ORIGINAL RESEARCH

Assessing the Severity of ODT and Factors Determinants of Late Arrival in Young Patients with Acute Ischemic Stroke

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Background: Acute ischemic stroke (AIS) is increasingly affecting younger populations, necessitating prompt thrombolytic therapy within a narrow therapeutic window. Pre-hospital delays are prevalent, particularly in China, yet targeted research on the youth population remains scarce.

Methods: In this retrospective cohort study, data from AIS patients aged 18–50 admitted to Longhua District People's Hospital, Shenzhen from December 2021 to December 2023 were analyzed using XGBoost and Random Forest machine learning algorithms, coupled with SHAP visualization, to identify factors contributing to pre-hospital delays.

Results: Among 1954 AIS patients, 528 young patients were analyzed. The median time to hospital arrival was 8.34 hours, with 82.0% experiencing delays. Analysis of different age subgroups showed that young patients aged 36–50 years old had a higher delay rate than patients under 36 years old. Machine learning algorithms identified stroke awareness, age, TOAST classification, ambulance arrival, dysarthria, mRS on admission, dizziness, wake-up stroke, etc. as important determinants of delay.

Conclusion: This study highlights the necessity of machine learning in identifying delay risk factors in young stroke patients. Enhanced public education, particularly regarding stroke symptoms and the use of emergency services, is crucial for reducing pre-hospital delays and improving patient outcomes.

Keywords: acute ischemic stroke, onset-to-door time, young adults, machine learning, emergency medical services

Introduction

Acute ischemic stroke (AIS), defined by cerebral artery occlusion and subsequent neuronal damage, is a leading cause of global mortality and disability, increasingly affecting younger individuals.[1,2] Timely revascularization and enhanced cerebral perfusion are critical, underscoring the need for rapid administration of thrombolytic therapy in AIS patients. The therapeutic window allows for intravenous thrombolytic treatment within 4.5 hours of symptom onset or endovascular thrombectomy within 6 hours.[3,4] Studies indicate that pre-hospital delays affect 88.21% of stroke patients in inland China and 82.52% in coastal regions.[5] In contrast, prehospital delay rates are relatively lower in South Korea (74.0%) and Japan (66.0%)[2,6]. Similarly, in Switzerland, prehospital delays occur in 42% of patients, and in Morocco, the median delay to hospital arrival is around 6 hours, affecting a significant portion of patients. Shenzhen is a special area with an extremely large youth population, and young stroke patients account for a large proportion of the stoke population. However, there have been few specialized research reports on the immediacy of pre-hospital treatment. Logically, the greater mobility of young AIS patients should result in quicker hospital arrivals. But as mentioned just now, the reality is not like this. According to previous non-targeted research data, the delay rate of young stroke patients may not be lower than that of elderly patients.[7] Therefore, we plan to conduct a detailed report on prehospital timely rates in the youth population.

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Prehospital delay issues include decision-making delays (the time between symptom onset and first receipt of medical attention) and transportation delays (the time between receipt of initial medical attention and arrival at the emergency center). Addressing delays is critical to improving treatment uptake and efficiency. Arrival at the hospital within the treatment window is beneficial to patient prognosis.[8] Although there have been several studies that have dissected the subject of prehospital delays in AIS and identified characteristics such as age, educational background, health insurance, initial symptoms, mode of arrival at the hospital, and stroke type as influencing factors of delay.[9–11] However, existing studies on prehospital delays, predominantly focused on older patients, do not adequately address the dynamics within the younger demographic. Therefore, this study focuses on clarifying the characteristics of patients who arrive late at the hospital and the influencing factors of delay among young AIS patients in China, aiming to provide scientific basis for the development of targeted intervention strategies.

While machine learning (ML) has advanced the screening of clinical features in stroke research, its "black box" nature can hinder interpretability.[12] The SHapley Additive exPlanation (SHAP) values, however, offer a method to decode ML model outputs comprehensively. Given the complexity of the stroke patient population, SHAP's ability to lift the veil on model predictions is invaluable, enabling healthcare professionals to make more informed and accurate decisions. Against this background, this study uses machine learning combined with SHAP visualization technology to clarify the current status of pre-hospital delays in young AIS patients and its influencing factors, hoping to provide a reference for formulating more detailed and targeted strategies.

