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Highlights

- Estimating individual effect of successful recanalization in ischemic stroke cases
- Machine learning models to improve personalize treatment of mechanical thrombectomy
- Counterfactual causal models to predict ischemic stroke outcome
- Factors associated with not benefiting from successful recanalization

Article Title

Estimating Individualized Effectiveness of Receiving Successful Recanalization for Ischemic Stroke Cases Using Machine Learning Techniques

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Acute ischemic stroke, Mechanical thrombectomy, Successful recanalization, Individual causal effect, Machine learning

CRediT authorship contribution statement

Vahid Farmani: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Helge Kniep:** Methodology, Data curation, Conceptualization. **Mate Maros:** Writing – review & editing, Conceptualization. **Olga Lyashevska:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Fiona Malone:** Writing – review & editing. **Jens Fiehler:** Methodology, Formal analysis, Conceptualization**. Liam Morris:** Writing – review & editing**,** Methodology, Conceptualization**.**

Abstract

Objectives: Directly measuring the causal effect of mechanical thrombectomy (MT) for each ischemic stroke patient remains challenging, as it is impossible to observe the outcomes for both with and without successful recanalization in the same individual. In this study, we aimed to use machine learning to identify characteristics influencing the likelihood of not benefiting from successful recanalization.

Materials & methods: A total of 1718 non-reperfused patients (Thrombolysis in Cerebral Infarction [TICI] ≤ 2a) and 10339 reperfused patients (TICI ≥ 2b) were included in the study as nonreperfusion and reperfusion groups, respectively. The primary target variable was probability of poor functional outcome after three months, defined by the modified Rankin Scale score of 3 to 6. Two random forest (RF) models trained on pre-treatment covariates of nonreperfusion and reperfusion groups, were used to predict the probability of poor outcome under unsuccessful and successful recanalization scenarios, respectively. The individual effect of successful recanalization was defined as the difference in predicted probabilities returned by the two models.

Results: Strong calibration was achieved by the RF models trained on nonreperfusion group (intercept: –0.027, slope: 1.030) and reperfused group (intercept: –0.010, slope: 1.017). The average risk reduction under successful recanalization scenario was 22.0% (95% CI [21.7% – 22.3%]) for the reperfused group and 19.8% (95% CI [19.1% – 20.5%]) for the nonreperfusion group. Key factors associated with not benefiting from successful recanalization included older age, higher pre-stroke mRS scores and higher National Institutes of Health Stroke Scale score at admission.

Conclusions: This study highlights the potential of predictive ML techniques to estimate the individual effect of successful recanalization on ischemic stroke patients undergoing MT.

Introduction

Stroke is among the leading causes of morbidity and mortality globally[1]. Mechanical thrombectomy (MT) is a standard treatment for ischemic stroke by restoring blood flow in occluded arteries[2]. However, the benefits of a successful recanalization can vary across patients[3,4]. It is crucial to understand the individual effectiveness of this procedure to optimize treatment strategies and improve patient outcomes. Identifying which patients benefit or do not benefit from recanalization can inform personalized treatment plans, ensuring patients receive the most appropriate care based on their specific response profiles[5].

Statistical techniques compare patients on a group level, failing to predict the clinical outcomes based on the recanalization status for each patient directly. This limitation, known as the fundamental problem of causal inference[6], arises because we can only observe the clinical outcome based on one recanalization scenario (for example successful recanalization), leaving the counterfactual clinical outcome (unsuccessful recanalization) unknown. Therefore, innovative and hypothetical methods are required to tackle this issue.

The primary objective of this study was to utilize supervised machine learning (ML) models, specifically random forest (RF), within a counterfactual framework to determine the individual effect of successful recanalization on ischemic stroke patients, with a particular focus on those who did not benefit from MT. RF models were selected for their ability to model complex, nonlinear relationships between features and the target variable and their performance in high-dimensional datasets [7–10]. Besides, RF models are known for their high accuracy[11] and widely used in stroke applications studies[12,13] which further underscores their reliability and utility in predicting outcomes in complex patient populations.

Standard ML models predict outcomes conditional on the observed treatments, whereas counterfactual ML models estimate potential outcomes under alternative treatment scenarios by being trained separately on treated and untreated patient populations. Counterfactual ML models have been employed to determine the effects of individual treatments in both medical[14,15] and non-medical[16] contexts. While these models have previously been applied to stroke patients[17,18], to the best of our knowledge, no studies have yet applied these models to estimate the individualized effect of MT in ischemic stroke cases. This study provides the first attempt to bridge this gap.

