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Review

Effectiveness of Code Stroke Activation Models on Clinical Decision-Making Quality: A Scoping Review

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ABSTRACT

Background: Traditional medicine is widely used worldwide, particularly in rural communities of developing countries. Cultural beliefs, cost, accessibility, and social factors influence its use. This study aims to identify factors associated with the use of traditional medicine for Ear, Nose, and Throat (ENT) conditions among patients in Kumasi.

Methods: This scoping review was conducted in accordance with PRISMA-ScR guidelines and used the PCC (Population, Concept, Context) framework and the Arksey & O'Malley approach. A systematic literature search was conducted in the PubMed, ScienceDirect, Scopus, and EBSCOhost databases for the period 2021–2026. Inclusion criteria included studies on the Code Stroke activation model in the prehospital and ED settings. In contrast, exclusion criteria included in-hospital activation in the ICU or wards without ED involvement. The screening phase was conducted independently by four reviewers using the PRISMA protocol. Data were mapped through a documentation process using the JBI critical appraisal tools, and data synthesis was performed via thematic analysis to group activation models.

Results: Of the 1,690 identified records, the literature was found to be dominated by single-center studies or those conducted in high-income countries with advanced technological infrastructure. In contrast, evidence regarding the effectiveness of these activation models in Low- and Middle-Income Countries (LMICs) and the specific context of Indonesia remains very limited. The synthesis results identified four main themes of activation models: (1) nurse-based activation, (2) AI-based models (such as automated LVO detection), (3) pre-hospital activation via ambulance notifications, and (4) workflow optimization through a "pit-crew" model that transforms sequential processes into simultaneous parallel ones. Although these models have proven effective at accelerating time metrics such as door-to-needle time, a research gap remains: a lack of direct comparative analysis between models in resource-limited settings.

Conclusion: The integration of nurse leadership, parallel task delegation, and advanced technological support is critical to minimizing permanent neurological damage. Practice and policy implications include the need to implement a "no-fault" activation system for triage nurses and standardize AI reporting. Future research should focus on validating these models in geographically challenging contexts, such as in Indonesia, and conducting multicenter comparative studies to determine the optimal balance between diagnostic accuracy and hospital resource availability.

Keywords: Stroke; Code Stroke; Clinical Decision-Making; Emergency Service; Quality of Health Care; Review.

Implications for Practice:

- To provide healthcare professionals with the knowledge to identify and select the Code Stroke Activation model most appropriate for the context of their healthcare facility to optimize the acute stroke care pathway
- To improve diagnostic accuracy and the appropriateness of therapy selection, thereby enhancing the quality of clinical decisions for acute stroke patients, a clear and structured Code Stroke Activation model should be implemented.
- For the implementation context in Indonesia, stroke care practitioners and administrators need to adapt and develop an evidence-based Code Stroke Activation model that accounts for local resources, thereby addressing knowledge gaps and serving as the foundation for developing national practice guidelines.
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Introduction

Stroke is an urgent global health issue, ranking among the leading causes of death and long-term disability worldwide. Globally, the burden of stroke continues to rise alongside population aging and the epidemiological transition. The World Stroke Organization (WSO) reports more than 12.2 million cases of stroke annually; between 1990 and 2019, the survival rate reached 85–102%, with mortality rates of 43–44% and Disability-Adjusted Life Years (DALYs) due to stroke amounting to 143%(Feigin et al., 2021). In the Asian region, East Asia has the highest burden of ischemic stroke. More specifically, China, India, Indonesia, and Japan are the countries with the highest burden of ischemic stroke in Asia (Liao et al., 2025).

In Indonesia, the burden of stroke is even more significant, with data showing high prevalence and incidence rates, making stroke a national health priority that requires strategic management. According to 2018 data from the Indonesian Agency for Health Research and Development, the prevalence of stroke in Indonesia reached 10.9 per 1,000 people, an increase from the previous period (Kementerian Kesehatan Republik Indonesia, 2018). The significant impact of stroke on individuals and the healthcare system underscores the urgency of optimizing every aspect of patient care in hospitals.

The fundamental principle in acute stroke management is "Time is Brain," a concept that emphasizes that every minute of delay in treatment results in irreversible brain cell damage. It is estimated that approximately 1.9 million neurons are lost every minute during an ischemic stroke without treatment (Saver, 2006). Speed is crucial because the time window for effective interventions, such as intravenous thrombolysis (alteplase) or mechanical thrombectomy, is very limited—generally less than 4.5 hours from symptom onset, according to international AHA/ASA guidelines. Therefore, the entire care system must be designed to minimize the time from patient arrival to the administration of definitive therapy, known as door-to-treatment time (DTN)(Hasan et al., 2021).

Code Stroke is a standardized rapid-response system designed to efficiently identify, evaluate, and manage patients with acute stroke by coordinating a multidisciplinary team that includes the emergency department (ED), neurology, radiology, and the laboratory. The success of Code Stroke implementation is traditionally measured through time-based metrics, particularly the reduction in door-to-needle (DTN) time for thrombolytic therapy. This protocol aims to ensure a seamless transition between departments so that patients receive diagnosis and treatment in the shortest possible time (Buleu et al., 2024; Kamal et al., 2018). The Code Stroke activation model is the primary variable (independent variable), which encompasses various activation methods (e.g., pre-hospital activation by the ambulance team/early notification, single-call activation in the ED, phased activation, nurse-led vs. physician-led, pre-triage vs. post-triage, direct-to-CT vs. standard workflow). This exposure is hypothesized to influence the acute management process (process variables), operationalized through time-based indicators (door-to-activation, door-to-CT, door-to-needle/door-to-treatment), multidisciplinary team coordination, and the smoothness of inter-unit workflow. Furthermore, changes in these processes are expected to impact the quality of clinical decision-making (primary outcome variable), which includes the accuracy of selecting candidates for reperfusion (ability to distinguish stroke from stroke mimics), the appropriateness of indications and contraindications for therapy, and the alignment of decisions with guidelines(Alijanpour et al., 2025). The downstream impact is reflected in patient clinical outcomes (secondary outcomes), such as the proportion of patients receiving IV tPA/thrombectomy, complications, mortality, and functional disability.

Although the objectives of the Code Stroke are uniform, the way these protocols are initiated—or their activation models—vary significantly across institutions. These models may include pre-hospital activation by the ambulance team (early notification), single-call activation in the emergency department, or a tiered notification system. The effectiveness of a protocol is not solely about speed but is also closely linked to the quality of clinical decision-making (Ebker-White et al., 2022). Different activation models can influence how information is presented to clinicians, which impacts diagnostic accuracy, such as the ability to distinguish stroke from stroke mimics (Baldereschi et al., 2012). For example, an overly sensitive model may speed up response time but risks triggering unnecessary activations (false positives), while a poorly integrated model can delay critical decisions even if the physical workflow is fast (Seah et al., 2019).

The clinical decision-making framework for Code Stroke can be understood as a structured pathway linking initial identification, risk screening, selection of diagnostic tests, and the decision to initiate reperfusion therapy. In the pre-hospital and ED triage phases, decision-making begins with screening for symptoms and risk factors using protocols such as BE-FAST and triage scales, which balance the need for sensitivity (to avoid missed strokes) with specificity to reduce stroke mimics and unnecessary activations(Alijanpour et al., 2025; Jamtli et al., 2024). In the diagnosis confirmation and patient selection phase, the decision framework integrates clinical data, imaging (CT/CTA, MRI), and algorithms or decision support (including AI) to determine the presence of large vessel occlusion, the time window, and eligibility for IV tPA/thrombectomy(Akay et al., 2023). In this framework, time (door-to-CT, door-to-needle, door-to-activation) serves as the primary process parameter, while decision quality is measured by diagnostic accuracy, patient selection precision, and the stroke-to-mimic ratio. The entire process is supported by multidisciplinary team coordination and standardized protocols (mothership vs. drip-and-ship, protected/STRAUMA code) to reduce individual variation and guide decisions toward the best functional outcomes for patients (Bentley et al., 2021).

Many studies have demonstrated that the implementation of a Code Stroke generally leads to significant improvements in time-based metrics. However, there is a gap in the synthesized scientific evidence regarding the comparative effectiveness of various Code stroke activation models and their specific impact on clinical decision-making processes and quality. Research conducted by Song et al. (2016) showed that shifting from a physician-led activation model to nurse-led Code stroke activation in the ED improved process metrics (faster stroke team mobilization and more timely laboratory testing) and increased the proportion of patients receiving IV TPA and endovascular procedures, although it did not significantly alter door-to-needle time. Other studies reported that nurse triage and activation models significantly reduced door-to-activation, door-to-CT, and door-to-needle times while maintaining clinical outcomes. Nevertheless, these studies generally evaluated a single model at a single care center, without directly comparing various activation formats (nurse vs. physician, triage vs. post-triage, direct-to-CT vs. standard workflow) or their impact on patient selection accuracy, the frequency of stroke mimics, and the quality of clinical decisions. These limitations underscore the need for more systematic comparative research on variations in Code stroke activation models and their implications for the quality of decision-making.

