

Prioritizing Early Post-Acute Care Transfer Planning After Stroke: An Interpretable and Calibrated Prediction Model for Functional Improvement During the PAC Episode

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Running head: Early PAC Transfer Planning After Stroke

39 **Abstract**

40 **Background:** In stroke care, the challenge is not just determining eligibility for Post-Acute
41 Care (PAC), but prioritizing transfer-planning when resources like beds and staffing are limited.

42 **Objective:** To clarify whether routinely available transfer-time variables can be used to
43 identify PAC-eligible stroke patients with a higher probability of marked functional
44 improvement during the PAC episode, and to translate this information into an interpretable,
45 threshold-based tool for prioritizing early transfer-planning activities.

46 **Methods:** We retrospectively analyzed stroke patients in a PAC program. The outcome was
47 marked functional improvement during PAC. A multivariable logistic regression model
48 included age, Barthel Index (BI), previous stroke, acute-care length of stay (LOS), and
49 Functional Oral Intake Scale (FOIS). Performance was assessed via discrimination, calibration,
50 and decision curve analysis (DCA).

51 **Results:** Younger age, no previous stroke, and higher BI at transfer were independently
52 associated with greater odds of marked improvement. The model demonstrated acceptable
53 discrimination and calibration. DCA indicated clinical utility across a practical threshold range,
54 with maximal incremental net benefit near 0.51. Visualization analyses revealed that BI acts as
55 the primary stratifier for recovery readiness, while FOIS provides crucial refinement for
56 patients near the DCA-supported decision boundary.

Conclusion: Among PAC-eligible patients, routinely available transfer-time data supports an interpretable tool for prioritizing coordination. While BI provides the main structural signal for prioritization, FOIS adds clinical value for borderline cases near the operational planning threshold.

Keywords: Post-Acute Care; Stroke Rehabilitation; Decision Curve Analysis; Barthel Index; Functional Oral Intake Scale

1. Introduction

Stroke remains a leading cause of long-term disability worldwide, and the absolute burden of stroke continues to increase with population ageing and growth. Global Burden of Disease (GBD) analyses have documented substantial increases in the absolute numbers of incident and prevalent stroke cases over recent decades, underscoring the escalating demand for coordinated post-acute rehabilitation and transitional services [1, 2]. This increasing demand places pressure on acute hospital capacity, particularly in settings where bed availability is constrained and emergency department crowding is sensitive to inpatient throughput.

Following stabilization in the acute phase, many stroke survivors experience residual functional deficits and require structured rehabilitation to maximize recovery and facilitate safe community reintegration. Post-acute care (PAC) models vary internationally, spanning inpatient rehabilitation facilities, skilled nursing/subacute rehabilitation, intermediate care, and early supported discharge (ESD) programs, but share the goal of providing coordinated, multidisciplinary rehabilitation during a transitional phase [3-8]. In Taiwan, national PAC programs for stroke have been associated with improvements in functional measures such as the modified Rankin Scale (mRS), Barthel Index (BI), and Functional Oral Intake Scale (FOIS) [4-7].

In real-world stroke services, however, the decision problem is often not whether PAC is broadly beneficial, but how to prioritize finite transfer-planning effort among patients who are

95 already considered appropriate for PAC. Earlier planning usually requires multidisciplinary
96 assessment, document preparation, bed matching, inter-unit communication, and family
97 counseling. When beds, staffing, and coordination time are limited, not every patient can
98 receive the same level of early transfer-planning effort at the same time. Clinicians therefore
99 need a grounded, patient-level way to identify which already-eligible PAC patients are more
100 likely to achieve meaningful functional improvement during the upcoming PAC episode.

101 Prediction modeling offers a practical framework for this problem, but contemporary
102 guidance emphasizes that rank-order discrimination alone is insufficient for clinical use. If
103 predicted probabilities are intended to trigger an operational action, they must also be
104 reasonably calibrated and interpretable, and their usefulness should be examined in a decision
105 context rather than by AUC alone [9-14].