The significance of this study lies in its potential to transform clinical practice by providing a framework for predicting the clinical outcome for different recanalization scenarios. By employing counterfactual ML models, we can move beyond traditional one-size-fits-all approaches towards more personalized treatment strategies, pre and post procedure. This shift promises not only to enhance patient outcomes but also to optimize resource allocation in healthcare settings by focusing on those who are least likely to benefit from MT, thus considering alternative interventions. Additionally, this study explores the characteristics and predictors of patients who did not experience positive outcomes from the procedure, offering insights that could improve personalized treatment strategies and enhance future research in this field.

Materials & methods

Data

Data were gathered from the multicenter German Stroke Registry, an open-label academic registry that includes medical history of 13082 ischemic stroke patients with large vessel occlusion treated by MT as part of standard clinical practice[19]. To address privacy concerns, the dataset was modified by one of the authors, specifically by adding small noise with a standard deviation of zero to only five of the covariates. Despite this modification, the resulting dataset remained closely aligned with the original data while preserving patient confidentiality.

Predictions were performed using all 23 clinically relevant pre-treatment features in the dataset. No explicit feature selection was performed to reduce potential bias from incomplete information and to reduce the risk of leaving out important confounding factors. Notably, the target variable of our ML models is a poor clinical outcome as defined by the modified Rankin Scale (mRS) score after three months of 3 to 6. Patients with a Thrombolysis in Cerebral Infarction (TICI) score of 0 to 2a, indicating unsuccessful restoration of blood flow, were labelled as the nonreperfusion group, while patients with a TICI score of 2b or 3, indicating better restoration of blood flow, were labelled as the reperfusion group. Table 1 describes the baseline characteristics of the included patients within the two groups.

Imputation of missing values

Baseline missing variables were imputed using k-nearest neighbors algorithm (k=5) based on the similarity between the patients. For the outcome variable (mRS after 90 days), random forest algorithm, which is known for its strong imputation capabilities[20], was employed to impute the missing values based on the available data. To minimize bias introduced by missing data, patients with more than 30% missing information were excluded from the study. An overview of the data exclusion and imputation steps is shown in Fig. 1.

Causal inference assumptions

In this study, we followed Rubin's causal model to estimate the individual causal effect of successful recanalization for ischemic stroke patients[21,22]. Rubin's framework allows us to compare the potential outcomes of patients who received successful recanalization to those who did not, even though only one of these outcomes can be observed for each patient. To estimate the individual effect of receiving successful recanalization for ischemic stroke patients, it is essential to consider the fundamental assumptions of causal inference including consistency, exchangeability, positivity and no interference [23]. Consistency allows the observational data to be linked to the counterfactual scenarios. Exchangeability allows the potential clinical outcomes to be independent of the recanalization status. All selected patients received the MT procedure ensuring the positivity assumption to be satisfied. The final assumption, no interference, ensures that the potential clinical outcome for each case is not influenced by another patient. For further insights, please refer to the existing literature [24–26].

Counterfactual ML Models

Two random forest (RF) models were developed, fine-tuned, and assessed to predict the potential poor clinical outcomes under both perfusion scenarios. The RF models trained on patients from the reperfusion and nonreperfusion groups are termed RF_R and RF_{NR}, respectively. Both models were trained with the pre-treatment data as shown in Table 1 using balanced accuracy as the optimization metric. This was necessary due to the imbalance between good and poor outcome classes, since balanced accuracy equally weights sensitivity and specificity to ensure the models perform well on both classes. The individual causal effect (ICE) for each individual was calculated for the two perfusion scenarios. For patient from reperfusion group (Fig. 2A), the ICE was found by subtracting the probabilities of a poor outcome returned by the two RF models which defined the effect each patient would acquire from receiving successful recanalization. On the other hand, the difference between the probabilities of a poor outcome for the nonreperfused patients defines the hypothetical effect each patient could have received if the patient had acquired a successful recanalization (Fig. 2B). Positive and negative ICE values (maximum range: -100% to +100%) indicate the percentage benefit and harm, respectively, due to successful recanalization.

To ensure the predicted probabilities are well-calibrated, Platt scaling[27] and isotonic regression[28] were applied to the RF_{NR} and RF_{R} models, respectively. Calibration was evaluated using the calibration intercept and slope, which assessed the degree of alignment between the predicted probabilities and the observed outcomes. The models' discriminatory power was evaluated using both the Area Under the ROC Curve (AUROC) and the Area Under the Precision-Recall Curve (AUPRC). To understand the distributional differences between patients with negative and positive ICE, Chi-squared tests were applied to nominal features, and Mann-Whitney tests were used for ordinal and numerical features.