The current literature tends to be fragmented and often describes only a single model at a single institution without in-depth comparative analysis. Particularly in Indonesia, with its unique characteristics regarding health resources and systems, there has been no comprehensive mapping of the most effective and applicable activation models for implementation. To fill this knowledge gap, a systematic literature mapping is required. Therefore, this scoping review aims to map and synthesize the available scientific evidence regarding the effectiveness of various Code stroke activation models on the process and quality of clinical decision-making. In addition, we used the scoping review method because it focuses on mapping models, contexts, outcomes, and gaps, whereas a systematic review would test the effects of specific interventions. In the area of Code Stroke activation, the evidence includes studies on quality, protocols, triage algorithms, and highly heterogeneous observational studies, without imposing a quantitative synthesis that might be inappropriate. This approach allows for mapping the relationship between activation models and the quality of decision-making with its diverse, fragmented scientific evidence, which encompasses various designs and contexts; a scoping review is more appropriate than a full systematic review. This approach enables a comprehensive mapping of models and indicators of decision quality.

Methods

Design

This scoping review was conducted following the methodological framework of Arksey and O'Malley(Arksey & O'Malley, 2005), as further refined by the Joanna Briggs Institute (JBI)(Joanna Briggs Institute, 2024), and reported in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist(Tricco et al., 2018). The review followed five core stages: (1) identifying the research question, (2) identifying relevant studies through comprehensive and structured searches, (3) selecting studies using pre-specified inclusion and exclusion criteria, (4) charting, categorizing, and mapping the data, and (5) collating, summarizing, and reporting the results. Study selection is described both narratively and via a PRISMA-ScR flow diagram to ensure transparency and reproducibility of identification, screening, eligibility assessment, and final inclusion(Tricco et al., 2018).

This review employed a scoping review rather than a traditional systematic review because the primary aim was to map the breadth and nature of the existing evidence, clarify concepts, and identify research gaps, rather than to produce a synthesized effect estimate or answer a narrowly focused question on intervention effectiveness or prognosis. Scoping reviews are particularly appropriate when the literature is heterogeneous, methodologically diverse, and not yet comprehensively reviewed, and when questions are broad (e.g., “what has been studied about…?”) rather than specific PICO-type questions. This approach allows inclusion of multiple study designs and non-research sources, supports exploration of key concepts and characteristics, and can inform whether future systematic reviews are feasible and where evidence gaps remain. This scoping review aims to map and synthesize scientific evidence on the code stroke activation model's effects on the process and quality of clinical decision-making. Specifically, this review is designed to answer the following research questions:

1. What are the types of Code Stroke Activation models documented in the literature?
2. How do these models influence the metrics process?
3. How do these models impact the quality of clinical decisions, including diagnostic accuracy and appropriateness of treatment?
4. What are the main gaps in the literature that could guide future research in the Indonesian context?

Eligibility Criteria

The inclusion criteria for this scoping review included: (1) Code stroke activation in Pre-Hospital and Emergency Department (ED) setting; (2) Articles published in Indonesian or English. This language restriction was chosen due to time constraints and limited translation resources and is supported by methodological studies showing that excluding non-English articles generally has only a minimal impact on effect estimates and review conclusions. This decision is based on the team’s resource constraints and on meta-epidemiological findings that restricting the analysis to English-language publications rarely alters the main conclusions of evidence synthesis, although we remain aware of potential language bias and will transparently report articles excluded due to language (Nussbaumer-Streit et al., 2020); and (3) Publications published between 2021 and 2026 were included. This time frame was chosen to ensure that the analyzed literature reflects the most recent developments in Code Stroke activation, including updates in clinical guidelines, advances in imaging and reperfusion therapies, and the impact of organizational changes and digital technologies on acute stroke pathways. Focusing on this period minimizes the influence of outdated practices and provides evidence that is more relevant to current stroke systems of care(Kuczynski et al., 2025).

Exclusion criteria included: (1) Intra hospital Code Stroke Activation in Intensive Care Unit or Post-operative Cardiac Surgery Units, where stroke events and code processes differ substantially from ED and pre-hospital pathways in terms of timing, eligibility for reperfusion, and workflow organization (Correia et al., 2025). (2) In-hospital Code Stroke activations on general wards without ED involvement, because in-hospital strokes show delayed symptom recognition(Kuczynski et al., 2025); and (3) Grey literature. Only studies published in peer-reviewed journals were included to ensure consistent methodological standards and reliable quality (Adams et al., 2017; Kitchenham et al., 2023). These criteria were established to ensure population homogeneity and a focus on the activation code in ED.

Setting inclusion criteria that limit the study to prehospital settings and ED between 2021 and 2026 risks introducing a bias toward high-tech models (such as AI) that are rapidly advancing in developed countries, thereby potentially limiting the generalizability of the findings when applied to regions with limited infrastructure, such as in developing countries. Furthermore, the exclusion of stroke activations in inpatient wards or ICUs also means that these findings cannot be generalized to the full spectrum of stroke care in hospitals. The decision to exclude grey literature and limit the search to articles in English and Indonesian may introduce publication bias, potentially excluding field operational data or local protocols that may not have been published in indexed journals but are highly relevant to resource-limited settings. This reinforces the existence of an evidence gap regarding the effectiveness of activation models outside of single-site treatment centers with comprehensive resources.

Information Sources

In this scoping review, a systematic literature search was conducted using several major electronic databases including PubMed, ScienceDirect, Scopus, and EBSCOhost. The reference lists of the included articles were traced backward (backward citation tracking) to identify additional sources that might meet the inclusion criteria. The search of all databases was conducted on April 1, 2026. Grey literature (e.g., theses, conference abstracts, policy documents, and non–peer-reviewed reports) was not searched, as the review was restricted to peer-reviewed, indexed journal publications. Grey literature is often unstandardized and difficult to track in a reproducible manner, whereas the latest JBI and PRISMA-ScR guidelines emphasize the importance of transparent and replicable reporting.

Search Strategy

The literature search strategy was developed using the PCC (Population, Concept, Context) framework, commonly used in exploratory reviews and helpful for aligning eligibility criteria and search terms with broad, exploratory research questions. The population in this study is Stroke Patients; the concept is Clinical Decision-Making; and the context is Quality of Care. The literature search was conducted systematically through PubMed, ScienceDirect, Scopus, and EBSCOhost, in line with guidance to use multiple databases to enhance coverage and reduce missed studies. To ensure reproducibility, the full search strings and field constraints have been predefined and applied consistently across the database, using the "all-field" option to access all resources. Keywords and search terms were tailored to each database and combined using Boolean operators (Stroke OR "Transient Ischaemic Attack" OR TIA) AND ("Clinical Decision Making" OR "Clinical Decision-Making Skills") AND ("Quality of Care" OR "Quality of Service").

A similar search term has been adapted for PubMed using Boolean operators (("Stroke"[Mesh]) AND ("Clinical Decision-Making"[Mesh]) AND ("Quality of Health Care"[Mesh])), employing the appropriate field tags and syntax. The complete search strategy will be included in the appendix, as recommended. The search was not restricted to improve precision while maintaining relevance, a common approach to balancing sensitivity and specificity.

Selection Process

The literature search for this study was conducted systematically and comprehensively using four major databases: PubMed, ScienceDirect, Scopus, and EBSCOhost. The initial search yielded 1,690 articles, comprising 532 from PubMed, 652 from ScienceDirect, 367 from

Scopus, and 139 from EBSCOhost. A systematic approach was applied to article screening and selection, following the PRISMA protocol. Of the 1,690 articles initially identified, 237 duplicates were removed, leaving 1,453 for initial screening. All titles and abstracts were screened independently by four reviewers, working in pairs, followed by independent full-text assessment by the same four reviewers. Discrepancies between reviewers at any stage were resolved through discussion in line with recommended PRISMA-based best practice and for independent screening. The screening process resulted in the exclusion of 912 articles due to their irrelevance to the year of publication. Of the remaining 541 articles, 96 full-text articles were reviewed. 83 articles were excluded for failing to meet specific criteria, leaving 13 articles that met all inclusion criteria (**Figure 1**).

Data Collection Process

Data from all included reports were collected using a standardized, pre-tested data extraction form, developed in advance and accompanied by detailed written instructions for its use. For each study, data were extracted by two reviewers working independently and in parallel; subsequently, all authors engaged in a discussion to determine and assess the eligibility of the articles for data extraction on all primary variables to minimize errors and bias. Discrepancies between extractors were identified by comparing data sets and resolved through discussion. If the information in the report was unclear or incomplete, we repeated the critique and assessment of the relevant findings. Where possible, we inputted the extractions, facilitated duplicate data entry, highlighted the extracted text, compared reviewer entries, and applied logic checks, while maintaining verification of all critical outcome data.

