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Artificial Intelligence algorithms for decision-making in thrombolysis and thrombectomy

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Acute ischemic stroke is a medical emergency in which every minute of delay results in irreversible loss of brain tissue. The main treatment modalities—intravenous thrombolysis and endovascular thrombectomy—have strict time windows and depend critically on the accuracy of neuroimaging. Conventional image interpretation requires substantial clinical expertise, is time-consuming, and is subject to interobserver variability. Modern artificial intelligence (AI) algorithms open new opportunities for the automated detection of vascular occlusions, assessment of ischemic core volume, and generation of real-time treatment recommendations. The application of these algorithms can significantly reduce the time from patient admission to the initiation of reperfusion therapy, improve the accuracy of patient selection, and standardize clinical decision-making.

Objective: To summarize current evidence on the role of AI algorithms in decision-making for thrombolysis and thrombectomy and to assess their potential to improve the speed and accuracy of patient selection.

Materials and methods: A literature review (2015–2025) was conducted using the PubMed, Scopus, Web of Science, and Google Scholar databases with the keywords “artificial intelligence,” “machine learning,” “deep learning,” “stroke,” “thrombolysis,” and “thrombectomy” to synthesize contemporary data on the use of AI algorithms in clinical decision-making for acute ischemic stroke. Clinical studies, reviews, and protocols describing the application of AI in neuroimaging, prognostication, and patient stratification were analyzed.

Results: Deep learning algorithms (e.g., Viz.ai, e-ASPECTS) enable automated processing of computed tomography and magnetic resonance imaging, rapidly identifying ischemic lesions and vascular occlusions. This reduces the time from diagnosis to treatment by 15–37 minutes, improves the reproducibility of assessments, and optimizes patient selection for reperfusion therapy. Models integrating clinical and neuroimaging data demonstrate superior predictive accuracy and allow consideration of individual patient characteristics.

Conclusions: Artificial intelligence is becoming an integral tool in stroke management by providing rapid, standardized, and objective data analysis. Its implementation reduces “door-to-needle” and “door-to-puncture” times, improves treatment outcomes, and decreases disability. The synergy between clinicians and AI heralds a new era of personalized stroke therapy aimed at preserving brain tissue and saving patients’ lives.

Keywords*: ischemic stroke; thrombolysis; thrombectomy; artificial intelligence; machine learning.*

Acute ischemic stroke is a critical medical condition in which every minute of delay results in the loss of viable brain tissue. In the absence of reperfusion, a patient with a large cerebral artery occlusion loses approximately 1.9 million neurons per minute [1]. This phenomenon, commonly referred to as “time is brain”, underscores the decisive importance of time in achieving successful treatment outcomes. The mainstay therapeutic approaches remain intravenous thrombolysis (administration of a thrombolytic agent) and endovascular thrombectomy (mechanical removal of the thrombus), both of which have clearly defined time windows and are based on the assessment of clinical data and neuroimaging findings [1]. Modern artificial intelligence (AI) algorithms open new opportunities for the automated detection of vascular occlusions, estimation of ischemic lesion volume, and real-time generation of treatment recommendations. Their implementation can substantially reduce the time from patient admission to the initiation of reperfusion therapy, improve the accuracy of patient selection, and standardize clinical decision-making.

Objective: To summarize current evidence on the role of AI algorithms in decision-making regarding thrombolysis and thrombectomy, and to evaluate their potential to improve the speed and accuracy of patient selection.

Materials and methods

This study is a narrative literature review aimed at synthesizing contemporary data on the use of AI algorithms for clinical decision-making in acute ischemic stroke. Literature searches were conducted in PubMed, Scopus, Web of Science, and Google Scholar databases covering the period from 2015 to 2025. The following keywords and their combinations were used: "artificial intelligence," "machine learning," "deep learning," "stroke," "thrombolysis," "thrombectomy," and "clinical decision support." Original studies, systematic reviews, meta-analyses, as well as clinical protocols and technical reports addressing the role of AI in neuroimaging assessment, outcome prediction, or determination of indications for thrombolysis and/or thrombectomy were analyzed.

