiological images. One prospective study concluded that AI can detect spinal cord compressions in MRI data with an accuracy of 94%, 88% sensitivity, 89% specificity and 82% precision [16].

AI was also successfully used in predicting surgical decision making and predicting clinical outcomes in spinal cord procedures, such as spinal stenosis [17]. In another study, an ML model achieved a 92.56% positive predictive value for postoperative surgical site infections in posterior spinal fusions. An ML model in a different study was trained to predict the frequency of blood transfusions following adult spinal deformity surgery, with an accuracy of 77% and sensitivity of 80%, [18] while another study found that yet another ML model achieved a 96.9% accuracy in predicting surgical satisfaction in patients with lumbar spinal canal stenosis [19].

According to these studies, ML models show decent potential in predicting outcomes in spinal surgeries, diagnosing disc herniation and vertebral fractures. The models demonstrate high accuracy as well as specificity in their diagnoses. Despite that, a greater number of studies examining the impact of AI in spinal diseases could prove useful to further confirm the findings.

3.2 AI in Surgical Planning and Intraoperative Support

3.2.1 Overview

Apart from assisting in making correct diagnoses and predicting treatment outcomes, studies have also shown AI to be a useful component of surgical planning, particularly in determining the appropriate surgical approach, as well as intraoperative support. Studies show that artificial intelligence has the potential to enhance surgical performance and reduce the risk of medical errors during the intraoperative phase of neurosurgery. It is important to note that a large portion of studies examining the utility of AI in neurosurgery focus mostly on diagnostic capabilities, and more research into other applications remains an important area for further study.

3.2.2 Neuro-oncology

In the case of neuro-oncology, AI in surgical planning and intraoperative support shows some promise. One group of scientists implemented deep convolutional neural networks in conjunction with indocyanine green fluorescence imaging and Raman spectroscopy to facilitate near-real-time intraoperative glioma diagnosis, allowing surgeons to receive needed information in less than 3 minutes, while the traditional method of rapid frozen section pathological diagnosis usually requires up to 30 minutes [20].

Another group of scientists used a random forest model in conjunction with high-resolution magic angle spinning nuclear magnetic resonance spectroscopy in order to intraoperatively determine the metabolic profile of the resected tissue with reasonably high accuracy, which allowed them to identify residual tumorous tissue in the excision cavity and thus help the surgeons achieve maximal possible resection of the tumor [21].

Yet another group applied automated DL analysis for intraoperative visually evoked potentials during endoscopic transsphenoidal surgery, which helped them prevent optic nerve injury and reduced labor-intensive work by electrophysiologists [22].

A reinforcement learning-based AI algorithm created for the purpose of planning an optimal surgical route was also developed, which can calculate the best possible skull entry points, granting the easiest possible access to the tumor for the purpose of surgical removal while keeping the risk of post-surgical complications to a minimum [23].

Another intraoperative problem in neurosurgery in which AI could provide assistance is the issue of intraoperative brain shifts – movement and deformation of the soft tissue of the brain, which can pose serious problems during cranial surgery, as it can cause inaccuracies in imaging-based navigation. With many possible factors that need to be taken into account in order to make accurate predictions, other, more traditional models have an average error of 1.4 mm, [24] while an AI model using ANNs and support vector regression in combination with the finite element method (FEM) to predict the deformation at each node in a brain tumor mesh model showed an average error of just 0.2 mm [24].

As shown above, AI shows great potential to facilitate the treatment of neuro-oncological diseases, including quick, intra-surgical diagnoses, finding optimal surgical routes and minimizing the problem of brain shifts. The applications are quickly growing across a wide variety of diseases with potential to improve outcomes; however, more research to further validate these results could provide useful additional data.

3.2.3 Vascular Neurosurgery

AI models have also proven to be helpful tools in intraoperative decision making and predicting surgical outcomes, such as predicting aneurysm rupture and post-operative neurological deficits. This is especially evident in complex cases, such as patients with multiple intracranial aneurysms, where AI has been shown to be able to differentiate between ruptured and unruptured aneurysms with a high degree of precision, taking into account the aneurysm's size and location as key predictive features [25].