106 Accordingly, this study had four objectives. First, we aimed to develop an interpretable
107 transfer-time prediction model for marked functional improvement among stroke patients
108 already selected for PAC. Second, we evaluated whether model performance was consistent
109 across internal validation strategies by comparing stratified 5-fold and 10-fold cross-validation.
110 Third, we assessed calibration and decision-curve clinical utility so that predicted probabilities
111 could be interpreted as operational planning thresholds rather than as rank-order scores alone.
112 Fourth, we summarized between-group differences with effect sizes to distinguish clinically
113 meaningful recovery-readiness signals from statistically significant but potentially small

differences.

2. Materials and Methods

2-1. Study Design and Participants

We conducted a retrospective cohort study using data from the Changhua Christian Hospital (CCH) system in Taiwan. The study protocol was approved by the CCH Institutional Review Board (IRB No. 241005) with a waiver of informed consent. Adult stroke survivors (aged ≥ 18 years) admitted to the CCH PAC center between January 1, 2016, and July 31, 2024 were screened. Inclusion criteria were: (1) confirmed diagnosis of acute ischemic or hemorrhagic stroke; (2) transfer from an acute care facility within the CCH system; (3) available pre- and post-PAC functional assessments; and (4) moderate to moderately severe impairment (mRS 3–4) with rehabilitation potential. Exclusion criteria were: (1) incomplete records for key variables; or (2) death or transfer during the PAC period. The final cohort comprised 610 patients (Figure 1 near here).

Within the CCH stroke pathway, patients were first managed during acute hospitalization and were then considered for transfer to a CCH-affiliated PAC facility once medically stable and judged appropriate for post-acute rehabilitation. During this transition, clinicians routinely documented transfer-time information used in everyday planning, including demographics, stroke subtype, acute treatments, previous stroke history, dates of acute admission and PAC

transfer, and functional measures. In particular, BI, mRS, and FOIS were recorded during the pre-transfer evaluation because these measures were already part of standard rehabilitation assessment, nursing handoff, and transfer-planning communication. After transfer to PAC, patients underwent multidisciplinary rehabilitation, and the same functional measures were recorded again at PAC discharge so that interval change during the PAC episode could be captured in a clinically consistent way.

2-2. Outcome Definition

Outcome captured functional improvement during the PAC episode and was defined as marked mRS improvement (Outcome = 1 if $mRS-1 - mRS < 0$; else 0), where baseline mRS was assessed at PAC transfer and follow-up (mRS-1) was assessed at PAC discharge. The mRS is a widely used global disability scale in stroke research and practice, while the BI and FOIS are established functional measures commonly used to characterize baseline disability and oral intake status in stroke rehabilitation [15-17].

2-3. Statistical Analysis

Before fitting multivariable logistic regression models, predictors that met the univariable logistic regression screening criterion ($p\text{-value} < 0.25$) were examined for correlation and collinearity. We inspected pairwise associations using Spearman correlation and correlation matrices for continuous/ordinal predictors, and computed variance inflation factors (VIF) from a preliminary multivariable design matrix. The relatively permissive screening threshold was

chosen to reduce the risk of prematurely excluding potentially important covariates, consistent with established methodological recommendations [18]. When substantial collinearity was detected, we selected a single representative variable based on clinical interpretability and data completeness to avoid unstable coefficient estimates. VIF results in this study indicated negligible multicollinearity among retained predictors (Age = 1.040; Acute care LOS = 1.079; BI = 1.248; Previous stroke = 1.024; FOIS = 1.241) [19].

For clinician-facing interpretation, we additionally performed two visualization analyses. First, we generated exploratory reduced-model boxplots (BI only, FOIS only, and BI+FOIS) using model-specific recalibrated probabilities on the held-out test set across baseline mRS strata in order to compare relative stratification patterns. Second, we created a conditional BI×FOIS probability surface from the final five-predictor model while fixing age and acute-care LOS at test-set median values and stratifying by previous stroke status (0 or 1). The contour corresponding to the DCA-supported threshold was overlaid to visualize the operational planning boundary. These figures were intended as interpretation aids rather than as independent re-estimations of the threshold.