Artificial intelligence in stroke neuroimaging

Neuroimaging is a key step in the evaluation of patients with stroke, as it allows confirmation of the ischemic nature of the event, identification of vessel occlusion, and assessment of the extent of brain injury. Contemporary AI algorithms are increasingly used for the automated analysis of computed tomography (CT), magnetic resonance imaging (MRI), and angiographic images. Convolutional neural networks are capable of detecting large vessel occlusion (LVO) on CT angiography with speed and accuracy comparable to those of expert radiologists [11]. Commercial software solutions, such as Viz.ai LVO, have demonstrated high specificity (95–97%) for detecting occlusion of the internal carotid artery or the proximal segment of the middle cerebral artery, although sensitivity remains moderate (78–82%) [2]. Importantly, the negative predictive value of such systems approaches 99%, indicating that only isolated cases are missed [2]. Automated LVO detection enables immediate notification of the stroke team about the presence of a thrombus, even while the patient is being transported to the hospital, thereby saving valuable time. For example, a multicenter study reported that implementation of automated occlusion alert software reduced the time from CT acquisition to initiation of thrombectomy by approximately 11 minutes on average [3], which was associated with nearly a 60% reduction in in-hospital mortality [3]. In addition to thrombus detection, AI can quantitatively assess the volume of ischemic brain injury. Algorithms for automated calculation of the Alberta Stroke Program Early CT Score (ASPECTS) analyze non-contrast CT images to identify early ischemic changes. The e-ASPECTS software has been shown to improve interobserver agreement among clinicians. According to published data, the use of e-ASPECTS increased the accuracy of ASPECTS assessment by neurologists from approximately 72% to 78%, while Cohen's kappa agreement improved from 0.60 to 0.65 ($p = 0.013$) [4]. Thus, AI reduces variability between different specialists and brings the performance of less experienced physicians closer to that of expert neuroradiologists [4].

More accurate and standardized assessment of infarct volume (ischemic core) is critical for treatment strategy selection. For instance, a very low ASPECTS score (indicating a large infarct) is a contraindication to early thrombectomy. Automated software packages such as RAPID analyze CT or MR perfusion data to calculate the volume of the ischemic core and the penumbra (hypoperfused tissue). These tools allow rapid (<5 minutes) generation of brain perfusion maps and calculation of mismatch parameters (core–penumbra discrepancy) [5]. Consequently, in extended time windows (beyond 6 hours from stroke onset), AI-based applications such as RAPID help identify patients with viable penumbral tissue who may be candidates for late endovascular intervention. The implementation of automated perfusion analysis was critical in clinical trials that expanded the indications for thrombectomy up to 24 hours in selected patients (e.g., the DAWN and DEFUSE 3 trials). In these studies, treatment decisions were made based on rapid software-based measurement of infarct and penumbra volumes [5].

AI also enables the use of telemedicine and real-time interaction in stroke care. In settings where a neurologist or radiologist is unavailable (e.g., primary stroke centers), algorithms can automatically analyze imaging data and transmit the results to specialists at a comprehensive stroke center. Systems such as Viz.ai send push notifications with annotated images highlighting the site of occlusion directly to physicians' smartphones, thereby facilitating and accelerating multidisciplinary consultation. Studies have shown that activation of such algorithms reduced interhospital transfer time from regional hospitals to comprehensive centers by approximately 37 minutes (from 141 to 104 minutes, $p = 0.04$) compared with the pre-implementation period [6]. In another center in the United Kingdom, the introduction of a comprehensive AI solution (e-Stroke by Brainomix) reduced the average door-in–door-out time (from admission to onward transfer) from 141 to 79 minutes (a reduction of 62 minutes, $p < 0.001$). This improvement was associated with a substantial increase in the proportion of patients undergoing thrombectomy and achieving functional independence (modified Rankin Scale score 0–2 in 48% with AI versus 16% without AI, $p = 0.04$) [7]. These findings indicate that integration of AI into "stroke network workflows" improves logistics and clinical outcomes.