Materials and Methods

Study Population

This retrospective cohort study comprised patients with AIS admitted to the neurology department of Longhua District People's Hospital, Shenzhen, from December 2021 to December 2023. A local database was developed to compile comprehensive stroke-specific data, spanning from pre-hospital details to six months post-discharge. Given its status as a first-tier city, Shenzhen hosts a comparatively youthful population relative to other regions in China. Shenzhen Longhua District People's Hospital is a tertiary-level hospital that provides primary medical care services to approximately 3 million surrounding residents. Recently, this hospital has recorded a notably high admission rate of stroke patients, among the highest in urban hospitals. The young AIS patients in this study, aged 18–50, were diagnosed based on CT or MRI results and had detailed data in the disease-specific platform.

Definitions

The age standard for young adults is based on the age classification standard of previous studies, that is, age ≤50 years old.[13,14] This age range captures younger adults who often experience non-traditional stroke causes like arterial dissection, with better outcomes compared to older adults due to fewer comorbidities and a greater capacity for recovery. Pre-hospital delay was defined according to national cerebrovascular disease prevention and treatment guidelines. The critical stages from the onset of stroke symptoms to seeking help, from making a phone call to arriving at the hospital, and from admission to starting treatment, should not exceed one hour. Therefore, the time from onset of symptoms to arrival at the hospital of more than two hours is designated as prehospital delay.[15]

Variables Selection

This study collected comprehensive information including patient demographic information, living environment, pre-hospital information, and in-hospital diagnosis and treatment. In detail, it includes age, gender, ethnicity, immigrants, residential status, health insurance, education, stroke knowledge awareness, wake-up stroke, the methods of arrived hospital(self-initiated hospital presentation, arrived by ambulance and referral), high blood pressure(HBP), diabetes mellitus(DM), onset symptoms (such as conscious disturbance, deviated mouth, smoking, drinking, dysarthria, aphasia, dizziness, vomit, and limb weakness), self-report HBP, self-report DM, TOAST classification, electrocardiogram (ECG) findings, atrial fibrillation (AF), recurrent stroke, dyslipidemia, cardiovascular disease and mRS on admission. Onset time, door arrival time, and ambulance call time were recorded to calculate pre-hospital time.

Data Collection Process

Data for this study were extracted from a localized, stroke-specific dataset encompassing hospital admissions, treatment interventions, nursing logs, and diagnostic records. These records are fully and accurately documented by the patient's treating physician. In order to ensure the integrity and traceability of the data, the data set has dedicated quality control personnel who regularly review the system's medical records to ensure its reliability. Two research nurses conducted data collection and entry, with all collected data securely stored within a dedicated local database. The database is managed by an appointed custodian, who also updates it regularly to ensure it contains the latest information about young stroke patients.

Statistical Analysis

A preliminary statistical description of the current status of pre-hospital delays in young AIS patients was performed, and the delay rates of young and middle-aged patients of different ages were presented in subgroups. Comparisons of continuous variables were performed using the *T* test or Mann–Whitney *U*-test, and comparisons of categorical variables were performed using the chi-square test or Fisher's exact test. In order to retain potential delay influencing factors as much as possible, we included those with P value <0.1 into the next analysis. We employed the XGBoost and Random Forest algorithms to enhance the predictive accuracy of our model. XGBoost sets the learning rate to 0.05, the maximum depth to 4, and the number of boosting iterations to 150. The random forest was set up with 1000 decision trees and the random state was set to 42 to ensure reproducible results. During model building, use SHAP values to account for the impact of each feature. The SHAP summary chart provides a comprehensive overview of feature importance, while the SHAP bar chart ranks them based on their overall importance.

Results

Comparison of Baseline Characteristics

This study enrolled 1954 patients with AIS, of whom 528 were under the age of 50 and had complete datasets (Figure 1). Among the young AIS cohort, 82.0% (n = 433) experienced pre-hospital delays, averaging 8.34 hours. The mean age of delayed patients was 42.13 years, significantly higher than that of the non-delayed group, which was 39.99 ± 7.72 years.