2-4. Model Building and Variable Selection

To obtain a parsimonious final model, we considered a commonly used backward stepwise (backward elimination) approach with Akaike information criterion (AIC) as a selection aid. Specifically, we started from an initial model containing prespecified clinically important

variables (e.g., age and sex when applicable) plus predictors meeting the univariable screening threshold, then iteratively removed variables that did not contribute to model fit, guided by AIC and clinical plausibility. The final model is reported as adjusted odds ratios (aOR) with 95% confidence intervals and *p*-values.

DCA was emphasized because discrimination alone cannot determine whether acting on a model output would improve real-world care. For transfer planning, the relevant question is not simply whether the model ranks patients correctly, but whether using a predicted probability to trigger earlier coordination provides more clinical value than default strategies of planning earlier for everyone or for no one. DCA addresses this directly by incorporating the harm–benefit trade-off implied by a chosen threshold probability, making it particularly suitable for capacity-limited planning decisions in PAC services.

The primary model was prespecified to include Age, BI, Previous stroke, Acute care LOS, and FOIS to reflect variables available at the PAC transfer time point and are clinically usable for real-world transfer planning. As a sensitivity analysis, we also applied backward AIC selection on a broader candidate set, and summarized the resulting final model parameters and performance metrics in the Results section.

Participants were grouped by Outcome status (improved vs non-improved). Continuous variables were examined using the Shapiro-Wilk test and summarized as mean $\pm$ SD. Group comparisons used independent-samples *t* tests for approximately normal distributions and

Mann-Whitney U tests otherwise. Categorical variables were summarized as n (%) and compared using chi-square or Fisher exact tests, as appropriate. To avoid relying only on sample-size-driven statistical significance, Table 1 additionally reports effect sizes: Cohen's d for continuous variables, and odds ratios with 95% confidence intervals plus Cramer's V for binary categorical variables.

Candidate predictors were first evaluated in univariable logistic regression models and reported as OR (95% CI) with p -values. Predictors with $p < 0.25$ were retained as candidates for multivariable consideration, consistent with recommendations to avoid excluding potentially important confounders too early [18]. Candidate variables were then reviewed for clinical interpretability, availability at the PAC transfer time point, potential post-baseline leakage, and collinearity using correlation inspection and variance inflation factors. AIC-guided backward elimination was used as a selection aid, but the final primary model was prespecified to include Age, BI, Previous stroke, Acute care LOS, and FOIS because these variables are routinely available at transfer and clinically usable for early planning.

We used a stratified 80/20 train-test split. The random seed was fixed at 20260126 for the train-test split, cross-validation shuffling, and bootstrap resampling. Within the training set, stratified 5-fold cross-validation was used as the main internal-validation procedure, and stratified 10-fold cross-validation was added as a sensitivity analysis to examine whether the estimated discrimination was consistent when the validation folds were made smaller. The final

209 model was refit on the full training set and evaluated on the held-out test set; test-set AUC
210 uncertainty was estimated using 1,000 bootstrap resamples.

211 Calibration was assessed on the test set using logistic recalibration (intercept and slope),
212 a decile-based calibration plot, the Hosmer-Lemeshow goodness-of-fit test, and the Brier score.
213 These measures were selected because contemporary prediction-model guidance recommends
214 reporting both discrimination and calibration, while recognizing the limitations of relying on
215 any single calibration statistic [9, 10, 14].

216 On the held-out test set, calibration was summarized by the logistic recalibration intercept
217 and slope (intercept = 0.071, slope = 0.920), Hosmer-Lemeshow goodness-of-fit test (chi-
218 square = 5.47, $p = 0.706$), and the Brier score (Brier = 0.217). Clinically, calibration determines
219 whether a predicted probability can be interpreted as an approximate observed risk; this is
220 essential when a threshold probability (p_t) is used to trigger an operational action. We used 10
221 bins (deciles) because decile grouping is a conventional compromise between resolution and
222 stability in moderate sample sizes; fewer bins provide smoother but less detailed patterns,
223 whereas too many bins can yield unstable observed event rates because of small bin counts.