Decision-making algorithms for thrombolysis

Intravenous thrombolysis (administration of recombinant tissue plasminogen activator) is an effective treatment for ischemic stroke when performed within the first 4.5 hours after symptom onset. Determining eligibility for thrombolysis requires assessment of the "therapeutic time window" and identification of contraindications, such as intracranial hemorrhage or a large established infarct volume. Artificial intelligence (AI) can assist in addressing both tasks. First, based on clinical data and neuroimaging, algorithms can estimate the actual time window and the condition of brain tissue. For example, in strokes with an unknown time of onset ("wake-up" strokes), the decision to administer thrombolysis may be made if MRI demonstrates a small diffusion-restricted lesion without a corresponding FLAIR signal, indicating a recent stroke. Automated software can interpret such MRI findings or CT perfusion studies and recommend treatment for patients with a substantial penumbral zone and a small infarct core, even when the standard time threshold has been exceeded [5]. This approach underlies extended treatment protocols. For instance, the EXTEND trial demonstrated the efficacy of thrombolysis up to 9 hours after symptom onset in patients selected on the basis of perfusion imaging.

Second, AI enables rapid detection of contraindications to thrombolytic therapy. The most critical contraindication is the presence of intracerebral hemorrhage on CT. Neural networks trained on thousands of CT scans have demonstrated sensitivities of approximately 82–93% for the detection of acute hemorrhage, comparable to the accuracy of experienced radiologists. In one study, a deep learning algorithm outperformed medical interns in hemorrhage detection sensitivity (0.82 vs. ~0.70) while maintaining a specificity of approximately 0.90 [8]. Thus, AI systems can promptly identify hemorrhagic changes on imaging and prevent inappropriate thrombolysis. Another important contraindication is a large infarct volume, defined as involvement of more than one third of the middle cerebral artery territory. As noted above, automated tools (e.g., ASPECTS analyzers and infarct segmentation software based on perfusion maps) provide standardized assessments of lesion size. This is particularly valuable in emergency settings, where clinicians under time pressure may overlook subtle imaging features, whereas AI performs parallel analysis and highlights signs of extensive infarction or mass effect due to edema [6–8].

Beyond immediate assessment, AI algorithms can also predict the risk of thrombolysis-related complications. One of the most serious complications is symptomatic intracranial hemorrhage (sICH) following thrombolytic therapy, which occurs in 2–5% of cases and markedly worsens prognosis. Using large stroke databases, machine learning models have been developed that integrate clinical variables (age, blood glucose level, blood pressure, National Institutes of Health Stroke Scale [NIHSS] score) and neuroimaging findings to estimate the probability of hemorrhage prior to thrombolysis. According to a multicenter study published in 2023 involving approximately 9,000 cases, the area under the ROC curve (AUC) of the best-performing ML model reached ~0.87 for predicting the risk of symptomatic hemorrhage [9], substantially outperforming traditional prognostic scales. The authors recommended the neural network model with the highest accuracy as a decision-support tool, enabling clinicians to weigh the predicted risks and benefits of thrombolysis for individual patients [9]. Although an AI-based risk estimate does not constitute a formal contraindication, prior knowledge of a high hemorrhagic risk may prompt clinicians to adjust subsequent management, such as stricter blood pressure control or avoidance of aggressive interventions after thrombolysis.

In summary, AI algorithms function as an "electronic assistant" during patient selection for thrombolysis, simultaneously screening imaging for hemorrhage, estimating infarct volume, and providing prognostic insights. This approach accelerates decision-making and enhances its evidentiary basis, reducing the impact of human factors in high-stress clinical settings.

Decision-making algorithms for thrombectomy

Mechanical thrombectomy for occlusion of proximal cerebral arteries (e.g., the internal carotid artery, the M1 segment of the middle cerebral artery) can dramatically improve stroke outcomes when performed in a timely manner. Current guidelines define clear indications: the presence of large vessel occlusion (LVO) causing neurological deficit within 6 hours from symptom onset constitutes an unconditional indication for thrombectomy; in the 6–24-hour time window, the procedure is recommended for patients selected on the basis of advanced imaging demonstrating a small infarct core and a large penumbral region [5]. Artificial intelligence (AI) plays a crucial role at all stages of this decision-making process.

Algorithms for LVO detection on angiographic images help prevent missed occlusions, which is particularly important in cases with atypical or subtle findings. Studies have shown that the Viz.ai LVO system correctly identifies approximately 81% of internal carotid or proximal middle cerebral artery occlusions, while also providing negative results in 99% of cases without occlusion [11]. Although false-positive alerts do occur, a specificity exceeding 95% indicates that the vast majority of LVO notifications are reliable. Moreover, contemporary software versions can classify the exact location of the occlusion, for example, distinguishing thrombi in M_{2-} segments or in the basilar artery, which is diagnostically more challenging. Consequently, neurosurgeons or interventional radiologists receive not only an alert regarding the presence of a thrombus but also precise information on its localization, allowing advance planning of the interventional strategy [11].