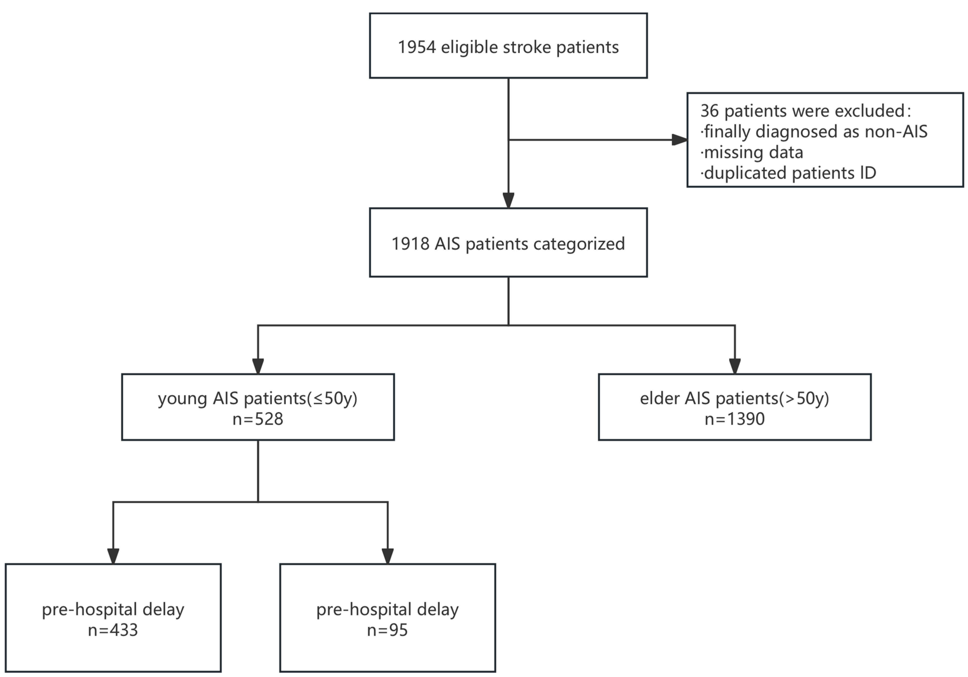

Figure 1 Flowchart of Study Design and Patient Selection Process.

The proportion of delayed male patients was 82.1% (n=385), compared to 81.4% for female patients. A higher incidence of pre-hospital delays was observed in patients with junior high school education or lower (88.5%), compared to those with a high school education or above (80.1%). Further details are provided in Table 1.

Visualization of delay rates by age revealed that patients aged 36–40, 41–45, and 46–50 years exhibited delay rates exceeding 80%, a trend markedly higher than in patients under 35 years (Figure 2).

Table 1 Characteristics of Young AIS Patients

Variable	Category	AIS Patients (≤50y)		P-value	Median ODT (hours)
		Non-delay, n=95 (%)	Delay, n=433 (%)		
Age	/	39.99±7.72	42.13±6.45	0.005	8.34
Gender	Male	84 (17.9%)	385 (82.1%)	0.999	9.75
	Female	11 (18.6%)	48 (81.4%)		8.06
Ethnicity	Han	92 (18.0%)	419 (82.0%)	0.997	9.57
	Others	3 (17.6%)	14 (82.4%)		24.81
Immigrants	Yes	90 (17.6%)	422 (82.4%)	0.182	10.08
	No	5 (31.2%)	11 (68.8%)		3.32
Residential status	Living with others	84 (17.3%)	402 (82.7%)	0.218	11.48
	Living alone	11 (26.2%)	31 (73.8%)		5.02
Health insurance	Yes	76 (19.0%)	323 (81.0%)	0.328	8.87
	No	19 (14.7%)	110 (85.3%)		9.98
Education	Junior high school or lower	3 (11.5%)	23 (88.5%)	0.599	19.25
	High school	48 (19.9%)	193 (80.1%)		10.83
	Bachelor or above	44 (16.9%)	217 (83.1%)		8.02
Stroke knowledge awareness	Lack of awareness	11 (3.7%)	287 (96.3%)	0.000	3.92
	Partial understanding	84 (36.5%)	146 (63.5%)		18.98
Self-initiated hospital presentation	No	36 (34.3%)	69 (65.7%)	0.000	3.45
	Yes	59 (13.9%)	364 (86.1%)		13.35
Arrived by ambulance	No	25 (41.7%)	35 (58.3%)	0.000	12.32
	Yes	70 (15.0%)	398 (85.0%)		2.32
Referral	No	91 (18.5%)	400 (81.5%)	0.338	10.25
	Yes	4 (10.8%)	33 (89.2%)		4.75
Self-report HBP	No	48 (19.0%)	205 (81.0%)	0.654	10.11
	Yes	47 (17.1%)	228 (82.9%)		9.09
Self-report DM	No	83 (18.4%)	368 (81.6%)	0.664	9.47
	Yes	12 (15.6%)	65 (84.4%)		22.7
Smoking	No	59 (18.9%)	253 (81.1%)	0.586	7.99
	Yes	36 (16.7%)	180 (83.3%)		19.01
Drinking	No	65 (17.4%)	309 (82.6%)	0.655	17.25
	Yes	30 (19.5%)	124 (80.5%)		9.32
mRS on admission	0–2	41 (12.8%)	279 (87.2%)		19.25
	3–6	54 (26.0%)	154 (74.0%)	0.000	9.020
TOAST classification	Large-artery atherosclerosis stroke	29 (20.3%)	114 (79.7%)	0.013	9.60
	Small-vessel occlusion stroke	19 (10.2%)	167 (89.8%)		21.53
	Cardioembolic Stroke	12 (26.1%)	34 (73.9%)		6.87
	Other known cause stroke	32 (22.7%)	109 (77.3%)		6.91
	Stroke of undetermined etiology	3 (25.0%)	9 (75.0%)		9.24
ECG findings	Normal	92 (17.7%)	429 (82.3%)	0.114	10.04
	Abnormal	3 (42.9%)	4 (57.1%)		7.59
AF	No	95 (18.2%)	427 (81.8%)	0.597	9.75
	Yes	0 (0.0%)	6 (100.0%)		2.96