224 Clinical utility was evaluated using DCA based on recalibrated predicted probabilities.
225 The model-based policy was defined as triggering early transfer planning when predicted
226 probability met or exceeded a chosen threshold probability. Net benefit was compared with
227 treat-all and treat-none strategies, and bootstrap optimism correction with 1,000 resamples was

used to assess robustness [11-13, 20]. Net benefit was computed as shown in Formula (1), and incremental net benefit was computed as shown in Formula (2).

$$NB_{model}(p_t) = \frac{TP(p_t)}{N} - \frac{FP(p_t)}{N} * \frac{p_t}{(1 - p_t)} \quad (1)$$

p_t : Threshold probability for triggering early transfer planning. $NB_{model}(p_t)$: Net benefit of the model-based strategy at p_t ; interpreted as the net proportion of appropriately triggered early transfer planning decisions after accounting for the harm of unnecessary triggers. The term $\frac{p_t}{1-p_t}$ represents the harm-to-benefit trade-off implied by the chosen threshold, i.e., the relative weight of a false-positive trigger compared with a true-positive trigger. $TP(p_t)$: True positives at threshold p_t ; number of patients with Outcome present (Outcome = 1, marked mRS improvement during PAC) who are correctly flagged by the model ($\hat{p} \geq p_t$) for early transfer planning. $FP(p_t)$: False positives at threshold p_t ; number of patients without Outcome (Outcome = 0, no marked mRS improvement during PAC) who are incorrectly flagged by the model ($\hat{p} \geq p_t$) for early transfer planning. N : Total number of patients in the evaluation sample used for DCA (e.g., the held-out test set or the full cohort, depending on the analysis).

Where relevant for clinical interpretation, net benefit can be read as the net proportion of appropriately triggered early transfer-planning decisions after accounting for unnecessary triggers at a chosen threshold probability (p_t). The term $\frac{p_t}{1-p_t}$ expresses the harm-benefit trade-

off implied by that threshold - that is, how much the team is willing to tolerate an unnecessary trigger relative to the benefit of correctly prioritizing a patient who is more likely to improve.

$$INB(p_t) = NB_{model}(p_t) - \max\{NB_{all}(p_t), NB_{none}(p_t)\} \quad (2)$$

$INB(p_t)$: Incremental net benefit at threshold p_t ; the net improvement in decision utility of the model-based strategy compared with the better-performing default strategy at the same p_t . $NB_{all}(p_t)$: Net benefit of the treat-all strategy, i.e., triggering early transfer planning for all patients regardless of predicted risk. $NB_{none}(p_t)$: Net benefit of the treat-none strategy, i.e., triggering early transfer planning for no patients. For binary outcomes in standard DCA, $NB_{none}(p_t) = 0$ for all p_t . $\max\{NB_{all}(p_t), NB_{none}(p_t)\}$: The best default strategy at threshold p_t , used as the reference comparator when computing INB.

We reported the principal p_t range where the model outperformed treat-all/none and the p_t^* maximizing INB, as shown in formulas (3). Bootstrap optimism-corrected DCA based on 1,000 resamples of the full cohort was used as a robustness analysis.

$$p_t^* = \underset{p_t}{argmax} INB(p_t) \quad (3)$$

The threshold p_t^* therefore represents the point, within the pre-specified candidate range, at which the model provided the greatest incremental decision value over the default strategies in this dataset.