Other surgeries where AI has been demonstrated to reliably predict the risk of both long- and short-term complications include aneurysm surgeries as well as microsurgical clipping. In aneurysm surgery, machine learning models trained on preoperative patient and aneurysm characteristics were able to fairly reliably predict post-surgical neurological deficits, as well as functional surgical outcomes using Rankin Scale scores [26].

In the case of microsurgical clipping, AI models were able to predict surgical outcomes with ROC-AUC values in the range of 0.72–0.78, while also identifying factors influencing clinical outcomes [27].

Some research shows that AI can be useful for the triage, diagnosis, patient selection, and outcome prediction for large-vessel occlusion stroke. However, far fewer studies have been conducted in these applications, with the vast majority focusing on diagnosis, where, as previously mentioned, the AI models show reasonably high accuracy [28].

In the case of vascular neurosurgery, studies demonstrate the applications of artificial intelligence mostly in AI's ability to predict surgical outcomes. This field of application shows promise; however, more research is required for other applications such as intraoperative support.

3.2.4 Functional Neurosurgery

In the case of functional neurosurgery, in recent years AI has been increasingly applied in a range of different ways in both surgical planning and intraoperative support, mainly in procedures such as deep brain stimulation (DBS), epilepsy surgery and lesioning techniques. In these surgical procedures, AI models can be used with reasonably high accuracy to improve target localization, help find the optimal electrode placements, as well as to predict surgical outcomes.

In DBS, one of the most important challenges is the identification of the most optimal stimulation targets, such as the subthalamic nucleus or globus pallidus internus. Machine learning models have been used in locating these targets based on MRI and Diffusion Tensor Imaging (DTI) data, in order to facilitate finding and delineation of specific subregions. These methods have been proven to be more precise than traditional ones, especially in patients with a high degree of anatomical variability [29].

The first attempt to use AI in predicting the outcomes of epilepsy surgeries was performed in 1998, when an SNN (Simulated Neural Network) was used to predict whether seizures would subside after anterior temporal lobectomy. Despite the model being less developed than modern ones and having fewer input variables, it achieved reasonably high accuracy in predicting Class 1 (completely seizure-free) and Class 2 (almost seizure-free) outcomes. The SNN's accuracy in this study was measured at 81.3% and 95.4%, respectively [30].

AI models have also been utilized intraoperatively as a tool helping surgeons locate the correct electrode placement through the analysis of microelectrode recordings. Deep learning approaches can classify electrophysiological signals in real time, enabling the identification of relevant anatomical regions with a high degree of accuracy (AUC up to 0.94) [31]. This reduces reliance on subjective interpretation of data and may improve intraoperative decision-making and targeting precision [31].

As mentioned above, AI shows potential to facilitate the treatment of functional neurosurgical diseases such as identifying functional targets in DBS, predicting the surgical outcomes of epilepsy surgeries, and assisting in electrode placement. The applications have been steadily increasing in recent years; however, more research on larger groups of patients utilizing new ML models could prove a needed direction for future research in this topic.

3.2.5 Spinal Neurosurgery

AI has brought significant innovation in spine surgery, with consistently high accuracy of outcome data. Its potential has been increasingly explored mostly in the context of degenerative diseases, but also in deformity correction and spinal instrumentation.

One group of scientists developed different AI models aimed at predicting the 30-day post-operative adverse event rate in patients with Lumbar Degenerative Spondylolisthesis (LDS). The study encompassed a large dataset of 80,610 patients, 4.9% of whom suffered adverse effects in the studied timeframe. The models identified 10 predictive factors: age, gender, American Society of Anesthesiologists grade, autogenous iliac bone graft, instrumented fusion, levels of surgery, surgical approach, functional status, preoperative serum albumin [g/dL] and serum alkaline phosphatase [IU/L]. Logistic regression (enter, stepwise, and forward) and LASSO (least absolute shrinkage and selection operator) methods were used, with the former consistently achieving higher predictive capabilities [32]. This study highlights the feasibility of developing machine learning algorithms from large datasets to provide useful tools for patient counseling and surgical risk assessment.