(*Continued*)

Table 1 (Continued).

Variable	Category	AIS Patients (≤50y)		P-value	Median ODT (hours)
		Non-delay, n=95 (%)	Delay, n=433 (%)		
Recurrent stroke	No	90 (18.4%)	398 (81.6%)	0.467	9.47
	Yes	5 (12.5%)	35 (87.5%)		16.83
Dyslipidemia	No	93 (18.1%)	420 (81.9%)	0.892	10.80
	Yes	2 (13.3%)	13 (86.7%)		9.05
Cardiovascular disease	No	86 (17.0%)	420 (83.0%)	0.009	8.70
	Yes	9 (40.9%)	13 (59.1%)		9.97
HBP	No	45 (19.4%)	187 (80.6%)	0.529	9.98
	Yes	50 (16.9%)	246 (83.1%)		9.57
DM	No	72 (19.4%)	300 (80.6%)	0.257	9.60
	Yes	23 (14.7%)	133 (85.3%)		11.38
Metabolic disorder	No	73 (18.5%)	321 (81.5%)	0.675	9.60
	Yes	22 (16.4%)	112 (83.6%)		10.50
Wake-up stroke	No	91 (19.8%)	368 (80.2%)	0.008	10.18
	Yes	4 (5.8%)	65 (94.2%)		9.57
Limb weakness	No	14 (7.9%)	164 (92.1%)	0.000	15.73
	Yes	81 (23.1%)	269 (76.9%)		9.02
Consciousness disturbance	No	45 (13.6%)	287 (86.4%)	0.001	9.60
	Yes	50 (25.5%)	146 (74.5%)		8.95
Dizziness	No	86 (20.0%)	343 (80.0%)	0.016	9.57
	Yes	9 (9.1%)	90 (90.9%)		10.18
Sensory disturbance	No	91 (18.9%)	391 (81.1%)	0.129	9.57
	Yes	4 (8.7%)	42 (91.3%)		24.16
Dysarthria	No	47 (13.8%)	293 (86.2%)	0.001	10.81
	Yes	48 (25.5%)	140 (74.5%)		8.49
Vomiting	No	94 (17.9%)	430 (82.1%)	0.549	9.60
	Yes	1 (25.0%)	3 (75.0%)		21.08
Facial asymmetry	No	94 (18.1%)	424 (81.9%)	0.804	9.38
	Yes	1 (10.0%)	9 (90.0%)		12.87
Aphasia	No	95 (18.1%)	431 (81.9%)	1.000	9.60
	Yes	0 (0.0%)	2 (100.0%)		5.80
Diplopia	No	94 (18.1%)	424 (81.9%)	0.804	9.60
	Yes	1 (10.0%)	9 (90.0%)		9.90

Characteristics Comparison Between Delayed and Non-Delayed

Significant differences in pre-hospital delay rates were observed across various patient characteristics, including age ($P = 0.005$), stroke knowledge awareness ($P < 0.001$), stroke knowledge awareness ($P < 0.001$), arrived by ambulance ($P<0.001$), mRS on admission($P<0.001$), TOAST classification($P=0.013$), cardiovascular disease($P=0.009$), wake-up stroke($P=0.008$), limb weakness($P<0.001$), consciousness disturbance ($P=0.001$) and other independent variables have statistical differences in the pre-hospital delay of patients. The detailed results are shown in Table 1.