AI systems also assess the status of collateral circulation—the network of alternative pathways that partially supply blood to the ischemic territory. Good collateral circulation is associated with slower infarct progression and more favorable outcomes after thrombectomy. Automated collateral assessment on CT angiography (e.g., the e-CTA module within the e-Stroke system) can quantitatively rank distal vessel opacification beyond the site of occlusion [10]. In a 2024 study involving 97 patients, AI-based analysis classified 58.8% of patients as having "good" collaterals. The presence of good collateral circulation was associated with a statistically significant reduction in the risk of death or severe disability by hospital discharge (odds ratio 0.27, $p = 0.003$). Accordingly, the AI-derived collateral index is considered an important biomarker: patients with favorable collateral status may remain candidates for intervention even at later time points after stroke onset, whereas poor collaterals are associated with a lower likelihood of benefit [10]. Automation not only saves time but also provides a more objective assessment than visual grading by clinicians, which is often characterized by substantial interobserver variability.

AI algorithms further support the identification of candidates for thrombectomy in the late time window (>6 hours). As noted above, software such as RAPID rapidly quantifies infarct core volume (using diffusion-weighted MRI or CT cerebral blood flow maps) and hypoperfused tissue volume (using Tmax maps). A small core combined with a large penumbra constitutes a mismatch profile, in which thrombectomy may be beneficial even 9, 12, or 16 hours after stroke onset. Automated algorithms calculate the penumbra-to-core ratio and determine whether the patient meets criteria analogous to those used in the DAWN and DEFUSE trials. In an Indian study employing RAPID, volumetric results and mismatch ratios were obtained within 5 minutes for each patient. Three patients treated beyond the conventional 6-hour window achieved good functional outcomes at 3 months [5]. Owing to such technologies, indications for thrombectomy have been expanded. In 2018, the American Heart Association/American Stroke Association recommended mechanical thrombectomy up to 16 or 24 hours in patients selected using perfusion-based screening [1]. AI thus represents an integral component of this screening process, ensuring both speed and standardization across centers.

An additional important application of AI is outcome prediction after thrombectomy. Not all patients achieve comparable recovery even after successful vessel recanalization, as outcomes depend on age, comorbidities, infarct size, ischemia duration, and other factors. Machine learning models can use early clinical and imaging data, often within the first 24 hours, to predict whether a patient will achieve functional independence at 3 months (modified Rankin Scale [mRS] 0–2).

A large study based on the German Stroke Registry recently reported the development of a neural network trained on 7,485 thrombectomy cases [12]. The model analyzed 30 variables (including age, NIHSS score at admission and at 24 hours, use of thrombolysis, infarct volume, and presence of hemorrhage) to identify key prognostic factors. After optimization, only seven predictors were sufficient for accurate model performance, achieving an AUC of approximately 0.90 for predicting favorable outcomes. By comparison, neurologists' prognostic accuracy on the second hospital day is typically substantially lower. This model provides clinicians with an individualized probability of recovery and may support planning of rehabilitation, communication with patients' families, and therapeutic decision-making (e.g., consideration of more aggressive management in patients with an unfavorable prognosis). Notably, the authors designed the model to be interpretable, indicating which factors most strongly influenced the predicted outcome for a given patient (for example, very high NIHSS scores and intracranial hemorrhage worsen prognosis, whereas younger age and absence of prior stroke improve it) [12]. Such transparency enhances clinicians' trust in AI-based tools and facilitates their integration into clinical reasoning.