An unsupervised AI study was also conducted, aimed at measuring the applicability of AI in predicting surgical outcomes in adult spinal deformity (ASD). The study involved 570 patients divided into three groups: young patients with coronal deformity (n = 195), older patients with a history of spinal surgery (n = 157), and older patients without prior surgeries (n = 218). The study utilized unsupervised hierarchical clustering in order to generate representative clusters of patients, apart from which they were also categorized into 12 groups based on osteotomy type, instrumentation, and interbody fusion. The identified factors allowed the AI to predict which patients would undergo surgery with minimal risk. It was concluded that Unsupervised Hierarchical Clustering can identify data patterns that may augment preoperative decision-making [33]. Some limitations are present, however, such as the study's dependency on small sample size and the need for additional research to confirm the tested hypotheses.

AI has also found use in intraoperative navigation systems. By using CT and MRI data, AI models can assist in finding anatomical landmarks and thus can offer real-time guidance in order to facilitate pedicle screw insertion. Some studies have reported an accuracy comparable to or even exceeding traditional navigational methods, while also reducing radiation exposure present in fluoroscopy and decreasing operational time [34].

The studies show promise in treating a variety of different spinal diseases, both in predicting surgical outcomes and in facilitating surgery itself. The AI models in these studies have shown a consistently high degree of accuracy; however, the lack of training data and limited data diversity remain limitations of model development.

3.3. Artificial Intelligence and Virtual Reality in Neurosurgical Education

Surgeon proficiency plays a pivotal role in the outcomes of surgical procedures and significantly influences adverse events, morbidity, and mortality. As such, finding efficient methods of training new surgeons is of paramount importance. Virtual reality has, over recent years, proven itself as a valuable tool for training new neurosurgeons. AI-powered VR simulations offer a safe environment for learning how to conduct complicated neurosurgeries and increase newly trained neurosurgeons' confidence, required to properly perform complicated surgeries without risking the safety of real patients. Studies also show that neurosurgeons who practiced in such controlled environments exhibit less stress during real surgery [35] – a factor which plays a significant role in reducing hand tremors, which are generally believed to increase the rate of complications in patients undergoing surgical procedures, though literature containing specific data is somewhat lacking. Different AI models have been incorporated in surgical education in the form of virtual reality and 3D simulators, to ensure sufficient, skill-oriented training of resident and mid-career surgeons to augment their confidence and reduce hand tremors during actual surgeries [35].

The value of AI-powered simulations lies also in their ability to provide comprehensive evaluations of surgical skills. This allows neurosurgeons to receive constructive feedback on their performance and correct any possible deficiencies, which the AI can identify [36]. Thanks to this technology, it is also possible to objectively evaluate surgeons' competence in order to ensure patient safety. For this purpose, specialized tools were developed, such as sensors affixed to surgical instruments to measure force and electromagnetic trackers to monitor the movements of surgeons' hands or instruments. The data from these devices is then interpreted by AI models, with little to no human intervention [36]. It is important to note that some current, advanced AI models can evaluate a surgeon's skills even without these instruments, judging the surgeon's skills by watching a video of their performance. AI models were developed which can evaluate the probability of surgical outcomes with a high degree of precision [36].

Studies show that the educational impact of VR sessions was greater in trainees, but also present in expert surgeons, as 3D modeling of patient-specific imaging effectively increased surgeons' understanding of patient-specific anatomy and helped determine surgical strategy in certain cases, especially those involving complex and challenging anatomy [13].

In one study, 92.1% of young doctors surveyed viewed AI-powered VR simulations as a useful tool, and 89.5% expressed a desire to learn and apply new technological skills in their work, with neurosurgical trainees once again having a more positive attitude toward these new technologies than experts [37]. A likely explanation is that younger people find operating these simulations easier, and doctors who are just beginning their journey with neurosurgery also have much more to learn from these simulations than doctors who have been practicing their neurosurgical skills on real patients for many years and have already become proficient in their line of work over those years.