Individual Analysis of SHAP Values

We applied the SHAP approach to explore individual-level risk factors for prehospital delay in young AIS patients. A median-delay case (SHAP value = 0.84) involved a 43-year-old smoker with cardioembolic stroke, who self-initiated hospital presentation and presented with atypical symptoms (Figure 3A). In contrast, the shortest delay (SHAP value = 0.35) was observed in a patient who lived alone, self-reported HBP, had partial stroke awareness, onset with dysarthria, and did not use ambulance services (Figure 3B). The longest delay (SHAP value = 0.93) occurred in a patient with small

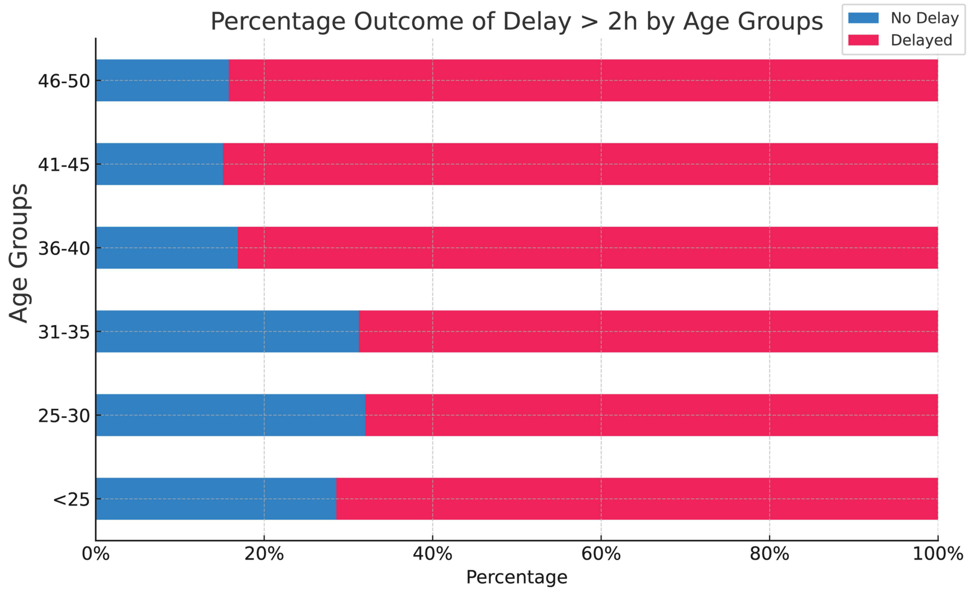

Figure 2 Subgroup analysis of the delay occurrence rates in young stroke patients by age group.

Figure 3 Analysis of individual characteristics of SHAP values in young AIS patients. (**A**) is the patient with the longest delay time; (**B**) is the patient with the shortest delay time; (**C**) is the patient with the median delay time; (**D**)Patient with the lowest f(x) value; (**E**) Patient with the highest f(x) value.

vessel occlusive stroke, no smoking history, and a lack of stroke awareness, who also did not use an ambulance (Figure 3C). Additionally, Figure 3D highlights a patient with no stroke awareness and a significant prehospital delay, while Figure 3E shows a patient with an in-hospital mRS score of 1, no ambulance use, and delayed hospital arrival despite stroke awareness.

Influencing Factors

As depicted in Figure 4, feature values are represented by color in the results, with each point corresponding to a case in a row. Red dots indicate higher feature values, while blue dots signify lower values. Smaller feature values (less than 0), indicate a negative impact; larger feature values, with SHAP values (greater than 0), signify a positive impact. Both the