3. Results

3-1. Clinical problem framing and transfer-time differences

In the PAC-only cohort (N = 610), 313 patients (51.3%) achieved marked functional improvement during PAC, whereas 297 did not. Patients in the improved group were younger (61.83 ± 13.60 vs 68.04 ± 12.83 years; $p < 0.001$; Cohen's $d = -0.47$) and had a lower prevalence of previous stroke (15.0% vs 27.6%; $p < 0.001$; OR = 0.46, 95% CI 0.31-0.69; Cramer's V = 0.15). They also had fewer vascular comorbidities relevant to recovery potential, including hyperlipidemia (55.9% vs 64.3%; $p = 0.042$; OR = 0.70, 95% CI 0.51-0.97; Cramer's V = 0.09) and heart disease (16.0% vs 24.9%; $p = 0.008$; OR = 0.57, 95% CI 0.38-0.86; Cramer's V = 0.11). Regarding the acute clinical course, acute care LOS prior to PAC transfer was shorter in the improved group (18.41 ± 7.00 vs 20.05 ± 7.09 days; $p = 0.003$; Cohen's $d = -0.23$), whereas PAC LOS was longer among those who improved (49.58 ± 23.19 vs 45.21 ± 25.84 days; $p = 0.016$; Cohen's $d = 0.18$). Functional status at PAC transfer showed clearer separation in recovery-readiness signals: Barthel Index was higher in the improved group (48.29 ± 14.63 vs 40.71 ± 15.72 ; $p < 0.001$; Cohen's $d = 0.50$), and FOIS was also higher (6.36 ± 1.43 vs 5.75 ± 1.78 ; $p < 0.001$; Cohen's $d = 0.38$), while baseline mRS did not differ materially (3.84 ± 0.37 vs 3.82 ± 0.38 ; $p = 0.690$; Cohen's $d = 0.03$). At PAC discharge, the improved group exhibited markedly better outcomes across mRS, BI, and FOIS (all $p < 0.001$), consistent with the

definition of Outcome and supporting internal coherence of the endpoint (Table 1 near here).

3-2. Recovery-readiness predictors

In univariable logistic regression, older age was associated with lower odds of marked improvement (OR = 0.965 per year, 95% CI 0.953–0.977; $p < 0.001$). Previous stroke was similarly associated with reduced odds (OR = 0.463, 95% CI 0.310–0.692; $p < 0.001$), and heart disease showed a negative association (OR = 0.573, 95% CI 0.384–0.855; $p = 0.006$). Baseline Barthel Index and FOIS at PAC transfer were positively associated with improvement (Barthel: OR = 1.034 per point, 95% CI 1.022–1.046; $p < 0.001$; FOIS: OR = 1.267 per level, 95% CI 1.142–1.405; $p < 0.001$). Longer acute care LOS prior to PAC transfer was associated with lower odds of improvement (OR = 0.967 per day, 95% CI 0.946–0.990; $p = 0.004$). In the prespecified multivariable logistic regression model (Age, Barthel Index, Previous stroke, acute care LOS, FOIS), age (aOR = 0.969 per year, 95% CI 0.955–0.984; $p < 0.001$), Previous stroke (aOR = 0.470, 95% CI 0.289–0.765; $p = 0.002$), and Barthel Index (aOR = 1.029 per point, 95% CI 1.015–1.043; $p < 0.001$) remained independently associated with Outcome. After adjustment, acute care LOS (aOR = 0.978, 95% CI 0.952–1.006; $p = 0.122$) and FOIS (aOR = 1.077, 95% CI 0.945–1.227; $p = 0.267$) attenuated, indicating that part of their univariable signal overlapped with global functional severity and recovery potential captured by age, previous stroke, and Barthel Index (Table 2 near here).

3-3. Model performance

Model discrimination was moderate and internally consistent across validation strategies. In the training set, the model had an apparent AUC of 0.707. Stratified 5-fold cross-validation yielded a mean AUC of 0.697 ± 0.033 , and stratified 10-fold cross-validation yielded a mean AUC of 0.697 ± 0.040 . The near-identical mean AUCs suggest that the estimated discrimination was not dependent on the choice of 5-fold versus 10-fold internal validation. In the held-out test set, the final model achieved AUC = 0.713 with a bootstrap 95% CI of 0.610-0.801, showing comparable discrimination when evaluated on previously unseen data (Figure 2 near here).