Integration of algorithms into clinical practice

The implementation of artificial intelligence (AI) in stroke care systems is occurring gradually. Decision-support systems are being developed that integrate with hospital Picture Archiving and Communication Systems (PACS) and image-sharing networks. This is particularly relevant within the "hub-and-spoke" model commonly used in stroke services, where AI can serve as a critical link enabling rapid patient triage and routing. Software solutions such as Viz.ai or e-Stroke automatically transmit imaging analysis results between hospitals, reducing delays associated with awaiting radiology reports and conducting telephone consultations. Many centers have reported reductions in door-to-needle and door-to-groin times following the adoption of these tools. According to a randomized cluster trial, the mean time from hospital admission to arterial puncture for thrombectomy was reduced by 11.2 minutes through automated occlusion detection and team-wide notification via a secure messaging platform [3]. Another study demonstrated a reduction in interhospital transfer time of approximately 37 minutes when Viz.ai software was installed at spoke hospitals compared with centers without the system ($p = 0.04$) [6]. In a UK center, implementation of the e-Stroke platform resulted in a 62-minute reduction in door-in–door-out time [7]. These time savings translate into preservation of a greater volume of viable brain tissue and enable a larger proportion of patients to receive appropriate treatment. Following the introduction of AI-based LVO analysis, a reduction in mortality among stroke patients was observed (13% vs. 31%, $p < 0.001$), although functional outcomes at 90 days did not differ significantly [3]. It is plausible that faster care prevented some fatal complications (e.g., earlier thrombectomy reducing the risk of hemorrhagic transformation or cerebral edema), even though no significant differences in neurological deficit were detected.

The integration of AI into clinical practice requires organizational adaptations, including the establishment of protocols governing human–algorithm interaction. Telemedicine consultants (neurologists, neurosurgeons) must have real-time access to AI-generated analyses. These systems are often accompanied by mobile applications that allow physicians to review image series with AI-annotated regions (ischemic core, collateral circulation, occlusion) on their smartphones while off-site and to promptly provide recommendations regarding thrombolysis or patient transfer. In the United States, such applications have already been certified by the Food and Drug Administration (FDA) as medical software devices. In a large hospital network (Atrium Health, USA), implementation of Viz.ai enabled the establishment of a unified "code stroke" protocol: when stroke is suspected, CT angiography is automatically uploaded to a cloud-based service, where AI screens for vessel occlusion; if detected, all members of the stroke team receive an alert with the relevant images. This capability is particularly valuable in smaller hospitals lacking 24/7 neuroradiology coverage. The algorithm addresses this gap by performing rapid image screening without the need to wait for an expert radiological opinion [2]. While the final clinical decision always remains with the physician, AI provides more comprehensive information more rapidly than previously available. Within telemedicine-based care models, AI also contributes to reducing unnecessary activations of tertiary teams (e.g., avoiding false nighttime mobilization of angiography teams when no LVO is present), as preliminary AI-based filtering can prevent unwarranted escalations.

Challenges and limitations

Despite substantial progress, the implementation of artificial intelligence (AI) in stroke medicine faces several important challenges. The first concerns the reliability and validity of algorithms across different populations and clinical settings. Deep learning models are often trained on data from a single region or even a single center. When applied in other hospitals, their performance may decline because of differences in scanners, imaging protocols, or patient characteristics [13]. For example, a model trained predominantly on a Caucasian population may exhibit reduced accuracy in Asian populations with distinct risk profiles (certain vasculopathies, such as moyamoya disease, are prevalent in Asian countries but rare in Western populations) [14]. Similarly, an algorithm trained on MRI slices with 1-mm thickness may lose sensitivity when applied to images with 5-mm slice thickness. Therefore, extensive multicenter validation is required before widespread deployment. Developers are gradually addressing this issue by incorporating data from multiple countries into training datasets, adapting algorithms to different acquisition parameters, and conducting post-marketing surveillance to monitor AI performance after deployment in new environments and to retrain models when necessary [13].

The second major challenge relates to transparency and explainability. Most contemporary AI models function as "black boxes," producing outputs (e.g., "occlusion present" or "ASPECTS = 7") without clarifying how these conclusions were reached [15]. Such opacity can undermine clinicians' trust. Physicians are accustomed to understanding the rationale underlying a diagnosis, for example, by directly visualizing hemorrhage on imaging. If an AI system indicates the presence of hemorrhage without highlighting its location or if the features are not readily apparent to the human eye, clinicians may question the result and spend additional time verifying it. Consequently, a "trust deficit" represents a significant barrier to AI adoption. For high-risk decisions—such as withholding thrombolysis or proceeding with surgery—clinicians are reluctant to rely on algorithmic recommendations without a clear explanation [13]. This has led to growing interest in Explainable AI (EAI), which aims to make model decisions interpretable. Techniques such as Gradient-Weighted Class Activation Mapping (grad-CAM) can highlight image regions that contributed most to the model's output, thereby indicating where features of occlusion were detected [16]. Another approach involves developing more interpretable models that output clinically meaningful parameters (e.g., penumbral volume in milliliters, collateral indices) rather than abstract probabilities. Insufficient interpretability is now formally recognized as a factor that reduces trust and delays the integration of AI into medical practice [17].