The data were randomly split into training and test sets in an 80/20 ratio using a fixed random seed to ensure reproducibility. Notably, the test set remained entirely isolated during the training phase ensuring that the reported performance metrics accurately reflect the generalization capability of the models on unseen data. The models were implemented using Python 3.10.4 and the Scikit-learn package version 1.2.0[29]. Hyperparameters, which are parameters that are set before the training process, including maximum depth, minimum samples per leaf, and minimum samples to split a node were optimized using grid search technique with 5-fold cross validation on the training data. RF hyperparameters were tuned via grid search; search ranges are listed in Supplementary Table 1. The final evaluation of the models was conducted using a hold-out test set approach on the remaining 20% of the data. The python code of the models is publicly available in an online repository (https://github.com/V-Farmani/CF_models_MT).

Results

Models' performance

The RF_{NR} model demonstrated strong performance across key metrics. Calibration metrics (intercept: –0.027, slope: 1.030) confirmed predicted probabilities were well-aligned with actual outcomes. An AUROC of 0.85 (95% CI [0.79 – 0.90]) and an AUPRC of 0.97 (95% CI [0.96 – 0.98]) confirmed its accurate discrimination between good and poor outcomes (Fig. 3(A&B)). Cross-validation and test accuracies were 87.12% and 87.21%, respectively, showing no signs of overfitting or underfitting.

Similarly, the RF_{R} model showed well-aligned calibration of the prediction probabilities (intercept: -0.010, slope: 1.017). Strong discriminatory power was observed with AUROC of 0.85 (95% CI [0.83 – 0.86]), and AUPRC of 0.91 (95% CI [0.89 – 0.92]) (Fig. 3 (C&D)), while no sign of overfitting or underfitting was found with cross-validation and test accuracies of 75.75% and 77.37%, respectively.

The distribution of individual treatment effects

The effectiveness of receiving successful recanalization varied across patients, with the estimated reduction in the risk of poor outcomes ranging from -6.7% to 65.3% in reperfusion group and -5.8% to 61.5% in nonreperfusion group. A risk reduction was estimated in almost 86% of the patients. However, for reperfusion and nonreperfusion groups, some patients had negative or close to zero individual effects, suggesting that recanalization was non-beneficial or hypothetically harmful for them. These variations in risk reduction are shown in Fig. 4A and Fig. 4B for reperfusion and nonreperfusion groups, respectively.

Average causal effect

The average causal effect of having successful recanalization was 22.0% (95% CI [21.7% – 22.3%]) for the reperfusion group and 19.8% (95% CI [19.1% – 20.5%]) for the nonreperfusion group. These results indicate that receiving successful recanalization increases the chance of having good functional outcome. However, despite this overall benefit, 1364 (13.2%) patients (95% CI [1294 – 1431]) from the reperfusion group, did not benefit from the procedure. On the other hand, 1417 (82.5%) patients from the nonreperfusion group (95% CI [1384 – 1444]), would have benefited from a successful recanalization.

Comparison of beneficial and non-beneficial groups

The analysis revealed significant differences between patients with positive and negative individual effects across key demographic and clinical features in both reperfusion (Supplementary Table 2) and nonreperfusion (Supplementary Table 3) groups. Regarding the reperfusion group, patients with positive effect were younger (median age 74 vs. 84, $P<0.001$) and had lower National Institutes of Health Stroke Scale (NIHSS) scores at admission (median 13 vs. 18, $P<0.001$). The positive group had higher Alberta Stroke Program Early CT Score (ASPECTS; median 9 vs. 8, $P<0.001$), and lower pre-stroke mRS (median 0 vs. 3, $P<0.001$). A higher proportion of females were in the negative effect group (68.40% vs. 48.25%, $P<0.001$). Comorbidities such as hypertension (93.4% vs. 74.56%, $P<0.001$), atrial fibrillation (69.87% vs. 38.71%, $P<0.001$), and diabetes (28.23% vs. 21.25%, $P<0.001$) were more common in the negative effect group. Intravenous thrombolysis (IVT) was used more frequently in the positive effect group (50.26% vs. 36.07%, $P<0.001$). Higher proportion of occlusion in the posterior circulation occurred for the negative effect group (11.79% vs. 8.58%, $P<0.001$). While occlusions in the distal M1 segment of the middle cerebral artery were more common in patients with negative effect (24.63% vs. 20.61%, $P<0.001$). The positive group had a higher proportion of M2 segment occlusions (24.57% vs. 17.23%, $P<0.001$). Occlusion in the intracranial carotid artery at the T-junction was more frequent in the negative group, while higher proportion of occlusion was observed in the vertebral and extracranial cerebral arteries for the positive group.

Similar significant differences were observed for the baseline characteristics and comorbidities of nonreperfusion patients. Proximal M1 occlusion was more common in the negative group (32.56% vs. 25.97%, $P=0.024$), while occlusion in the extracranial carotid artery (32.56% vs. 25.97%, $P=0.024$) and intracranial carotid artery not at the T-junction (8.19% vs. 4.65%, $P=0.047$) was more common in patients with hypothetical benefit.