Data Charting Process

This review employed JBI critical appraisal tools and validated the findings by having two researchers independently extract data (double extraction), with the first researcher's work reviewed by a fourth researcher to minimize bias and errors; all researchers assessed the content of the articles to ensure the findings aligned with the topics we had identified. For the locked sections of the article, we contacted the original authors of the study to request the articles we used in this research, and we conducted internal verification through cross-checking among team members before the data were analyzed and synthesized.

Data Items

Data were collected for a number of key variables that had been operationally defined in accordance with the PCC (Population, Concept, Context) framework. For the Population component, study characteristic variables included year of publication, country or location, study design, target population, and the specific model used (Code Stroke). For the Concept component, process variables include the intervention or phenomenon under study (including category, content, process components, and model of code stroke to inform clinical decision-making), measurement methods (instruments and data sources), and the analysis procedures applied. For the Context component, outcome variables include relevant primary and secondary indicators, including clinical outcomes, effectiveness in clinical decision-making, and the benefits and barriers of assistive media in the specified healthcare setting.

Critical Appraisal of Individual Sources of Evidence

Critical appraisal of the included sources of evidence is essential because the existing literature on Code Stroke activation and AI-based decision support exhibits a high level of heterogeneity in reporting practices, data modalities, and methodological robustness. Many sources present significant threats to validity, including insufficient reporting on technical measures such as data splitting and hyperparameter tuning, as well as a systematic lack of demographic descriptions, which limits the generalizability of the findings. To address these issues, the review utilized validated tools to assess methodological quality and risk of bias; in this study, JBI was used. Furthermore, data extraction was conducted by independent reviewers using prespecified templates to ensure accuracy and consistency across diverse evidence types. This appraised information was then integrated into the data synthesis to identify systemic pitfalls, categorize the strength of evidence regarding functional outcomes, and determine the optimal balance between diagnostic sensitivity (recall) and resource precision within various activation models.

Consultation to Expert

In the process of identifying gaps and providing context for the mapped literature, we held discussions and assessed the quality of the literature using the JBI to evaluate the quality and relevance of the articles' content for this review. The consultation phase with experts/stakeholders was not conducted in this scoping review because, in accordance with the Arksey and O'Malley framework, the consultation component is optional and not a mandatory element of the scoping review methodology (Buus et al., 2022). Additionally, we chose not to include expert consultation in order to focus on a literature mapping phase that is traceable, transparent, and consistent with the JBI and PRISMA-ScR methodological guidelines, which emphasize the importance of clarity regarding objectives, inclusion criteria, and the evidence synthesis process (Peters et al., 2021; Pollock et al., 2021). Consequently, we decided not to seek expert opinions to assess the suitability of the articles we synthesized.

Synthesis of Results

The charted data were synthesized using a descriptive thematic analysis approach. Extracted data from the included studies were systematically compared and categorized according to similarities in activation models, implementation processes, technological integration, and reported outcomes. The findings were then grouped into four major themes: (1) standard clinical activation, (2) nurse-led activation, (3) technology- and artificial intelligence–driven activation, and (4) pre-hospital activation. Within each theme, key characteristics, workflow components, process indicators (e.g., door-to-needle and door-to-CT times), and clinical outcomes were summarized narratively. This approach enabled the identification of common patterns, differences between activation models, implementation feasibility, and existing evidence gaps related to the effectiveness of Code Stroke activation in improving clinical decision-making and quality of care.

Results

Selection of Sources of Evidence

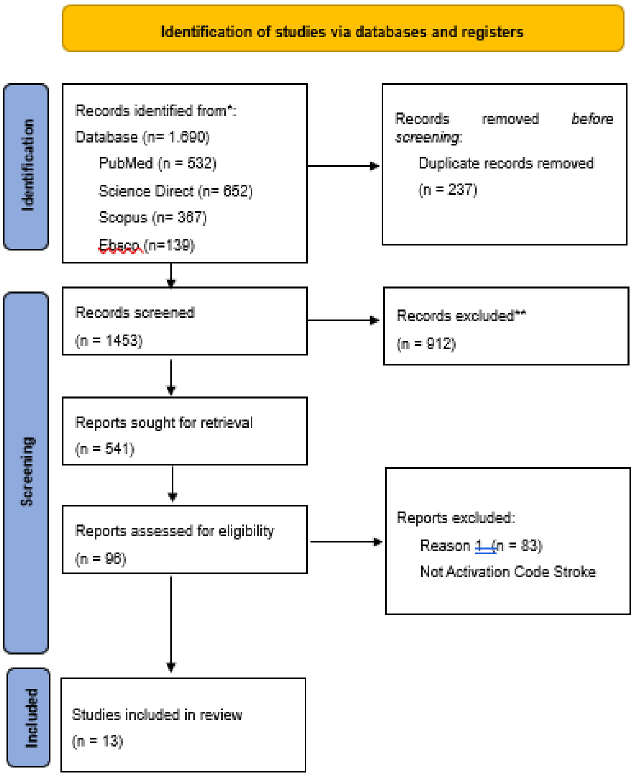


Figure 1. Illustrate the PRISMA Flow Diagram.

The implementation of the scoping review follows the five core stages of the methodological framework established by Arksey and O'Malley (2005) and further refined by the Joanna Briggs Institute (JBI). These stages involve identifying the research question, conducting comprehensive searches for relevant studies, selecting evidence based on pre-specified inclusion and exclusion criteria, charting and categorizing the data, and finally collating and reporting the results. To ensure the study remains focused and structured, the PCC (Population, Concept, Context) framework was utilized to operationally define the key variables: the population (stroke patients), the concept (clinical decision-making), and the context (quality of care). Adherence to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines ensures that the entire process is transparent, reproducible, and clearly documented via a flow diagram. This specific methodological approach was chosen because it excels at mapping the breadth of heterogeneous literature and identifying research gaps, which is more appropriate for the broad questions surrounding Code Stroke activation than a narrow systematic review. While the Arksey and O'Malley framework includes an option for expert consultation, this implementation prioritized a traceable and transparent literature mapping phase consistent with JBI and PRISMA-ScR standards, ultimately deciding to omit the consultation component to focus on evidence synthesis (**Figure 2**).

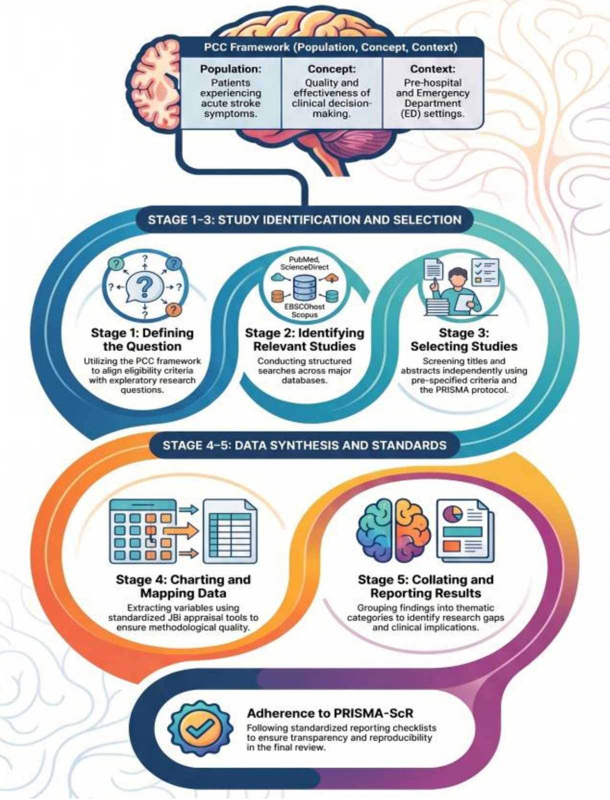


Figure 2. Illustrate The Five Stages Framework Integration

Characteristics of Sources of Evidence

The sources of evidence in this literature are characterized by a wide diversity of methodologies and data types, ranging from high-level systematic reviews and randomized clinical trials (RCTs) to large-scale retrospective cohort studies. These sources utilize various primary and secondary data sources, including hospital stroke registries, electronic medical records (EMR), and national health administrative data that employ ICD-10 codes to efficiently identify patient clinical outcomes. Additionally, there is a utilization of new granular data through body camera technology to objectively measure the duration of each clinical workflow process with precision down to the second, which overcomes the limitations and subjectivity of self-reported data.