Calibration on the held-out test set was acceptable, with a recalibration intercept of 0.071 and slope of 0.920, a Hosmer–Lemeshow chi-square of 5.47 ($p = 0.706$), and a Brier score of 0.217. The decile-based calibration plot showed that observed event rates generally tracked predicted probabilities across risk strata, supporting the interpretability of the model’s predicted risks for threshold-based decision making (Figure 3 near here).

3-4. Operational meaning across decision thresholds

DCA using recalibrated test-set probabilities showed that the model-based strategy provided greater net benefit than treat-all and treat-none strategies across threshold probabilities range of approximately 0.21 to 0.705, with the maximal incremental net benefit at p_t^* approximately 0.51 (Figure 4 near here). In practical terms, p_t is the minimum predicted probability at which the team would judge earlier transfer planning to be worthwhile.

Trigger rate refers to the proportion of PAC-eligible patients who would be flagged for earlier planning at a given threshold. Thus, a lower threshold identifies more patients for earlier coordination and is useful when bed pressure and staffing pressure are modest, whereas a higher threshold is more selective and may be preferred when the service can only prioritize a smaller number of patients at one time.

As a sensitivity analysis, bootstrap optimism-corrected DCA based on 1,000 resamples of the full cohort showed a similar overall pattern of decision utility, suggesting that the observed net-benefit range was not solely an artifact of a single train-test split (Supplementary Figure 1 near here).

3-5. Clinical interpretation of the DCA-supported boundary

To clarify how the DCA-supported threshold mapped onto familiar clinical variables, we performed two clinician-facing visualization analyses. Using recalibration on the test set, the BI-only model separated baseline mRS strata more clearly than the FOIS-only model, with median predicted probabilities of 63.2% versus 48.1% for mRS 3 and mRS 4, respectively, whereas the FOIS-only model showed nearly identical medians (both 58.0%). The combined BI+FOIS model preserved the main BI-driven separation pattern while modestly shifting the median probability of the mRS 4 group to 51.3%, placing it close to the reference line corresponding to the final-model DCA threshold (Figure 5 near here).

When the final five-predictor model was projected onto the BI×FOIS plane while fixing

age and acute-care LOS at test-set representative values and stratifying by previous stroke status, the 51% contour behaved as a clinically interpretable planning boundary. The boundary was oriented predominantly along the BI axis in both previous-stroke scenarios, indicating that BI was the dominant first-line stratifier of transfer-time recovery readiness, whereas FOIS modified probabilities more subtly along the threshold-adjacent margin. In patients with previous stroke, the boundary shifted rightward, implying that a higher BI was needed to reach the same DCA-supported planning threshold when prior cerebrovascular burden was present (Figure 6 near here).

4. Discussion

4-1. Interpreting Transfer-Time Recovery Readiness Signals

The main clinical problem addressed by this study is straightforward: once a stroke patient has already been identified as appropriate for PAC, teams still need to decide who should receive earlier transfer-planning effort when beds, staffing, and coordination capacity are limited. The clinical finding is not merely that a statistical model achieved moderate AUC. Rather, the data suggest that transfer-time recovery readiness is primarily reflected by functional reserve at PAC entry, prior cerebrovascular burden, and age. The strongest transfer-time separation was observed for BI, whereas previous stroke and older age consistently indicated a lower probability of marked functional improvement. These findings are clinically

plausible and consistent with prior rehabilitation literature showing that baseline functional status, age, and previous neurologic burden are important determinants of post-stroke rehabilitation outcomes [21-24].

Acute care LOS should therefore be interpreted as a contextual planning variable rather than as a causal treatment target. Shorter LOS before PAC transfer was observed in patients who improved, but this does not imply that shortening hospitalization itself would improve recovery. A more clinically grounded interpretation is that patients who become medically stable and functionally ready for PAC earlier may also carry a more favorable recovery profile. In this framework, LOS helps the team time and prioritize transfer-planning activities, while BI, previous stroke, and age provide the core recovery-readiness signal.