Factors associated with negative individual effect

A multivariate logistic regression analysis identified key factors associated with not benefiting from receiving successful recanalization. The strongest predictors for the reperfusion group were older age (adjusted OR: 8.20, 95% CI [6.65 – 10.11]; $P<0.001$), higher pre-stroke mRS (aOR: 12.67, 95% CI [10.74 – 14.96]; $P<0.001$) and higher NIHSS at admission (aOR: 4.23, 95% CI [3.65 – 4.90]; $P<0.001$). Female sex, hypertension, atrial fibrillation, and antithrombotic medication use were also associated with negative individual effect in the reperfusion group. Similarly, older age, high pre-mRS and severe stroke at admission, were the most influential factors associated with negative effect in the nonreperfusion group (Table 2).

Discussion

In this study, we demonstrated the potential of ML techniques, particularly RF, to estimate individual-level causal effects of successful recanalization on a large multi-center dataset of ischemic stroke patients, offering a more personalized assessment of treatment efficacy. Our findings reveal that, despite the overall benefits of MT, a portion of patients did not benefit from the procedure. However, the estimated negative effects were not extreme, suggesting that the recanalization procedure did not have a significant adverse impact on the non-beneficial patients. As far as the authors are aware, this is the first study applying counterfactual ML models for all perfusion scenarios which predict the benefit or non-benefit of MT on an individual basis. This approach enables the direct estimation of individual effect for every patient, helping in identifying individuals who may have benefited from MT, even if the condition of the patient condition did not improve enough to avoid a poor outcome. This is critical in real clinical applications, as it helps clinicians understand that even when functional outcome is poor, the treatment might have prevented a worse outcome, enabling more accurate evaluations of treatment effectiveness.

Several studies have identified factors associated with futile recanalization, defined as poor outcomes despite successful recanalization[3,30–32]. According to Xu et al., factors such as older age, higher baseline NIHSS, and prevalence of hypertension were associated with futile recanalization based on a logistic regression analysis of 403 ischemic stroke patients with large vessel occlusion[33]. Shen et al. conducted a comprehensive meta-analysis on 39 studies involving a total of 11,700 acute ischemic stroke patients who underwent endovascular thrombectomy, to identify factors linked to futile recanalization[34]. Their findings revealed that factors including female sex, higher age, increasing NIHSS, lower APECTS, and conditions such as atrial fibrillation, hypertension, diabetes mellitus were associated with futile recanalization. In addition, they found that IVT usage reduces the likelihood of futile recanalization. These factors are consistent with our findings, supporting the reliability of our results. Effectiveness of successful recanalization has been previously explored in the literature. Kneip et al. used inverse-probability-weighted regression to estimate the average treatment effect of successful recanalization with a focus on M1 and M2 occlusions[35]. However, unlike these studies that assessed functional outcomes on group level, our work focused on directly estimating effectiveness of successful recanalization for each individual. This individualized approach enables clinicians to better anticipate how each patient may respond to treatment.

In recent years, predictive ML models have been used to predict futile recanalization at the individual level. Da Ros et al. used an ensemble model consisting of eleven classification ML models to predict futile recanalization using CT scan images of acute ischemic stroke patients[36]. They reported several factors associated with futile recanalization including arterial hypertension and diabetes mellitus. Lin et al. developed two sets of models, each consisting of four ML models using baseline and peri-interventional characteristics of acute ischemic stroke patients to predict futile recanalization before and after MT [37]. They showed that factors prior to endovascular thrombectomy including greater age and higher NIHSS were strongly associated with futile recanalization. While these factors align with our findings, in contrast to these ML models that predict outcomes based on baseline covariates of patients with futile recanalization, our approach estimates the effect of recanalization despite whether their observed clinical outcome is good or poor. For instance, a patient may experience a poor functional outcome but still have a positive individual effect, meaning that while the functional outcome is unfavourable, the successful recanalization likely improved the patient's condition compared to unsuccessful recanalization scenario.

Our models focused on pre-treatment predictions which is important for clinical decision making. By using all available pre-treatment data without feature selection, we aimed to include as much covariate as possible to avoid incomplete information bias. This provides a pre-clinical decision making tool that estimates the probable outcome for each patient, supporting better treatment planning. Post-treatment features were not included as the goal of this study was to estimate the effectiveness of MT prior to procedure, allowing for more informed decisions about whether to proceed with recanalization or explore alternative options.