These aforementioned studies show great potential in VR and AI as means of training new neurosurgeons. More research on this topic is certainly required to ensure our conclusions are correct, as well as to facilitate the creation of new, more advanced VR simulations which can take part in training new neurosurgeons. Some significant limitations are present, however, and will be explained in section 8. Limitations and Ethical Considerations.

3.4. Telemedicine in Neurosurgery

The U.S. Health Resources Services Administration defines telemedicine as "the use of electronic information and telecommunications technologies to support long-distance clinical healthcare," aided by technologies that include "video conferencing, the internet, store-and-forward imaging, streaming media, and terrestrial and wireless communications" [38]. Even though the first recorded attempts at telemedicine using a telephone occurred as early as the 1800s [39], only in recent years has it gained significant popularity [40]. The most important reason for this growth has been the rapid technological advancement and access to methods of real-time communication between patients and doctors, first using the telephone, and in recent years mostly the internet. This rise of medicine performed at a distance has also been made significantly faster as a result of the COVID-19 pandemic, during which regular face-to-face meetings with patients were avoided whenever possible, especially for the elderly and the immunocompromised.

Overall, the economic and clinical benefits of telemedicine come from diminished travel times for patients, remote consultations of subspecialty experts, such as neurosurgeons, and remote consultation to assist with triage and care in time-sensitive scenarios, including acute stroke care and "teletrauma", in which cases telemedicine may prove useful as a means of deciding whether expensive transfers from community hospitals to tertiary or quaternary care centers are required [41]. Other possible benefits include lower costs for patients, better access to medical care for rural or underserved populations, increased convenience, especially for chronic patients requiring repeat visits, as well as limiting the spread of infectious diseases.

Telemedicine made it possible to treat patients at a distance, including but not limited to neurosurgical patients. Crucial limitations in this method of monitoring and treating patients are, however, present and will be explained in more detail below. Due to high acuity and limited specialists, neurosurgery has favored in-person visits over telemedicine. As such, neurosurgical telemedicine has been mostly applied in outpatient postoperative care and follow-up visits [42].

Studies aiming to measure the cost-effectiveness of telemedicine across a wide array of medical specialties have shown mixed results [43]. In some contexts it is shown to be effective, in others somewhat promising, while in some contexts the evidence is insufficient to form any definite conclusions [43]. However, with potential benefits including cost savings, patient satisfaction, reduced wait times, diminished travel time, and reduced lost work time, telemedicine shows significant potential to improve access to medical care [42].

In the case of neurosurgery, high-quality studies measuring the cost-effectiveness of telemedicine are somewhat lacking. However, some recent research shows promising results. One study focusing on emergency and outpatient settings found an average reduction in time-to-specialist evaluation from about 160 to 38 minutes, and prevention of up to 44% of potential unnecessary patient transfers thanks to telemedicine [43]. The study also showed average patient satisfaction above 80%, surgical decision agreement comparable to in-person visits, and notable travel and cost savings, especially in pediatric teleclinics. Across various settings, telemedicine improved access, workflow efficiency, and cost-effectiveness, though challenges remained regarding connectivity, imaging interoperability, licensure differences, and digital inequality [43]. On the other hand, there are few quality studies measuring the usefulness of telemedicine in chronic neurological conditions. Some studies, however, show promise in this context as well. The Veterans Health Administration (VHA) established a prototypical model for telemedicine, and the results demonstrate substantial cost savings and high patient satisfaction in the case of remote care. Studies of VHA patients have found that telemedicine results in a 25% reduction in hospital days and a 19% reduction in hospital admissions [44]. Another study by the VHA focusing on movement-impaired patients living in rural areas with chronic neurological conditions found very promising results – 92% of surveyed patients reported that the telemedicine service saved them time, money, or both, and the authors estimated total savings of over $48,000 in time and travel costs for 354 patients. Patient response was overwhelmingly positive, with 95% of patients reporting that they wanted to continue their neurological care via telemedicine [45]. From this it can be concluded that telemedicine is, at least in these contexts, a cost-effective method of improving patient satisfaction. Specific studies focusing on patients with neurosurgical conditions are lacking; however, the large numbers of VHA patients treated remotely offer great opportunities for future studies aiming to further develop our understanding of the utility and efficiency of telemedicine in neurosurgery. Outside the VHA, a few studies also demonstrate that in the contexts of neurosurgical emergencies, including intracranial hemorrhage (in the context of telemedicine often called "telestroke") and neurotrauma (called "teletrauma"), the clinical outcomes are comparable to standard care, with largely reduced costs [46,47,48]. The most significant factor in the aforementioned reduction of costs was preventing the unnecessary and costly transport of patients from outlying hospitals to tertiary centers. Studies show a significant reduction especially in cases of "telestroke", where the feasibility of telemedicine services in the evaluation and management of acute ischemic stroke is well established. "Telestroke" allows for quick audiovisual contact between the patient and the physician, which has proven very useful in the context of strokes, considering the time sensitivity of decisions regarding the usage of thrombolytic therapy.