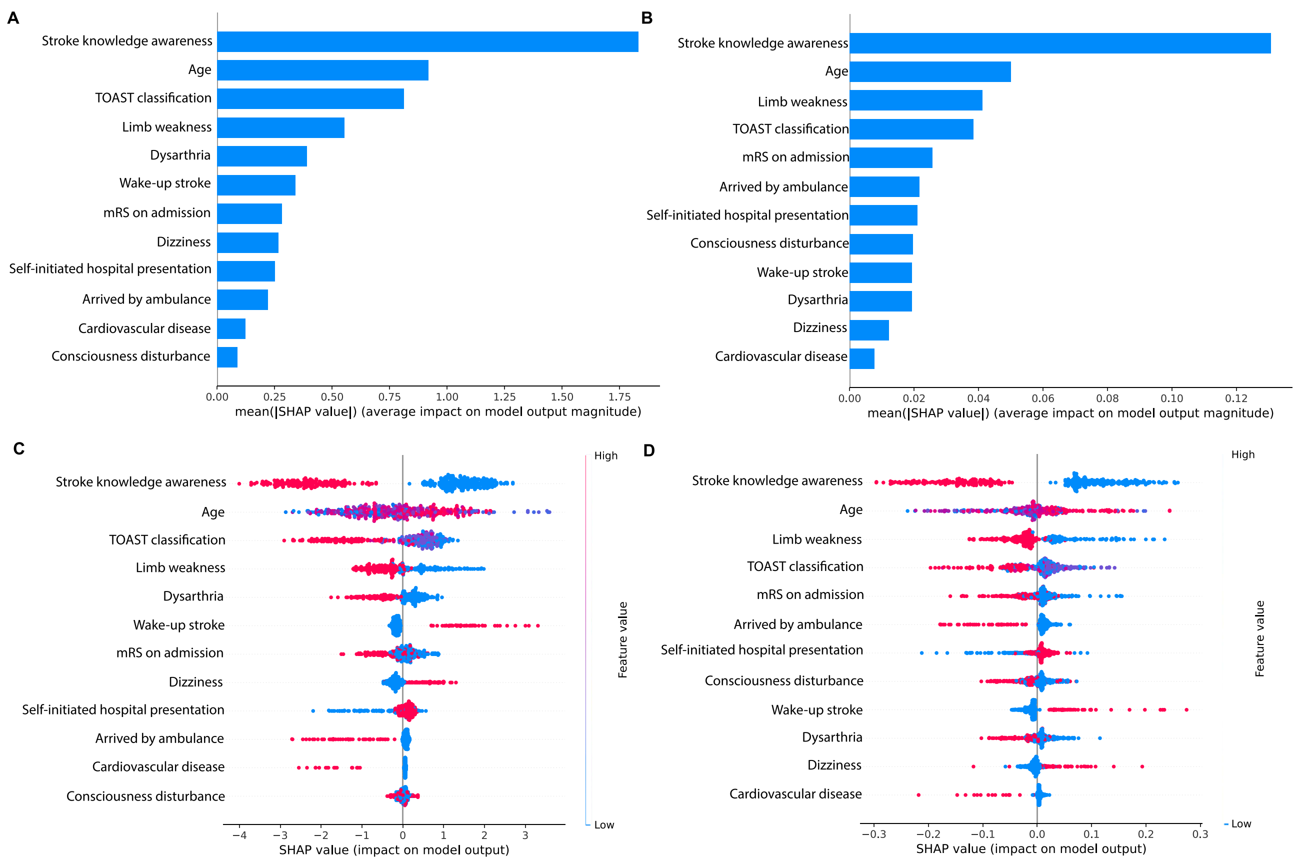

Figure 4 SHAP Summary Diagram: Comparison of Feature Importance and Impact on Model Output for XGBoost and Random Forest Algorithms. (**A**) Feature importance ranking for XGBoost. (**B**) Distribution of feature impact on XGBoost model output. (**C**) Feature importance ranking for Random Forest. (**D**) Distribution of feature impact on Random Forest model output.

XGBoost model and the random forest model identified stroke knowledge awareness, age, TOAST classification and limb weakness as the most important factors affecting pre-hospital delay in young patients (Figure 4A and B). These are followed by factors such as stroke after awakening, mRS on admission, dizziness, self-initiated hospital presentation, arrival by ambulance, cardiovascular disease, and consciousness disturbance, which also impact pre-hospital delay in young patients. Figure 4C and D illustrate the distribution of each feature's contribution to the XGBoost and Random Forest model outputs, respectively.

Discussion

Our study's application of machine learning algorithms, including XGBoost and Random Forest, represents a significant advancement in stroke care. By leveraging these advanced analytical tools, we were able to extract key risk factors for prehospital delay in young stroke patients with unprecedented precision.[16] This application provides novel insights into latency determinants and enables precise analyses of characteristics in young patients. Such models can characterize patients at high risk for delayed hospital admission. Implementing this approach in clinical settings may ensure more targeted and timely educational interventions, help complement prehospital management of AIS in young patients and help improve patient outcomes. This study highlights the pivotal role of machine learning in advancing patient care strategies, positioning our approach at the vanguard of technology integration within medical practice.

In our study, the median time from symptom onset to hospital arrival for young stroke patients was 8.34 hours. This result is better than previous data reports in China, which showed that the median time from onset to presentation in the entire population of 19,604 cases of stroke in 219 hospitals from 2012 to 2013 was 22 hours (IQR 5.5–53.5 hours).[17] In addition, we found that more than 80% of young patients are delayed in arriving at the hospital. This result is worse than that in other countries. For example, data from a multi-center study in the United States pointed out that only 21%-40%

of AIS patients can arrive at the hospital in time after the onset of stroke.[18] A more recent 2019–2020 study in Korea found that merely 28.4% (153/539) of patients arrived at the hospital within 4.5 hours to receive reperfusion therapy.[19] The significant difference in the proportion of young patients experiencing delays in China versus other countries underscores the unique challenges faced by the Chinese healthcare system. These findings suggest that despite some progress in reducing delays, there remain systemic and social factors that disproportionately impact timely hospital arrivals in China compared to the US and Korea. Despite a reduction in the median ODT among young AIS patients at our hospital compared to previous periods, substantial delays persist. This suggests that despite increased public awareness, substantial challenges persist in symptom recognition, emergency response, and effective utilization of medical services.