Limitations

Although missing data was addressed to minimize selection bias, the imputation methods may still have introduced bias through the estimation of missing values and patient outcomes. Furthermore, attrition bias could have happened from patients lost to follow-up, leading to potential lack of representation of certain patient groups. In addition, the exchangeability assumption may not fully hold in all cases[38]. Finally, while the consistency assumption is essential, it cannot be directly tested[25], which means that there may be differences between the predicted outcomes and those that would have occurred under counterfactual scenario.

Future research

Future research should focus on developing and testing different ML models to further improve prediction accuracy and reliability. It is also essential to validate the models using diverse datasets to ensure their robustness and generalization across different patient populations and clinical settings.

Conclusion

This study highlights the potential of ML techniques to estimate the effect of successful recanalization in ischemic stroke patients undergoing MT. A significant strength of this study is the use of counterfactual models, enabling the prediction of successful recanalization impact for a new patient prior to MT. Our counterfactual models provide clinicians with valuable insights into potential patient outcomes under different recanalization scenarios, helping them make more personalized and effective decisions.

Data access statement

The data supporting our findings are available upon reasonable request with GSR steering committee approval.

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Declaration of competing interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Figure Legend

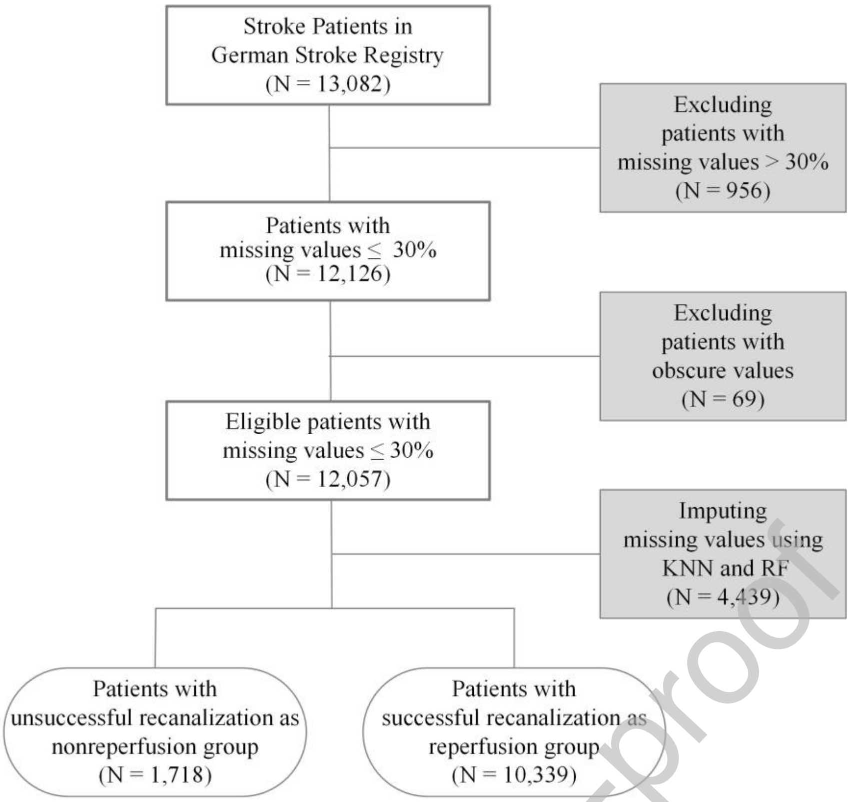

Fig. 1. Data distribution flowchart among nonreperfusion and reperfusion groups

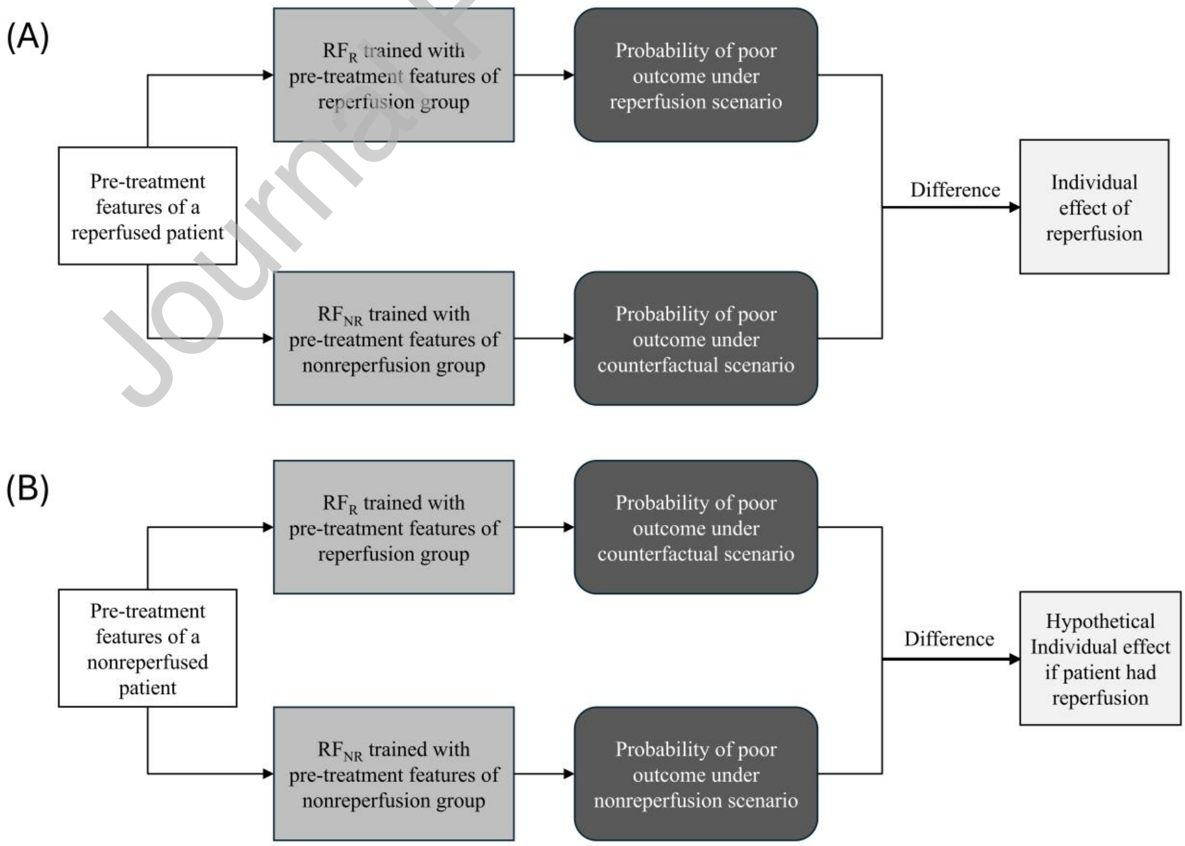

Fig. 2. Estimating individual effect of receiving successful recanalization for a patient. (A) Estimating individual effect of reperfusion for a reperfused patient. (B) Estimating hypothetical individual effect for a nonreperfused patient if they had successful recanalization