A third aspect involves legal and ethical issues of responsibility. When a physician makes a decision, accountability is clearly defined. However, when an algorithm contributes to the decision-making process, responsibility becomes less straightforward: who is liable if the AI system makes an error and the patient is harmed? Formally, the physician remains responsible for treatment decisions. Nevertheless, if the clinician followed an algorithmic recommendation, an ethical dilemma arises. Developers and vendors of AI systems are also stakeholders—should they bear partial responsibility for algorithmic errors? These questions remain insufficiently addressed within current regulatory frameworks [18]. Experts emphasize the need for clear boundaries, including transparent logging of AI actions, decision audit trails, and the ability to audit algorithms to identify the causes of errors. In addition, issues of informed consent emerge: should patients be informed that AI contributed to clinical decision-making, and should they consent to such an "assistive" mode of care? At present, this is rarely implemented explicitly in routine practice, but debate continues. Conversely, if an algorithm detects signs of stroke earlier than a physician and the clinician ignores the alert, does responsibility lie with the physician for disregarding the signal? Legal practice will likely evolve in parallel with the expanding use of AI [13].

The fourth challenge concerns validation and certification. For an algorithm to achieve widespread adoption, it must undergo clinical evaluation and demonstrate stable accuracy and tangible benefit. Health authorities and regulatory agencies (e.g., the U.S. Food and Drug Administration [FDA] and the European Medicines Agency [EMA]) impose increasingly stringent requirements on AI tools. Evidence from "real-world" data, comparisons with physician performance, and proof that algorithm use improves clinical outcomes are required. For systems that provide treatment recommendations, the threshold is even higher, as such tools effectively become part of the clinical decision itself rather than a supplementary imaging analysis. To date, most AI systems in stroke care have been approved as diagnostic decision-support tools, meaning they inform but do not replace clinical judgment. For example, e-ASPECTS and Viz LVO have been authorized in this category. Consequently, physicians must verify AI outputs before acting upon them [2,4]. Strict accuracy requirements also raise questions regarding sensitivity and specificity. If an algorithm misses even a small percentage of occlusions (approximately 18% are reportedly missed) [2], is this acceptable, given that a missed patient may lose the opportunity for treatment? Conversely, excessive sensitivity at the expense of specificity may lead to frequent false alarms and unnecessary mobilization of teams. Achieving an appropriate balance and defining acceptable thresholds are therefore critical technical and ethical considerations prior to implementation.

The fifth challenge relates to staff training. The adoption of new technologies requires education of physicians and nurses. Clear interfaces and protocols must be developed, specifying who reviews AI outputs, how results are documented, and how discrepancies between AI assessments and clinician judgment should be managed. Clinicians need to understand the limitations of AI, including scenarios in which errors are more likely. This represents a new category of clinical technology that necessitates formal training through courses and workshops. Some clinicians, particularly from older generations, may be skeptical or distrustful of algorithms. Providing robust evidence of benefit and training in appropriate interpretation of AI results are therefore essential. A culture of collaboration between clinicians and AI is required, in which the algorithm is viewed not as a competitor or a threat to professional authority but as a tool analogous to a new type of medical equipment [13, 18].

Finally, ethical considerations and bias must not be overlooked. AI algorithms are human-designed systems and may inadvertently inherit biases present in the underlying data. For instance, a model trained predominantly on male patients may perform less accurately in women. If training data are drawn mainly from urban hospitals, the algorithm may underestimate issues relevant to patients from rural settings. It is the responsibility of developers and clinicians to identify such biases and mitigate them through dataset optimization and appropriate corrective adjustments. From an ethical standpoint, AI use should remain patient-centered: patients are entitled to high-quality care with or without AI assistance, and technologies should be implemented to improve outcomes rather than for novelty or promotional purposes [18].