Another key characteristic is the high level of heterogeneity in reporting practices and data modalities, particularly in studies involving artificial intelligence (AI) and clinical decision support systems. Many sources show threats to validity due to insufficient reporting on technical robustness, such as data splitting and hyperparameter tuning, alongside low adherence to medical reporting standards. While some studies involve massive samples of tens of thousands of patients, a common characteristic is the dominance of single-center designs with limited sample sizes, which may restrict the generalizability of results to different healthcare infrastructures. This underscores the necessity for algorithm standardization and high-quality data collection to ensure evidence is reliably applicable in real-world clinical practice

Critical Appraisal Within Sources of Evidence

The resources include mixed designs (cluster RCTs, retrospective cohorts, before–after quality improvement, observational diagnostic/prognostic studies, and systematic reviews). Below is a concise, JBI-style critical appraisal focusing on key validity domains: design, bias, confounding, and applicability.

Table 3. Illustrates the JBI appraisal findings used JBI-style appraisal domains across stroke studies.

Study (design)	Sampling & Comparability	Measurement & Outcomes	Management of Confounding	Overall Internal Validity	Applicability
Cluster randomized stepped-wedge trial of AI LVO alerting (Martinez-Gutierrez et al., 2023)	Clear cluster frame; all EVT LVO patients in 4 CSCs, pre/post AI exposure; exclusions defined	Time metrics objectively from hospital systems; primary (door-to-groin) and secondary endpoints prespecified; 90-day mRS explored	Mixed-effects regression with random cluster effect and fixed exposure; adjustment for key severity covariates in functional outcome model	High: randomized stepped-wedge, appropriate analyses, clear outcome definitions	High for CSCs using EVT and AI LVO tools
ML stroke-alert trigger development (diagnostic/prognostic) (Sung et al., 2021)	Consecutive ED cohort within 12 h of onset, suspected stroke/TIA or stroke-related	Input features from routine triage; performance using AUPRC compared to	Internal validation across multiple ML methods; class imbalance handled with	Moderate–high: single-center retrospective; good internal	Moderate: EDs with similar triage data and IT infrastructure

Study (design)	**Sampling & Comparability**	**Measurement & Outcomes**	**Management of Confounding**	**Overall Internal Validity**	**Applicability**
	symptoms; 1361 patients	rule-based tools	undersampling, SMOTE, and class weighting	validation, but no external validation reported	
Continuous observation workflow time study (time–motion) (Wong et al., 2023)	100 Codes convenience sample (19.2% of all); single center	Detailed direct measurement of each workflow component; clear reporting of medians and ranges	Regression is used to explore associations, but observational design; no control group	Moderate-high: strong process data, limited by selection and single center	High for similar primary stroke centres examining workflow bottlenecks
Retrospective cohort, triage nurse- vs doctor-activated evaluation (Liang et al., 2022)	All non-EMS thrombolysed AIS over period; two groups defined by activation type; potential selection bias in who is nurse- vs doctor-activated	Time metrics clearly defined (DNT, DVT, DBT) and extracted systematically	Group comparisons with appropriate non-parametric tests; logistic regression used, but residual confounding likely in non-randomized comparison	Moderate-high: clear effect on time metrics, but non-random allocation and single-center	Moderate: generalizable to EDs with similar triage structure
Nonrandomized pre/post nurse-driven telestroke protocol (Olson et al., 2022)	Unit-level pre/post; 180 control and 267 postintervention encounters	Clear definition of stroke time metrics; use of medians and IQRs; some outcomes potentially influenced by external factors	No randomization; secular trends and co-interventions cannot be excluded	Moderate-high: feasible design, positive nurse-sensitive metrics, but limited causal certainty	Moderate–high for telestroke EDs considering nurse-led protocols
Nurse-led QI, telestroke DNT reduction (Powell et al., 2025)	Retrospective before–after analysis; details on sampling not provided in abstract	Outcome measures (DNT, thrombolytic rates) standard; effect sizes with CIs reported	Adjusted analyses performed, but specific covariates not listed in abstract	Moderate: typical QI limitations (no control, potential confounders)	Moderate for telestroke centers with similar staffing and workflows
Observational validation of ICD-10 stroke ascertainment (Raju et al., 2023)	9959 coded hospitalizations, 304 sampled for adjudication; VA population (mostly older, male)	Gold-standard chart adjudication by 3 reviewers; PPV calculated for each code	No adjustment needed (diagnostic accuracy focus); risk of sampling bias if non-representative subset	High for PPV of specific ICD-10 codes in VA setting	Moderate for similar administrative data–based stroke trials
Retrospective Code Stroke cohort	1354 Code Stroke activations over	Outcomes (final stroke/TIA	Multivariable analysis for predictors;	Moderate-high: robust sample,	High for large EDs with similar Code

Study (design)	Sampling & Comparability	Measurement & Outcomes	Management of Confounding	Overall Internal Validity	Applicability
(Ebker-White et al., 2022)	2 years; comprehensive capture	diagnosis, reperfusion therapy) standard; timing metrics (door-to-CT, door-to-needle) used	residual confounding likely	retrospective nature	Stroke systems
Retrospective pre/post AI triage (Viz LVO) (Morey et al., 2021)	Small sample (n=55) split into pre/post; transfer population only	Standard EVT time intervals; statistical significance only for door-to-notification	Simple group comparison; no detailed adjustment in abstract	Moderate-high: underpowered, observational	Moderate for centers adopting Viz in transfer workflows
Descriptive before–after service evaluation (Woodward et al., 2024)	Single hospital ED-SRU; no clear description of control/comparator group in abstract; sampling appears all eligible stroke patients after implementation, limiting comparability over time	Main outcomes are process times (door-to-needle) and "patient outcomes", but only time metrics are quantified; outcome definitions and ascertainment methods not detailed	No explicit identification or adjustment for potential confounders (case-mix, stroke severity, other workflow changes) in abstract	Moderate: clear temporal association but uncontrolled before–after design and limited detail on methods	High face-validity for similar ED settings; single-center nurse-led model may limit transferability without local adaptation
Cross-sectional observational (Mehdizadehfar et al., 2024)	Consecutive acute stroke patients with ESC activation or thrombolysis during 1 year at a single referral center, but no randomization; groups (ESC vs no ESC, tPA vs no tPA) may differ systematically	Clearly defined time metrics (arrival-to-CT, arrival-to-tPA), treatment use, hemorrhage, NIHSS and mRS, with quantitative results reported	Some descriptive reporting of reasons for no tPA, but no explicit statistical adjustment for confounders (e.g., severity, comorbidities) when comparing outcomes	Moderate-high: robust measurement of time and outcomes, but cross-sectional design and lack of adjustment constrain causal inference about ESC effect on clinical outcomes	High relevance for middle-income, high-volume centers with similar ESC systems; generalization beyond single center and region should be cautious
Systematic Review (Astasio-Picado et al., 2025)	Comprehensive search of 5 databases (2020–2025) with eligibility criteria; 13 studies, 80,555	Focus on functional prognosis, neurological status, independence, QoL; key	Confounding and bias addressed through ROBINS-I, ROBIS, and RoB2 across studies, with domain-level and	High internal validity for a review: structured methods and formal risk-of-bias	High: findings on Code Stroke timing and nursing-led neurorehabilitation are broadly

Study (design)	**Sampling & Comparability**	**Measurement & Outcomes**	**Management of Confounding**	**Overall Internal Validity**	**Applicability**
	patients; uses design-specific tools (JADAD, AMSTAR2, NOS) to appraise included studies, supporting comparability assessment	prognostic variables (age, lesion volume, time to treatment) extracted and synthesized	overall risk ratings	assessment; residual heterogeneity and underlying study quality still limit certainty	applicable to inpatient stroke care and rehab services
Systematic Review (Akay et al., 2023)	Full-text English studies proposing AI CDSS for adult AIS; 121 included, 65 fully extracted; selection and heterogeneity clearly described	Describes data sources, outcomes, model tasks; evaluates reporting against AI reporting standards	Confounding is mainly handled via critical assessment of model development/validation practices and concordance with standards; notes many “significant validity threats” across studies	High internal validity as a methods-focused review, but underlying primary studies frequently at risk of bias due to poor reporting and validation	Applicability currently limited: many systems are developmental; translation to real-world stroke care constrained by methodological and reporting weaknesses

The results of the critical appraisal reveal a wide variety of study designs evaluating innovations in acute stroke care, ranging from cluster randomized trials to comprehensive systematic reviews. In general, these studies have internal validity ranging from moderate to high, with strong methodology regarding the objectivity of clinical time metric measurements, meaning all of these articles meet the eligibility criteria based on the JBI Critical Appraisal Tools. This quality assessment process focuses on key validity domains, including study design strength, minimization of bias, management of confounding factors, and the applicability of results within stroke care systems. Studies with high internal validity, such as the cluster randomized stepped-wedge trial on the AI warning system, used mixed-effects regression analysis and strict covariate adjustment to ensure accurate results. The included systematic reviews also demonstrate robust methodology by using formal assessment tools such as AMSTAR2 or ROBINS-I to verify the quality of the primary studies they synthesize. Although some studies are retrospective or quality improvement (QI) projects with inherent limitations in non-randomized allocation, they are still categorized as having moderate to high validity due to their systematic data extraction processes. The objectivity of clinical time metric measurements is enhanced through the use of cutting-edge technologies, such as body-worn cameras, which can provide granular data down to the second for each workflow component, thereby addressing the subjectivity of manual reporting. However, the assessment also noted heterogeneity in technical reporting regarding artificial intelligence (AI)-based models, where some studies lacked sufficient technical details such as data partitioning or adequate demographic descriptions. Overall, this final selection of 13 articles provides a credible evidence base for mapping the effectiveness of the Code Stroke activation model on the quality of clinical decision-making (**Table 3**).