3.5. Limitations and Ethical Considerations

Using AI, VR and telemedicine has great potential to revolutionize neurosurgery; however, some considerations are certainly present. One of the most commonly voiced concerns regarding the implementation of AI in medicine is the growing concern that if AI continues improving, it may one day partially or even fully replace doctors, which could lead to large layoffs and decreases in wages in the medical community. Despite the loss of jobs to AI happening across a range of different professions worldwide, such concerns about AI-powered automation replacing doctors seem largely unfounded. According to current research, the implementation of AI in healthcare systems worldwide seems to augment physicians' work instead of replacing them entirely, and while AI has demonstrated significant capabilities in areas like diagnostics, data analysis, and even surgical assistance, its role is largely seen as complementary rather than substitutive [49,50]. Many experts argue that AI will enhance the efficiency and accuracy of medical practices rather than eliminate the need for human doctors altogether [51].

Another pressing concern is the problem of legal issues, present in all medical specialties where Artificial Intelligence can replace doctors in both diagnostics and treatment. Namely, the issue lies in who is to take legal responsibility in the case of AI algorithms' possible mistakes. Some would argue it ought to be the doctor using AI in their work, as the diagnoses or methods of treatment proposed by AI models should always be checked by the physician before making a diagnosis or beginning treatment. Others argue that if the fault for an incorrect diagnosis or method of treatment lies in the AI model, the company that developed it ought to be held liable for any consequences that arise as a result of its usage. Currently, with the usage of AI in medicine still in its infancy, the former view is the most prominent. But as the usage of Artificial Intelligence increases in the following decades, it is expected that more trust will be placed in the algorithms and perhaps legal changes may accompany this shift, with the latter view gaining more prominence worldwide [52]. These changes, however, remain largely speculative.

Another issue is the so-called algorithmic bias, which arises when algorithmic systems yield socially biased outcomes, thereby compounding inequalities in the workplace and in society. It should be noted that literature focusing on finding and analyzing cases of this specific bias in algorithms used in medical sciences is severely lacking [53]. Because of this, the extent of this issue is largely a matter of speculation.

Yet another problem is data privacy. Training AI models requires enormous amounts of data regarding patient histories, test results, etc. Considering such information may be deeply private, concerns are often raised over its confidentiality. Because of this, it is imperative to design a framework which helps protect the personal data of patients [54]. Literature on this issue is also severely lacking, so the extent to which patient data may be at risk remains an important area for future research.

However useful artificial intelligence, telemedicine and augmented reality are, in order to use them the medical personnel must have access to sufficient hardware, such as computers with a reliable internet connection with adequate bandwidth for high-resolution images or videoconferencing, as well as VR equipment in the case of using simulations for neurosurgeon training. Because of this, concerns may be raised over how much these new technologies will help patients in developing countries, where insufficient access to neurosurgical care is the largest problem, given that the same countries may not have the needed equipment nor sufficient funds to purchase it. Another problem worth noting is the degree of technological literacy, especially problematic among elderly patients and those from developing countries. This issue can be resolved by giving those who need it appropriate training in computer usage, which could help them connect with their physicians remotely. A 2010 WHO report showed that only 10%–15% of responding countries in the Eastern Mediterranean, Southeast Asian, and African regions reported having a national telemedicine policy, whereas 40% of European countries reported having such a policy [40]. In general, African countries were the least likely to report established telemedicine programs, at only 10%. Meanwhile, 50% of European countries and 75% of Southeast Asian countries reported established programs [40]. These findings show that in many developing regions of the world, access to these new digital technologies is lacking, and highlight where worldwide attempts to spread these technologies should focus. As such, focusing on improving these new digital technologies without financial support for struggling regions may not significantly improve access to high-quality neurosurgical care for patients from these regions [40].