Future perspectives

The prospects for the application of artificial intelligence (AI) in cerebrovascular medicine are exceptionally broad. One promising direction is the integration of AI algorithms with biomarkers and clinical scales to generate comprehensive prognostic assessments. For example, future models may incorporate not only imaging data but also genetic markers, coagulation parameters, and results of neuropsychological testing. This approach aligns with the concept of personalized medicine, in which therapeutic decisions are tailored to the individual patient. In the coming years, rapid blood assays for biomarkers of ischemic injury may become routine at hospital admission for stroke, with AI systems integrating these data with neuroimaging to more accurately estimate time since stroke onset or predict the likelihood of successful thrombectomy. Active research is ongoing to identify such biomarkers and to develop multifactorial predictive models [19].

Another promising area involves generative models and the simulation of clinical scenarios. Generative Adversarial Networks (GANs) are being used to create synthetic medical images that can augment training datasets [20]. In the context of stroke, this approach enables the "generation" of thousands of virtual CT scans with diverse ischemic patterns, thereby improving algorithm performance even in rare or atypical cases. Generative models may also be capable of predicting infarct evolution; for instance, based on an initial scan, they could simulate how brain tissue might appear after 6 hours without treatment. Such tools could inform therapeutic decision-making: if a model predicts rapid infarct expansion in the absence of intervention, this would support a more aggressive treatment strategy. The application of large language models (LLMs) opens an additional avenue, including improved clinical documentation and support for clinical reasoning [21]. In the future, clinicians may describe a patient's situation in natural language, and an AI system integrated with clinical knowledge bases could suggest treatment options based on the latest guidelines and evidence, adapted to the patient's specific parameters. In stroke care, this could be particularly valuable in nonstandard scenarios, such as ischemic stroke in the setting of recent surgery, where AI assistance could help assess thrombolysis-related risks [22].

From a health system perspective, future developments may include unified platforms for comprehensive stroke care, encompassing the entire patient journey from emergency medical services activation to rehabilitation. AI could provide continuous support across all stages: in the prehospital phase, assisting in stroke recognition based on symptoms (with existing prototypes already analyzing speech, facial movements, and coordination via smartphones); during hospitalization, interpreting CT or MRI scans and proposing treatment strategies; and after discharge, monitoring recovery through wearable devices that assess speech, gait, and cognitive exercises, while alerting clinicians to deviations or complications. In this way, AI may become embedded within the stroke care continuum, strengthening each component of care delivery [23]. Naturally, all these perspectives must be rigorously evaluated for safety and effectiveness; nevertheless, the overall trend is clear—AI is becoming an integral part of the evolution of stroke care. It is not an exaggeration to state that a new era in stroke treatment is emerging. AI integrated into stroke management has the potential to raise the standard of care by enabling faster, more accurate, and more personalized therapy. The gradual, evidence-based implementation of these technologies may in the near future substantially reduce the societal burden of stroke by lowering mortality and disability rates, improving patients' quality of life, and optimizing the use of healthcare resources. This represents a compelling example of how innovation at the intersection of information technology and medicine can directly benefit clinical practice by achieving the highest goal—saving human brain tissue and lives.

Conclusions

A clear transition is currently underway from experimental AI developments in stroke medicine to their implementation in real-world clinical practice. AI algorithms do not replace neurologists or neurosurgeons; rather, they serve as powerful tools that augment clinical expertise. At the diagnostic stage, AI provides speed (image analysis within minutes) and objectivity (standardized assessment of lesion volume, vessel occlusion, and related parameters). In decision-making for thrombolysis and thrombectomy, algorithms help exclude unsuitable candidates—thereby avoiding unnecessary or potentially harmful interventions—and identify patients who may benefit from aggressive treatment, even when such potential is not readily apparent to the human eye. The clinical impact of these technologies is reflected in improved patient outcomes: more individuals spared from severe disability, reduced stroke-related mortality, and faster return to active life. Notably, centers that have implemented AI solutions have achieved substantial reductions in key time metrics (e.g., "door-to-needle" and "door-to-puncture" times), with each minute saved potentially preserving millions of neurons.

However, AI implementation must proceed gradually and responsibly. Barriers must be addressed, ranging from technical challenges (data harmonization, cybersecurity) to human factors (user training, trust building). AI models should be sufficiently transparent to allow clinicians to explain decisions to patients. Physicians must maintain critical thinking and use AI as a "second opinion" or coordination tool that provides insights, while the final therapeutic decision remains with the clinician. The greatest potential lies in the synergy between human expertise and AI.

Disclosures

Conflict of interest

The authors declare no conflicts of interest.

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