Results of Individual Sources of Evidence

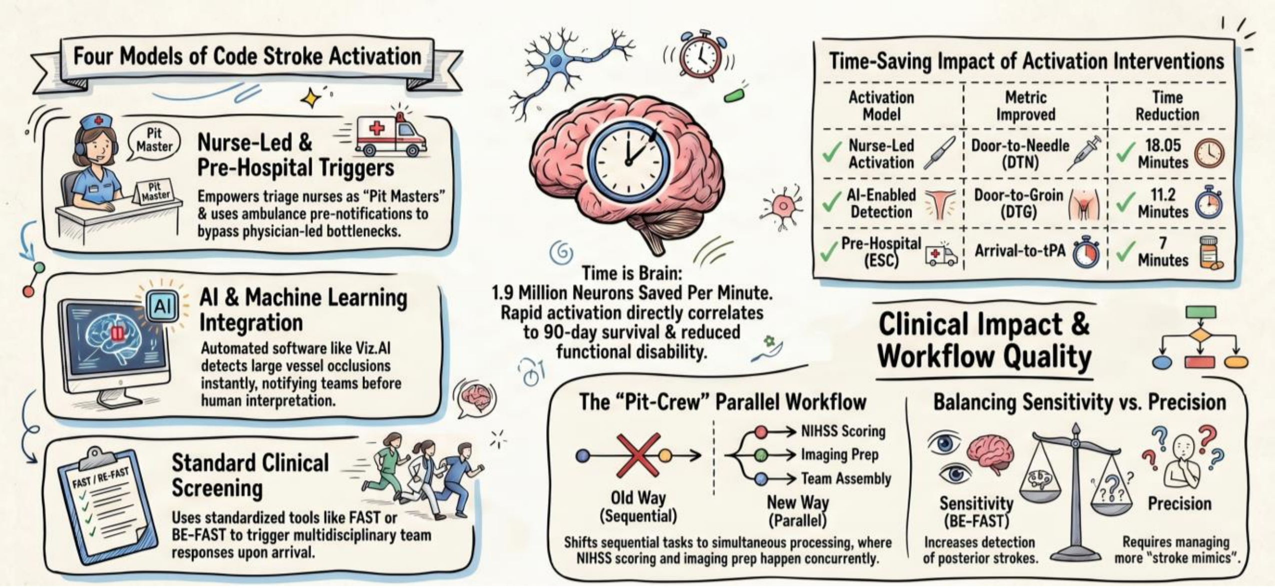
Table 4. Illustration Data Extraction Source of Evidence

Study Title	Authors (Year)	Activation Model Category	Specific Activation Protocol	Primary Process Metrics (e.g., DTN, DTC)	Key Clinical or Decision-Making Outcomes
Artificial Intelligence for Clinical Decision Support in Acute Ischemic Stroke	Martinez-Gutierrez, et al. (2023)	Technology and AI Driven	Viz.AI (AI-enabled LVO detection)	Reduction in DTG (door-to-groin) time of 11.2 minutes; 9.8 minute reduction in CT-to-EVT start.	Reduced mortality rates by nearly 60%; automated alerts faster than human interpretation.
Real-World Experience with Artificial Intelligence-Based Triage in Transferred LVO Patients	Morey, et al. (2021)	Technology and AI Driven	Computer-aided Triage (Viz LVO)	Team notification time faster (25 vs 40 minutes).	Decreased time variation; expedited neuroendovascular team notification for transfers.
Nursing-Led Quality Improvement Project Achieves 30-Minute Door-To-Needle Time	Powell, et al. (2025)	Nurse-Led Activation	Stroke Alert (Nurse-Led) / BE-FAST	Median DTN decreased by 18.05 minutes; door-to-CT time decreased by 10.65 minutes.	Proportion of IVT increased (14.0% vs 8.1%); improved identification through BE-FAST.
Nurse-Led Novel Stroke Response Unit Improves Door-to-Needle Metrics and Patient Outcomes	Woodward, et al. (2024)	Nurse-Led Activation	Code Stroke (ED-SRU Pathway) / Pit-crew	Significant reduction in DTN times; >50% of patients receive thrombolysis within <30 minutes.	Exceeding national benchmarks; improved patient outcomes via specialized neurocritical staff.
Triage Nurse-Activated Emergency Evaluation Reduced Door-to-Needle Time	Liang, et al. (2022)	Nurse-Led Activation	Urgent Emergency Evaluation (Nurse Triage Activation)	Median DNT reduced (28 vs 30 minutes); shorter door-to-vein and door-to-blood sample times.	95.6% of patients met target time <45 minutes; reduced 7-day NIHSS score.
Outcomes from a Nursing-Driven Acute Stroke Care Protocol for Telehealth Encounters	Olson, et al. (2022)	Nurse-Led Activation	Code Stroke (Telestroke) / NAS-Care Protocol	Reduction in median DTP (2 vs 5 minutes) and DTCT (5 vs 9 minutes); DTN not reduced.	Effective coordination via "pit-master" role during tele-stroke encounters.

Study Title	**Authors (Year)**	**Activation Model Category**	**Specific Activation Protocol**	**Primary Process Metrics (e.g., DTN, DTC)**	**Key Clinical or Decision-Making Outcomes**
Impact of Code stroke activation on Functional Outcomes and the Role of Nursing	Astasio-Picado, et al. (2025)	Nurse-Led / Standard	Code Stroke	Focus on DTN reduction.	Improved functional independence (mRS at 90 days) and quality of life via early rehabilitation.
Developing a stroke alert trigger for clinical decision support using machine learning	Sung, et al. (2021)	Technology and AI Driven	Stroke Alert Trigger (ML-based)	Improved AUPRC metrics and F1 scores.	Improved identification compared to FAST/BE-FAST; allows balancing accuracy vs resource availability.
Evaluating Code stroke activation Pathway in Emergency Departments study (ESCAPED)	Ebker-White, et al. (2022)	Standard Clinical / Pre-Hospital	Code Stroke / FAST-based protocol	Ambulance notification significantly reduced door-to-CT and door-to-needle times.	51% of patients diagnosed with stroke/TIA; identifies predictors of final diagnosis.
Optimizing Acute Ischemic Stroke Care: Evaluating ESC Activation and Thrombolytic Therapy	Mehdizadehfar, et al. (2024)	Pre-Hospital Activation	Emergency Code Stroke (ESC)	Reduced arrival to tPA injection from 44 to 37 minutes.	Evaluation of mRS scores and effectiveness of rapid initiation of intervention.
Using body cameras to quantify the duration of a Code Stroke and identify workflow issues	Wong, et al. (2023)	Standard Clinical (Monitoring-enhanced)	Code Stroke / Bodycam monitoring	Median code duration 54.2 minutes; administrative tasks took 21 minutes.	Identified administrative tasks as longest component; Tenecteplase prepared faster than alteplase.
Artificial Intelligence for Clinical Decision Support in Acute Ischemic Stroke	Akay, et al. (2023)	Technology and AI Driven	AI-based CDSS	Not in source	AI outperformed conventional clinical comparators in 75% of cases; improved patient stratification.

Note: The terms are explained in the section Synthesis of Result

Synthesis of Results



Four Models of Code Stroke Activation

Nurse-Led & Pre-Hospital Triggers

Empowers triage nurses as "Pit Masters" & uses ambulance pre-notifications to bypass physician-led bottlenecks.

AI & Machine Learning Integration

Automated software like Viz.AI detects large vessel occlusions instantly, notifying teams before human interpretation.

Standard Clinical Screening

Uses standardized tools like FAST or BE-FAST to trigger multidisciplinary team responses upon arrival.

Time is Brain:
1.9 Million Neurons Saved Per Minute.
Rapid activation directly correlates to 90-day survival & reduced functional disability.