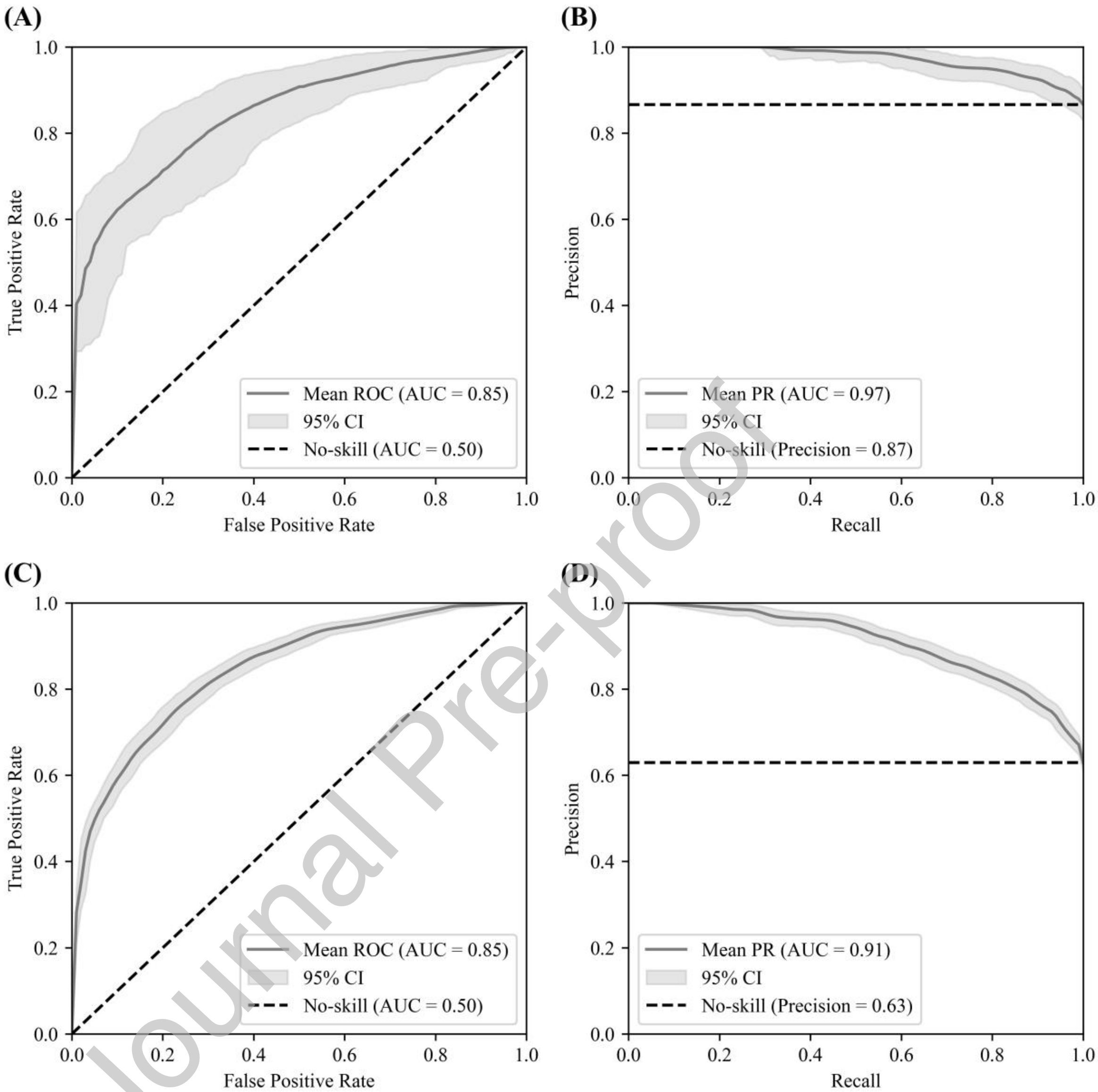

Fig. 3. Performance Evaluation of RFNR and RFR Models. (A) ROC curve for the RFNR model. (B) Precision-Recall curve for the RFNR model. (C) ROC curve for the RFR model. (D) Precision-Recall curve for the RFR model. Shaded areas indicate 95% confidence intervals.

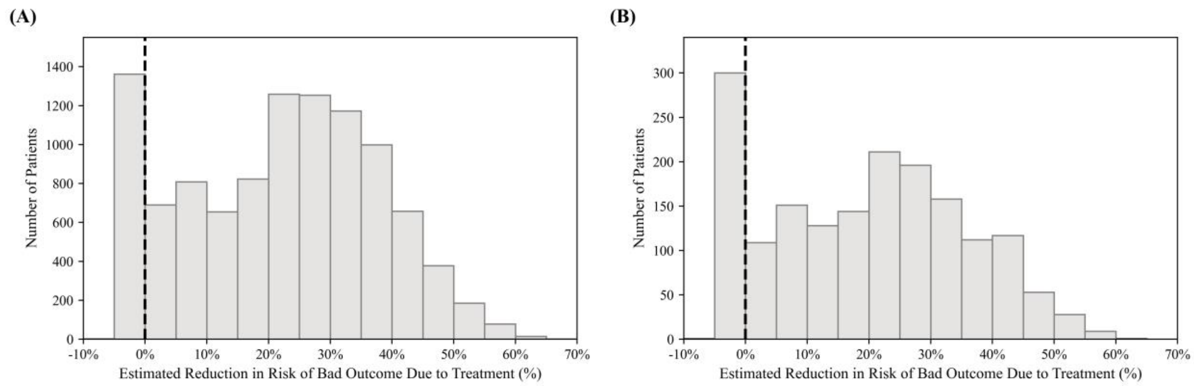

Fig. 4. Distribution of estimated reduction in risk of poor clinical outcome (A) for reperfusion group due to receiving successful recanalization (B) for nonreperfusion group if they had successful recanalization

Table 1. Baseline characteristics of the study population. Ordinal variables are presented as median (Interquartile range), and nominal variables as N (%).