In the case of telemedicine, its usage remains, according to some studies, far too low to fully utilize its potential, as significant issues are also present. Among several commonly cited reasons for telemedicine's limited utilization are an apparent lack of need for telemedicine services, lack of widespread reimbursement, lack of licensure reciprocity, lack of universal access to necessary resources and technology, concerns about maintaining patient confidentiality, and limited precedent regarding liability issues [55,56,57,58]. It can also be argued that telemedicine could weaken the physician-patient relationship. The apparent lack of need for telemedicine services can be partially explained by the insufficient amount of data to prove this method of treatment is effective with certainty, since many branches of medicine suffer from a lack of high-quality studies regarding the efficiency of telemedicine. In neurosurgery this is especially visible, as apart from telestroke, teletrauma and acute conditions, studies are severely lacking. Thus, some experts argue its implementation in healthcare systems worldwide can be described as premature [59].

It can be concluded that many of the issues with the usage of AI, especially regarding the lack of access to technology needed to fully utilize these technologies, can also be attributed to telemedicine.

To ensure the appropriate and ethical usage of these new technologies in neurosurgery, it is crucial to address the aforementioned concerns, especially regarding economics, legal responsibility, data privacy, and equity, as well as to address biases whenever they arise.

4. Discussion

The application of new digital technologies in neurosurgery shows great promise of improving the availability and quality of neurosurgical care worldwide, despite its limitations. Wider implementation of AI, VR and telemedicine, which will likely occur in the following decades, has great potential to transform our healthcare systems and neurosurgery as we know them. AI has proven itself an invaluable tool in tasks such as collecting and analyzing vast quantities of data and forming conclusions based on observed tendencies. VR is likely to serve as a tool for new neurosurgeons to learn their profession, while telemedicine is likely to make access to neurosurgical care easier, faster and more cost-efficient. If used correctly, taking into account and addressing their limitations, these technologies have the potential to become immensely powerful tools in bringing high-quality neurosurgical care to any patient that requires it. Most currently available studies about the usage of AI in neurosurgery focus mainly on its applications in neurological diagnostics, with other potential applications requiring more research.

5. Conclusions

Taking into account current rising trends, we should expect that the usage of new digital technologies in neurosurgery will increase in the following decades. Large-scale implementation of AI, telemedicine and VR in diagnostics, intraoperative support and training is to be expected. The exact extent to which these rising technologies will solve the many problems present in healthcare systems worldwide remains to be seen, but the technologies show great promise. The same can be said about the exact ways these technologies could negatively impact our healthcare systems in different respects: legal, with regards to data privacy and algorithmic biases, among others. Most research on the applications of AI in neurosurgery focuses on its diagnostic uses, and literature regarding other possible uses is lacking. Because of this, future research should focus more on applications in facilitating treatment in ways such as surgical planning and intraoperative support, across a wide range of neurosurgical subspecialties. More research regarding the potential applications of VR in neurosurgical training is also required. The same could be said about the efficiency of telemedicine – in order to increase access to high-quality neurosurgical care, more research is needed to prove its efficiency across a wide range of neurosurgical disorders.

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Resources: Rafał Kobylański
Data curation: Rafał Kobylański
Writing – original draft preparation: Rafał Kobylański
Writing – review and editing: Rafał Kobylański, Olha Levchenko, Katarzyna Nycz
Visualisation: Olha Levchenko, Katarzyna Nycz
Supervision: Olha Levchenko, Katarzyna Nycz
Project administration: Rafał Kobylański, Olha Levchenko, Katarzyna Nycz

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