Time-Saving Impact of Activation Interventions

Activation Model	Metric Improved	Time Reduction
✓ Nurse-Led Activation	Door-to-Needle (DTN)	✓ 18.05 Minutes
✓ AI-Enabled Detection	Door-to-Groin (DTG)	✓ 11.2 Minutes
✓ Pre-Hospital (ESC)	Arrival-to-tPA	✓ 7 Minutes

Clinical Impact & Workflow Quality

The "Pit-Crew" Parallel Workflow

Shifts sequential tasks to simultaneous processing, where NIHSS scoring and imaging prep happen concurrently.

Balancing Sensitivity vs. Precision

Increases detection of posterior strokes.

Requires managing more "stroke mimics".

Figure 4. Illustrate the Models of Code Stroke Affects Clinical Impact and Workflow Quality

Based on the articles we reviewed, code stroke activation models can be thematically grouped into four main categories according to their initiators, workflows, and degree of technology integration. First, standard clinical activation relies on clinician- or scale-based suspicion of acute stroke, such as activation triggered by FAST (Face, Arm, Speech, Time)/BE-FAST (Balance, Eye, Face, Arm, Speech, Time) screening or clinical assessment by ED physicians or paramedics on arrival, often within a defined onset window (e.g. <4.5–24 hours). Second, nurse-led activation shifts the trigger from physicians to trained ED or triage nurses, including nurse-driven stroke alerts, triage nurse-activated evaluations using FAST/BE-FAST, pit-crew style pathways in dedicated stroke response units, and nurse-driven telestroke preparation protocols; these models consistently shorten door-to-activation and door-to-needle times while maintaining outcomes. The first category is standard clinical activation, which includes: The Standard Code Stroke is activated for patients suspected of having an acute stroke based on findings from the FAST screening tool or through clinical assessment by an emergency department physician or paramedic (Ebker-White et al., 2022). Standard Stroke Alert is initiated immediately upon the patient's arrival at the ED if they exhibit stroke symptoms with an onset time (last known well) of less than 24 hours (Powell et al., 2025; Woodward et al., 2024). BE-FAST screening is an extension of FAST that adds balance and eye components to improve sensitivity in detecting stroke symptoms, including posterior circulation strokes (Ebker-White et al., 2022; Powell et al., 2025; Sung et al., 2021) **(Figure 4).**

The second category is Nurse-Led Activation, which includes: Nursing-Led Stroke Alert. This model empowers emergency department nurses to independently initiate a stroke alert without waiting for a physical examination by a physician, thereby accelerating intervention (Powell et al., 2025). Triage Nurse-Activated Emergency Evaluation: This model involves specialized triage nurses who have undergone intensive training to immediately activate the stroke team using the FAST scale as soon as the patient arrives, which has been shown to significantly reduce door-to-needle time (Liang et al., 2022). ED-SRU (Emergency Department–Stroke Response Unit) Code Stroke Pathway: A response pathway led by a specialized neuroscience nurse in a dedicated ED unit (Stroke Response Unit) using a "pit-crew" approach to simultaneously perform NIHSS (National Institutes of Health Stroke Scale) assessment and coordinate imaging (Woodward et al., 2024). The NAS-Care protocol, a nurse-driven protocol to coordinate patient data collection before a telestroke specialist joins via a video conferencing system, uses a "pit-stop" model for efficiency (Olson et al., 2022).

Third, technology and AI(Artificial Intelligence)/ML-driven (Machine Learning Driven) ctivation uses automated tools such as AI platforms for LVO (Large Vessel Occlusion) detection and care coordination (e.g. Viz.AI), machine-learning–based stroke alert triggers embedded in electronic triage, and AI-based CDSS (Clinical Decision Support Systems) to support risk stratification—to accelerate notification of stroke and neurointerventional teams and modestly reduce treatment delays, which includes: AI-Enabled LVO Detection (Viz.AI), a cloud-based algorithm that automatically analyzes CTA (CT Angiogram) images and sends instant notifications in the form of alerts to the medical team's mobile devices if a large vessel occlusion (LVO) is detected (Martinez-Gutierrez et al., 2023; Morey et al., 2021). Computer-Aided Triage (Viz.LVO) functions as an automated early warning system that expedites notifications to the neuroendovascular team, particularly for LVO stroke patients transferred between hospitals (Morey et al., 2021). ML-Driven Stroke-Alert Trigger is a warning trigger system embedded within an electronic triage system that uses algorithmic models to identify stroke patients based on primary complaint data, age, and vital signs during triage. AI-based CDSS directly links patient characteristics to predictions of clinical outcomes to assist physicians in treatment stratification (Sung et al., 2021).

Fourth, pre-hospital activation encompasses EMS prenotification, pre-arrival ambulance alerts, and structured pre-hospital triage protocols that trigger in-hospital stroke pathways before arrival, leading to shorter door-to-CT and door-to-needle times and higher accuracy of stroke identification, which includes: the Emergency Code Stroke (ESC), a coordination protocol between emergency medical services (EMS) in the field and the hospital stroke team to trigger the team's response before the patient arrives at the hospital (Mehdizadehfar et al., 2024). Ambulance Pre-arrival Notification is a Code Stroke activated by paramedics en route that allows the hospital to prepare resources, which has been shown to significantly reduce "door-to-CT" and "door-to-needle" times. The PAST Protocol is a pre-hospital acute stroke triage protocol designed to increase the rate of thrombolytic therapy (tPA) administration through early notification (Ebker-White et al., 2022).

Across these themes, most studies evaluate single models in single centers, focus heavily on time metrics (door-to-activation/CT/needle), and rarely compare models head-to-head or report detailed clinical decision-making quality (e.g. stroke mimic rate, appropriateness of reperfusion decisions, or downstream outcomes). This reveals a key research gap: the lack of comparative, multi-context analyses of different activation categories—and their hybrids on both process efficiency and decision accuracy, particularly in low-resource or non-thrombectomy settings.

The coding procedure within the Code Stroke framework is a standardized rapid-response system designed to efficiently identify, evaluate, and manage patients with acute stroke through the coordination of a multidisciplinary team involving the emergency department (ED), neurology, radiology, and the laboratory. This procedure begins with activation, which can be triggered through various methods, ranging from standard clinical screening using the FAST or BE-FAST scales, self-activation by a triage nurse acting as a “pit master,” early notification from the ambulance team before the patient arrives at the hospital, to the use of AI algorithms that automatically detect large vessel occlusions. In practice, this procedure employs a “pit-crew” workflow model that transforms sequential processes into simultaneous parallel processing, where various critical tasks such as NIHSS scoring, intravenous access placement, and CT scan preparation are performed concurrently by different team members. This entire coding procedure is based on the “Time is Brain” principle, which aims to minimize the time from patient arrival to therapy administration (door-to-needle) to save millions of neurons and improve patients’ functional recovery. In addition to clinical operations, this system is also supported by quality monitoring through the coding of administrative data (such as ICD-10) to identify patient clinical outcomes and ensure the ongoing accuracy of diagnoses.

Implementation feasibility in resource-rich systems is often defined by the integration of advanced technological support, such as AI and ML-Driven platforms, into highly standardized clinical workflows. In these environments, systems like Viz.AI can automatically detect large vessel occlusions and synchronize multidisciplinary teams via secure mobile alerts, significantly reducing door-to-treatment times. These settings benefit from robust infrastructure, including stable internet connectivity, integrated Electronic Medical Records (EMR), and the availability of specialized neurocritical staff, which allows for the successful adoption of "pit-crew" models that prioritize simultaneous parallel processing. However, even in these high-tech centers, feasibility requires balancing diagnostic sensitivity with resource precision to prevent clinician burnout from unnecessary code activations caused by "stroke mimics".

In contrast, resource-limited systems, such as those in many parts of Indonesia, face substantial feasibility barriers due to geographical challenges, limited access to specialists, and infrastructural gaps in power, internet, and imaging facilities. In these contexts, feasibility depends on adapting evidence-based models to local constraints by prioritizing staff empowerment and process simplification rather than high-cost technology. Research indicates that even hospitals without internal CT scanners can implement effective Code Stroke protocols through multidisciplinary training and established referral pathways. Nurse-led activation models are particularly feasible in these settings, as they grant triage nurses the authority to trigger alerts independently, bypassing physician-led bottlenecks without requiring advanced AI infrastructure. Thus, while resource-rich systems focus on technological optimization, resource-limited feasibility is primarily achieved through workflow reorganization and training-driven efficiency.