Variable	**Reperfusion group (N = 10339)**	**Nonreperfusion group (N = 1718)**	**P-value**
Age (years)	76 (65 – 83)	77 (67 – 84)	< 0.001
Female	5263 (50.9%)	926 (53.9%)	0.023
Antithrombotic medication	4394 (42.5%)	741 (43.1%)	0.642
pre-mRS	0 (0 – 1)	0 (0 – 2)	< 0.001
NIHSS at admission	14 (9 – 19)	15 (9 – 19)	0.116
Hypertension	7966 (77%)	1357 (79%)	0.081
Diabetes mellitus	2292 (22.2%)	385 (22.4%)	0.848
Dyslipidemia	4256 (41.2%)	661 (38.5%)	0.038
Atrial fibrillation	4427 (42.8%)	637 (37.1%)	< 0.001
ASPECTS	9 (7 – 10)	9 (7 – 10)	< 0.001
IVT	5003 (48.4%)	746 (43.4%)	< 0.001
TICI before angiography 2b,3	932 (9%)	13 (0.8%)	< 0.001
Occlusion locations			
Posterior circulation	1175 (11.4%)	182 (10.6%)	0.371
Anterior CA	355 (3.4%)	76 (4.4%)	0.048
Posterior CA	331 (3.2%)	67 (3.9%)	0.153
Intracranial CA at the T-junction	1675 (16.2%)	263 (15.3%)	0.370
Intracranial CA not at the T-junction	604 (5.8%)	130 (7.6%)	0.007
Extracranial CA	621 (6.0%)	172 (10.0%)	< 0.001
Proximal M1	3215 (31.1%)	466 (27.1%)	0.001
Middle CA distal M1	2186 (21.1%)	297 (17.3%)	< 0.001
Middle CA M2	2440 (23.6%)	465 (27.1%)	0.002
Basilar artery	935 (9.0%)	122 (7.1%)	0.010
Vertebral artery	219 (2.1%)	42 (2.4%)	0.440
Bad functional outcome after 90 days	6474 (62.6%)	1487 (86.6%)	< 0.001

mRS, modified Rankin Scale; NIHSS, National Institutes of Health Stroke Scale; ASPECTS, Alberta Stroke Program Early CT Score; IVT, Intravenous thrombolysis; TICI, Thrombolysis in Cerebral Infarction; CA, Cerebtal Artery

Table 2.Adjusted Odds Ratios and P-values for predictors of non-beneficial in the reperfusion and nonreperfusion groups

	Reperfusion group		**Nonreperfusion group**	
Variable	**Adjusted Odds Ratio (95% CI)**	**P-value**	**Adjusted Odds Ratio (95% CI)**	**P-value**
Intercept	0.00 (0.00 – 0.00)	< 0.001	0.00 (0.00 – 0.00)	< 0.001
Age	8.20 (6.65 – 10.11)	< 0.001	6.68 (4.31 – 10.35)	< 0.001
Female sex	1.13 (1.00 – 1.27)	0.046	1.34 (1.03 – 1.74)	0.030
Antithrombotic medication	1.32 (1.17 – 1.48)	< 0.001	1.67 (1.3 – 2.15)	< 0.001
pre-mRS	12.67 (10.74 – 14.96)	< 0.001	8.55 (6.22 – 11.75)	< 0.001
NIHSS at admission	4.23 (3.65 – 4.90)	< 0.001	4.9 (3.52 – 6.82)	< 0.001
Hypertension	2.69 (2.24 – 3.24)	< 0.001	1.9 (1.29 – 2.8)	0.001
Diabetes mellitus	1.05 (0.94 – 1.16)	0.408	1.1 (0.87 – 1.39)	0.443
Dyslipidaemia	0.97 (0.86 – 1.08)	0.562	1.28 (0.99 – 1.64)	0.059
Atrial fibrillation	1.50 (1.33 – 1.70)	< 0.001	1.55 (1.22 – 1.98)	< 0.001
ASPECTS	0.66 (0.59 – 0.74)	< 0.001	0.75 (0.58 – 0.96)	0.021
IVT	0.78 (0.70 – 0.88)	< 0.001	0.75 (0.58 – 0.98)	0.032
TICI before angiography 2b,3	0.59 (0.53 – 0.66)	< 0.001	0.87 (0.7 – 1.09)	0.226
Occlusion locations				
Posterior circulation	0.57 (0.39 – 0.82)	0.003	0.71 (0.31 – 1.65)	0.423
Anterior CA	0.97 (0.87 – 1.09)	0.642	1.12 (0.89 – 1.4)	0.339
Posterior CA	1.03 (0.88 – 1.19)	0.170	0.92 (0.6 – 1.4)	0.685
Intracranial CA at the T-junction	1.01 (0.89 – 1.15)	0.845	1.01 (0.77 – 1.32)	0.956
Intracranial CA not at the T-junction	1.06 (0.94 – 1.19)	0.359	1 (0.76 – 1.31)	0.981
Extracranial CA	0.92 (0.80 – 1.07)	0.278	0.99 (0.75 – 1.31)	0.950
Proximal M1	0.91 (0.77 – 1.07)	0.240	1.63 (1.19 – 2.24)	0.002
Middle CA distal M1	0.83 (0.71 – 0.97)	0.021	1.04 (0.78 – 1.38)	0.781
Middle CA M2	0.70 (0.60 – 0.82)	< 0.001	1.37 (1 – 1.88)	0.045
Basilar artery	1.16 (0.85 – 1.59)	0.344	1.11 (0.54 – 2.27)	0.780

Vertebral artery	0.94 (0.79 – 1.12)	0.489	1.27 (0.9 – 1.78)	0.170

Declaration of competing interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.