Our detailed analysis of young adults in different age groups shows that patients aged 36–50 have a higher delay rate than patients aged 35 and under. Three factors—work and family responsibilities, socioeconomic considerations, and comorbidity profiles—emerge as critical drivers of these delays. In the context of work and family responsibilities, the age group 36–50 is often at the peak of their professional careers and deeply engaged with familial duties. The competing demands of work deadlines, childcare, and eldercare may lead these individuals to minimize or overlook stroke symptoms, delaying crucial medical intervention.[20] Furthermore, socioeconomic factors also play a substantial role. Individuals in the 36–50 age bracket may face transitional socioeconomic statuses, like changes in employment or health insurance coverage, potentially affecting their ability to promptly seek care.[21] Finally, the onset of conditions such as hypertension or diabetes often occurs in this age range, which can obscure or mimic stroke symptoms, leading to misjudgment about the seriousness of the situation.[22] Together, these factors underscore a critical gap in current stroke education and intervention strategies.

In this study, stroke knowledge awareness mainly includes a thorough understanding of the main symptoms, related risk factors and preventive measures of stroke. We found that both XGBoost and Random Forest algorithms screened out poor stroke awareness as a significant risk factor for prehospital delay, underscoring the importance of awareness in expediting patients seeking medical intervention. This finding is supported by previous research by Gonzalez-Aquin et al found that only 22.1% (189 patients) were able to recognize that their own symptoms could be signs of AIS.[23] Furthermore, Li et al observed that 74.03% (305 patients) of patients with an onset-to-door time (ODT) > 4.5 hours had less than 12 years of education, in contrast to only 36.23% (46 patients) with higher education (≥12 years) arriving within the same timeframe. Arrived at the hospital 4.5 hours later. This suggests that patients with higher levels of education are more likely to notice the signs and symptoms of an AIS event and to seek emergency treatment in a timely manner.[19] Although no statistical difference was found in our data results, the fact does exist that low educational levels account for a higher proportion of delays. And previous learning experiences may include or contribute to the early identification of AIS symptoms. This understanding is not limited to the theoretical realm; it directly affects patients' daily health decisions and actions. Nevertheless, despite extensive research underscoring the crucial role of stroke awareness in facilitating timely medical intervention, over half of the young AIS patients in our study exhibited a significant lack of such awareness. Misinterpretations of stroke symptoms, such as dizziness and limb weakness, as general fatigue or minor illnesses delayed recognition and subsequent hospital visits, exacerbating conditions. This underscores an urgent need to enhance stroke education, especially targeting high-risk groups. We strongly advocate for closer collaboration between the public and healthcare professionals to foster the dissemination of stroke awareness, aiming to improve the management and treatment outcomes of stroke. Digital and face-to-face educational initiatives can raise awareness of stroke symptoms and the necessary steps to seek medical assistance.[24] Our findings suggest that national policies should focus on increasing public health funding for targeted stroke awareness campaigns, especially in regions with high rates of delayed hospital arrivals. Moreover, incorporating stroke education into primary healthcare systems and leveraging digital platforms for broader reach could help mitigate these delays. Policymakers should also consider expanding emergency medical services (EMS) in under-resourced areas to reduce barriers to timely care.

Self-initiated hospital presentations in AIS cases can lead to increased pre-hospital delays, highlighting the critical role of emergency medical services (EMS) in reducing overall delay time. Rossnagel et al highlighted EMS as critical in lowering median ODT to 151 minutes and boosting the rate of patients arriving within 3 hours to 54%.[25] Immediate contact with emergency services through the national emergency number, followed by ambulance transport, is recommended to minimize delays. The misperception of quicker arrival by self-transportation, potentially complicated by traffic and parking issues, not only risks delays but may also reflect an underestimation of the situation's severity. Ambulance transport ensures quicker assessment and treatment, highlighting the need for public education on stroke symptom recognition and the urgency of engaging EMS.[26,27] This approach facilitates not just a swift arrival at medical facilities but also early intervention, significantly narrowing the gap in receiving critical medical aid.