Discussion

The findings from this preliminary review indicate that stroke activation protocols are a key component in reducing door-to-needle time, with various protocols reported to have a positive impact on process quality and the quality of decision-making. Reducing door-to-needle (DTN) time is critical in the management of acute ischemic stroke, as every minute of delay results in the loss of millions of neurons, which worsens patients' functional outcomes (Astasio-Picado et al., 2025). Nurse-led interventions, such as the activation of immediate emergency assessment by triage nurses, have been shown to significantly reduce the median DTN to 28 minutes, with 95.6% of patients meeting the target time of under 45 minutes (Liang et al., 2022). Additionally, the implementation of stroke response units in emergency departments managed by specialized neuroscience nurses consistently exceeds national benchmarks, with over 50% of patients receiving thrombolytic therapy within less than 30 minutes (Woodward et al., 2024). This success is supported by the empowerment of nurses through protocols emphasizing early stroke recognition and the optimization of parallel workflows, which collectively reduced the median DTN to 18.05 minutes (Powell et al., 2025). Although the use of telestroke technology sometimes faces challenges related to delays, nurse-driven workflows remain a key factor in ensuring the rapid and efficient administration of reperfusion therapy to save brain tissue (Powell et al., 2025; Woodward et al., 2024).

The implementation of artificial intelligence (AI) technology in acute ischemic stroke management workflows has proven highly effective in accelerating critical medical intervention times. The use of AI algorithms integrated with secure messaging systems, such as Viz.AI, can automatically detect large vessel occlusion (LVO) through CT angiography scans in just minutes (Martinez-Gutierrez et al., 2023). Based on a randomized clinical trial, this intervention significantly reduced the average door-to-groin (DTG) time by 11.2 minutes compared to conventional methods (Martinez-Gutierrez et al., 2023). Additionally, the duration from the start of the CT scan to the initiation of endovascular thrombectomy (EVT) was reduced by 9.8 minutes. This efficiency is achieved because automated alerts often arrive well before human interpretation is available in the clinic's PACS system, enabling the multidisciplinary team to work within a more synchronized parallel workflow. By facilitating transparent and rapid communication via a mobile app, this technology acts as a crucial early warning system to ensure no LVO patients are missed or receive delayed care (Martinez-Gutierrez et al., 2023).

Workflow optimization through the "pit-crew" model revolutionizes acute stroke care by shifting the paradigm from sequential processing to simultaneous parallel processing. Within this framework, various critical tasks are completed simultaneously by different team members, rather than waiting for one task to finish before starting the next. For example, a nurse can perform the NIHSS assessment while the patient is being prepared for a CT scan, while other team members simultaneously collect clinical data or establish intravenous access (Olson et al., 2022). This workflow is typically led by a nurse acting as a "pit master" to coordinate role delegation and ensure all aspects of the Code Stroke protocol run efficiently. The implementation of this parallel processing strategy, often supported by integrated communication systems, has proven effective in reducing critical medical intervention times such as door-to-needle and door-to-groin metrics. In addition to accelerating treatment times, the clear division of roles in this model also minimizes duplication of work, ensuring every second is optimally utilized to save the patient's brain tissue (Martinez-Gutierrez et al., 2023; Olson et al., 2022).

The use of body-worn cameras is an innovative method capable of providing granular and objective data on every second of the Code Stroke workflow. Based on a continuous observational study conducted by Wong et al. (2023), it was found that administrative tasks utilizing body-worn cameras helped evaluate the entire process, with a median time of 21 minutes. This administrative burden includes critical activities such as typing medical records, charting, patient handover procedures, and discussion or debriefing sessions with family members. Interestingly, this administrative duration far exceeds the time spent on clinical decision-making by the neurology team, which is often considered the primary bottleneck but in fact accounts for only a small portion of the process. Identifying these barriers through video recordings also demonstrates that managerial interventions, such as deploying additional medical staff, can effectively reduce the time spent on these administrative tasks to improve workflow efficiency. Supported by studies by Janssen et al. (2019) and Koca et al. (2023), workflow optimization (parallel processing, team protocols, real-time feedback, and stroke team consistency) shortens door-to-treatment time by tens of minutes and improves functional outcomes in EVT and AIS.

The implementation of expanded screening scales such as BE-FAST (balance and eyes) has been shown to significantly improve the sensitivity (recall) of stroke detection, particularly for identifying posterior circulation strokes that are often missed by the standard FAST scale. Although its sensitivity is higher, the use of broader criteria in BE-FAST tends to reduce precision compared to the standard FAST, as symptoms like vertigo often stem from non-stroke conditions that trigger excessive false alarms. The use of Machine Learning (ML) models can further improve diagnostic accuracy, where specific ML techniques such as the Classification and Regression Tree (CART) demonstrate significantly superior recall and F1 scores compared to both FAST and BE-FAST (Sung et al., 2021; Zheng et al., 2022). The primary advantage of these ML models is their ability to provide probability estimates that can be tailored to the specific needs of an emergency department; thresholds can be adjusted for high recall to avoid the risk of malpractice, or for high precision to prevent physician burnout resulting from unnecessary code stroke activations (Sung et al., 2021). Thus, integrating clinical features during triage into ML systems enables higher-quality and more efficient clinical decision-making by balancing diagnostic accuracy with resource availability.

Artificial intelligence (AI)-based clinical decision support systems offer an innovative approach that goes beyond traditional population-based thresholds by providing individualized, data-driven decision support. AI algorithms have the capability to perform high-dimensional data analysis to identify complex associations among variables and directly correlate patient characteristics with expected clinical outcomes. Based on the findings of Akay et al. (2023), the integration of this technology is highly beneficial for patient stratification by providing complementary information regarding the potential benefits of a specific treatment, which in turn supports the selection of more personalized therapies. Through machine learning (ML) models, the system can provide probability estimates regarding the severity or likelihood of a stroke, allowing clinicians to adjust decision thresholds to balance diagnostic accuracy with hospital resource availability. If implemented correctly, the use of this individualized patient data holds significant potential for improving patient functional outcomes and the quality of care in cases of acute ischemic stroke. Supported by the research findings of Baydoun et al. (2023) and Esteva et al. (2022) on prostate cancer, deep learning AI models for prostate cancer combine clinical data and histopathological images to predict long-term outcomes and outperform standard risk stratification tools, allowing doctors to select therapies with the highest likelihood of success and the lowest toxicity. In another study by Vaghari et al. (2025) on Alzheimer's disease, an AI model (PPM) classified patients into slow- and fast-progressing groups; only the slow-progressing group derived meaningful benefit from medication—a finding not evident with conventional selection criteria such as β-amyloid status.

The use of administrative health data through the development of ICD-10 algorithms offers an efficient research tool for identifying stroke to support pragmatic clinical trials and quality monitoring. Based on the study by Raju et al. (2023), certain codes demonstrate very high validity. For example, code I61 (non-traumatic intracerebral hemorrhage) has a positive predictive value (PPV) of 100%, while code I63 (cerebral infarction) achieves a PPV of 90%. Developing accurate algorithms is crucial as it can reduce or eliminate the need for manual medical record review (adjudication), which is costly and time-consuming. By grouping codes based on their association levels (such as the high PPV category ≥80% for "definite stroke"), the system can automatically classify the majority of cases, thereby improving the efficiency of large-scale research data collection. Although the use of electronic algorithms still carries a risk of misclassification that must be considered when determining sample size, the integration of these administrative datasets is viewed as a reliable alternative to conventional methods for monitoring clinical outcomes and disease burden at the population level.

Positive impacts on clinical outcomes for stroke patients are highly dependent on the speed of intervention, given the loss of approximately 1.9 million neurons every minute during impaired cerebral perfusion, which directly worsens patient prognosis. Rapid Code stroke activation and the implementation of reperfusion therapy, whether through intravenous thrombolysis or mechanical thrombectomy, have been shown to improve neurological status and quality of life (Astasio-Picado et al., 2025). Reducing DTN time is closely associated with improved 90-day survival, reduced risk of hemorrhagic transformation, as well as lower mortality rates and frequency of rehospitalization within one year (Liang et al., 2022). The implementation of AI technology for detecting LVO has also shown promising results, with reports indicating that its use can increase the rate of early intervention (Martinez-Gutierrez et al., 2023). In addition to acute-phase management, early nurse-led neurorehabilitation (within the first 24–72 hours) is a key determinant in restoring patient independence, reducing residual symptoms such as motor or cognitive deficits, and improving functional scores on the Barthel Index and Fugl-Meyer Assessment scales (Astasio-Picado et al., 2025). Overall, the integration of a responsive system and continuous care is crucial for minimizing permanent neurological damage and optimizing long-term recovery in stroke patients.

Empowering the nurse's role through the "pit-crew" model is essential for efficiently coordinating the entire acute stroke evaluation process. Within this framework, a nurse acts as the "pit master" or protocol coordinator, leading the team, delegating tasks, and ensuring all aspects of the stroke protocol are completed on time (Olson et al., 2022). Nurses are empowered as managers of the entire process, ranging from conducting the NIHSS scale assessment, collecting clinical data, to establishing intravenous access while the patient is being prepared for a CT scan (Woodward et al., 2024). The implementation of a no-fault system also grants triage nurses full authority to trigger a stroke alert immediately upon symptom identification, which has been shown to accelerate patient entry into the care pathway (Powell et al., 2025).

Interdisciplinary collaboration between physicians, nurses, and the radiology team is now supported by real-time communication technology to ensure multidisciplinary team synchronization. The use of secure messaging apps and AI-based platforms on mobile devices allows all team members, including neurologists and neuroradiologists, to receive alerts regarding large vessel occlusion simultaneously within minutes of the scan's completion (Martinez-Gutierrez et al., 2023; Powell et al., 2025). Information transparency through this chat function facilitates faster decision-making compared to conventional telephone systems, allowing the team to work within an integrated parallel workflow. Efficient synchronization between services such as anesthesia, patient transport, and neurology is critical to minimizing every second of delay in intervention (Morey et al., 2021).

The implementation of ongoing education and regular simulations is a key factor in improving team comfort and workflow efficiency. Training through "mock stroke alerts" helps medical staff hone their communication and problem-solving skills in high-pressure emergency situations (Powell et al., 2025; Woodward et al., 2024). In addition to nurses and physicians, education is also provided to radiology and administrative staff regarding the importance of timely imaging and blood pressure management guidelines. Real-time feedback and case-by-case evaluations allow the team to learn from both successes and challenges, thereby maintaining a culture of quality care (Powell et al., 2025). Overall, readiness honed through simulation helps hospitals exceed national benchmarks for the speed of reperfusion therapy delivery.

All interventions nurse-led stroke activation protocols, the use of artificial intelligence, the "pit-crew" model, and the use of body-worn cameras contribute to the same goal, accelerating the acute stroke care pathway (DTN/DTG) through optimized workflow and team communication. Complementarily, direct clinical interventions (nurse-led protocol, pit-crew) focus on executing parallel actions at the bedside, while AI and body-worn cameras serve as supporting technologies: AI accelerates LVO detection and real-time team coordination, while body-worn cameras reveal hidden administrative barriers for managerial improvement. Implied potential contradictions arise from reliance on high-tech solutions (AI, telestroke, body-worn cameras), which may introduce new delays or additional administrative burdens in contrast to nurse-driven and pit-crew approaches that emphasize process simplification and staff empowerment. However, the overall evidence points more toward a synergistic relationship than a conflicting one, where technology and team-based protocols complement each other to maximize the speed and quality of clinical decisions.

Research in Indonesia indicates that a stroke protocol can be effectively implemented and accelerate care, but readiness heavily depends on trained personnel, workflow, and facilities such as a CT scanner in the emergency department. Based on the findings of Wisni et al. (2025) hospitals without an internal CT scanner can still establish a stroke protocol with a multidisciplinary team, a CT referral pathway, and alteplase administration, achieving good clinical outcomes. Additionally, multidisciplinary training (involving physicians, ED/ICU nurses, radiology, lab, pharmacy, and inpatient staff) significantly improved the Code Stroke team's knowledge (pre-test scores increased from 34% to 68%) and markedly enhanced service efficiency in Code Stroke protocols (Hunaifi et al., 2023). A study by Rasyid et al. (2022) reported on DTC time performance in Code Stroke management at Cipto Mangunkusumo Hospital. There was a downward trend in the time required for stroke patients to undergo a CT scan from the time of hospital arrival during the period from November 2016 to April 2019; the median DTC time target achieved by the end of the study was 19.5 minutes. This figure meets global guidelines (AHA), which recommend a DTC time of less than 25 minutes. A key determining factor is that the location of the CT scan significantly affects DTC time; patients undergoing a CT scan within the ED are far more likely to receive timely care compared to those whose CT scan is performed outside the ED.

Implementation readiness in Indonesia faces challenges such as geographical factors and referral procedures from non-specialist healthcare centers, which significantly prolong treatment times. According to Wenang et al. (2021), as a large archipelagic nation, Indonesia has many remote, border, and small island regions with difficult access and long distances to referral facilities, making travel time the primary barrier to timely care. Additionally, many rural and remote areas have limited availability of healthcare personnel and specialists, forcing patients to be referred far away and prolonging the overall treatment time. Furthermore, not all facilities are yet equipped to implement integrated systems utilizing technology. Integration of technology between AI and hospital electronic medical record (EMR) systems must be in place at every hospital planning to implement an AI-supported system. According to Wibowo et al. (2025), limitations in internet connectivity, electricity, and digital devices particularly in remote areas hinder the nationwide adoption of EMR and AI. The adoption of EMR systems in Indonesia is also inconsistent; while the national EMR mandate encourages adoption, some hospitals are still in the process of transitioning from paper-based to electronic systems, with a striking disparity between developments on the island of Java and other regions in Indonesia.

Implications and limitations

The "Time is Brain" concept underpins the paradigm shift in stroke workflow management from sequential processing to simultaneous parallel processing through the "pit-crew" model. This conceptual implication redefines traditional clinical hierarchies by positioning nurses as the "pit master" or protocol coordinator who leads task delegation to ensure system efficiency under high pressure. Practically, empowering triage nurses to independently activate the Code Stroke without waiting for a physician's examination has been shown to significantly reduce door-to-needle (DTN) time and accelerate patient access to reperfusion therapy. The integration of Artificial Intelligence (AI) technology and real-time communication platforms further reinforces this practice by enabling synchronization of multidisciplinary teams through automatic alerts of large-vessel occlusions received simultaneously. For implementation in Indonesia, practitioners need to adapt this evidence-based model by considering the availability of local resources to address the unique challenges of an archipelagic setting.

The effectiveness of Code Stroke activation models depends heavily on balancing diagnostic accuracy (sensitivity/recall) and the efficient use of hospital resources (precision). The use of broader screening tools such as BE-FAST or machine-learning algorithms can increase sensitivity for detecting posterior circulation strokes, but often lowers precision due to more over-triage and “stroke mimics” that trigger false alarms. This balance requires adjustment of decision thresholds, with high recall prioritized to avoid malpractice risk, while high precision is needed to prevent burnout among healthcare workers in facilities with limited staff. On the other hand, there are several limitations in the current literature, including small sample sizes, single-center retrospective study designs, and a lack of uniform reporting standards (such as MINIMAR), which hinders global generalizability. In addition, infrastructural constraints such as unstable internet connectivity and limited CT scanning facilities in remote areas remain major barriers to the widespread adoption of AI-based activation technologies.

Relevance to Practice

Practitioners can optimize the acute stroke care pathway by empowering nurses to serve as "pit masters" or protocol coordinators who manage simultaneous parallel processing to ensure efficient task delegation and avoid sequential bottlenecks. Implementing a "no-fault" activation system that grants triage nurses full authority to trigger alerts immediately upon symptom identification via FAST or BE-FAST scales is essential to drastically accelerate patient access to reperfusion therapy. Additionally, hospitals should integrate AI technology and real-time communication platforms to facilitate multidisciplinary synchronization, ensuring that large vessel occlusion alerts are received simultaneously by the entire team within minutes of imaging completion. Maintaining team readiness through routine "mock stroke alert" simulations and objective workflow evaluations using body cameras allows healthcare professionals to identify administrative barriers and improve performance under high pressure. For practice in regions with limited resources, such as Indonesia, these models must be adapted to local infrastructure and geographical constraints while ensuring that early nurse-led neurorehabilitation begins within the first 24 to 72 hours to maximize functional independence.

Conclusion

This study aimed to examine various Code Stroke activation models to assess their effectiveness on the speed and quality of clinical decision-making. The findings demonstrate that the implementation of nurse-led "pit-crew" models which shift emergency workflows from traditional sequential processing to simultaneous parallel processing significantly reduces DTN times, often achieving treatment goals in under 30 minutes. Additionally, the integration of AI and ML-Driven improve multidisciplinary synchronization and more personalized patient stratification, identifying large vessel occlusions within minutes of imaging completion. Main of the message is that an integrated, time-sensitive approach combining empowered nursing leadership, parallel task delegation, and advanced technological support is essential to minimize permanent neuronal loss and maximize functional recovery for stroke patients. For the future, it is recommended that healthcare facilities implement "no-fault" activation systems that grant triage nurses full authority to trigger alerts and utilize "mock stroke" simulations to enhance team readiness under pressure. Furthermore, practitioners in regions with limited resources, such as Indonesia, must adapt these evidence-based models to local geographic and infrastructure constraints while policymakers work to standardize AI reporting requirements and validate administrative data algorithms to monitor service quality globally.

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CrediT Authorship Contributions Statement

Purwandi: Conceptualization, Methodology, Supervision, and Writing – Original Draft.

Pahria, T.: Methodological validation and critical revision of the manuscript.

Pratiwi, S. H.: Data interpretation, strengthening of the discussion, and final manuscript review.

Fauzan, N. H.: Methodology, Writing – Original Draft, Review & Editing, and Visualization.

Conflicts of Interest

There is no conflict of interest.

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