This study found that a lower mRS score (0–2 points) on admission was associated with a higher risk of delay. The mRS score for the first time after hospitalization reflects the severity of the first symptoms of AIS patients, which is also closely related to the urgency of their medical seeking behavior. Additionally, literature supports this association; for instance, Nagao et al discovered that factors such as higher mRS scores before onset and onset at home were associated with delays in hospital admission, while early admission led to lower mRS scores at discharge.[28] Similarly, Lee et al found that early hospital arrival significantly correlated with favorable outcomes (mRS 0–2), identifying lower initial NIHSS scores and greater pre-stroke mRS scores as independent predictors of late arrival.[19] These findings highlight the critical need for increased public awareness and education on recognizing stroke symptoms promptly, irrespective of their initial severity, to reduce pre-hospital delays and enhance clinical outcomes.

In addition, young patients with different first symptoms and causes of stroke may have different immediacy of treatment, such as consciousness disturbance and limb weakness, inherently intensify patient concern, catalyzing a more immediate response to seek medical assistance.[29] This urgency is particularly acute in cases of cardioembolic stroke, which generally presents with more severe symptoms than those associated with large artery atherosclerosis.[30] The latter's often milder symptomatology may inadvertently contribute to a delayed recognition of the stroke severity, prolonging the interval before medical intervention is sought. A history of cardiovascular disease appears to sensitize patients to the onset of stroke symptoms, predisposing them to seek medical attention with greater alacrity. This pattern underscores the critical role of symptom awareness and early recognition in influencing patient behavior and the timeliness of their response to emerging stroke signs.[31] These findings illuminate the complex dynamics between the nature of stroke symptoms, the patient's immediate interpretation and reaction to these signs, and the subsequent clinical pathway embarked upon. They reinforce the imperative within public health paradigms to prioritize initiatives aimed at enhancing early symptom recognition and expediting access to medical intervention. Such strategies are pivotal not only for optimizing individual patient outcomes but also for mitigating the broader public health impact of stroke-related morbidity and mortality.

The study focused primarily on prehospital delays (ODT) and did not examine the relationship between ODT and the modified Rankin Scale (mRS) at 90 days. Exploring this relationship could provide further insights into the long-term impact of delayed hospital admission on patient outcomes. Future research should address this gap to determine whether reducing prehospital delays correlates with improved functional outcomes in young stroke patients.

Conclusion

Our study contributes valuable insights into the dynamics of prehospital delays in young stroke patients by utilizing machine learning algorithms to identify relevant risk factors. The analysis confirmed that multiple factors, including stroke awareness, stroke type, and different first symptoms, lead to delayed admission to hospital in young people with stroke. Enhanced public education on stroke symptoms, particularly through targeted awareness campaigns aimed at young adults, and the promotion of emergency medical services are crucial steps toward reducing delays and improving outcomes. Implementing community-based educational programs, leveraging digital platforms for widespread information dissemination, and incorporating stroke education into primary healthcare practices should be prioritized. Ultimately, our research underscores the necessity of integrating advanced analytics and targeted interventions to revolutionize stroke care for young adults. Future research should focus on developing and testing specific interventions, such as real-time risk factor monitoring systems or public health initiatives tailored to different socioeconomic groups, to evaluate their effectiveness in reducing prehospital delays.

Abbreviations

ODT, Onset-to-door time; AIS, Acute ischemic stroke; ML, Machine learning; HBP, High blood pressure; DM, Diabetes mellitus; ECG, Electrocardiogram; AF, Atrial fibrillation; EMS, Emergency medical services; SHAP, the SHapley Additive exPlanations.

Ethics Statement

Ethics approval was exempted by the Ethics Committee of Shenzhen Longhua People's Hospital due to the retrospective nature of this study and the exclusive use of anonymized data. All data were sourced from routine medical records in the stroke archive system, and access to this data was granted following strict ethical approval protocols. Stringent anonymization procedures were implemented to ensure the complete protection of patient privacy. As a result, informed consent was not required under the privacy provisions set by the Ethics Committee. This study fully complies with the ethical guidelines outlined in the Declaration of Helsinki regarding patient data confidentiality and ethical compliance.

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Author Contributions

All authors made a substantial contribution to the reported work, whether in conception, study design, execution, acquisition of data, analysis and interpretation, or all these areas; participated in drafting, revising, or critically reviewing the article; and gave final approval for publication version; and agree to be accountable for all aspects of the work.

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Disclosure

The authors report no conflicts of interest in this work.

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