4-2. Clinical Problem and Practical Implications

The clinically important question in this study is not simply whether a longer acute hospitalization is associated with worse subsequent outcome. Rather, among patients who ultimately enter PAC, the issue is how to prioritize earlier transfer-planning effort when coordination resources are finite. In this cohort, transfer-time recovery readiness - most clearly reflected by younger age, no previous stroke, and higher BI - was consistently associated with a higher probability of marked functional improvement during the PAC episode. This pattern is broadly consistent with prior PAC and transfer-system studies from Taiwan, which have shown that coordinated multidisciplinary PAC pathways are associated with better functional

377 recovery trajectories in selected stroke populations [4-8, 25, 26].

378 FOIS should be interpreted in the same clinical manner. Its univariable association with
379 improvement suggests that oral intake and swallowing-related recovery are relevant to PAC
380 readiness, but its attenuation after adjustment indicates overlap with broader functional reserve
381 captured by BI and other transfer-time variables. This interpretation is compatible with
382 evidence that dysphagia and oral-intake recovery after stroke are multifactorial and influenced
383 by demographic, stroke-related, and physiological features rather than by a single swallowing
384 indicator alone [27]. At the same time, the negative coefficient for age should be interpreted as
385 a population-level prognostic signal rather than as a reason to deny rehabilitation, because older
386 stroke survivors may still achieve meaningful gains when appropriately selected and treated
387 with structured rehabilitation intensity [28].

388 The proposed model should not be interpreted causally. Specifically, these findings do not
389 show that shortening acute-care length of stay itself improves outcomes. Rather, the model is
390 intended to support risk-stratified coordination: when the predicted probability of improvement
391 is sufficiently high relative to a locally acceptable harm-benefit trade-off, clinicians may
392 activate early transfer-planning activities such as bed requests, family counseling, and inter-
393 unit scheduling [11-13, 20, 29].

394 The test-set AUC of 0.713 indicates moderate discrimination, but implementation
395 decisions cannot rest on discrimination alone. Contemporary guidance on prediction-model

evaluation emphasizes that clinical use also depends on calibration and decision utility, not only rank-order performance [9, 10, 12, 14]. This is where the present study adds value beyond a conventional prognostic-factor paper: it translates routinely available transfer-time information into a threshold-based operational framework. If a hospital adopts a specified threshold probability (p_t) for triggering early planning, that threshold makes explicit the local harm-benefit trade-off between unnecessary planning activation and missed opportunities for timely coordination. Decision-curve analysis then shows whether the model improves on default strategies of triggering planning for everyone or for no one. In this cohort, the model demonstrated higher net benefit than these default strategies primarily across p_t approximately 0.21-0.705, with maximal incremental net benefit at p_t^* approximately 0.51.

In practical clinical terms, threshold probability (p_t) in this study means the minimum predicted chance of marked PAC improvement at which the team judges earlier transfer planning to be worthwhile. It is therefore not a purely statistical cut-off. Rather, it expresses how selective the service wishes to be when using limited coordination resources such as multidisciplinary review, bed requests, document preparation, family counseling, and inter-unit scheduling. Lower thresholds are suitable when the service is willing to plan earlier for a broader group in order to miss fewer potentially responsive patients, whereas higher thresholds are suitable when the service must focus on a smaller group because beds, staffing, or coordination time are constrained [11-13, 20, 29].

Related decision-curve terms can also be interpreted in clinician-facing language. Trigger rate is simply the proportion of PAC-eligible patients who would be flagged for earlier planning at a given threshold; operationally, it reflects how many patients the team would need to place on the earlier-planning list. Net benefit reflects the clinical decision value of using the model after balancing the value of correctly prioritizing patients who are more likely to improve against the burden of unnecessarily prioritizing those less likely to do so. Incremental net benefit (INB) is the extra decision value of the model compared with the better of the two default strategies at the same threshold - namely, prioritizing everyone or prioritizing no one. In other words, INB does not represent financial profit; in this study it represents additional net clinical value in deciding how to allocate limited transfer-planning effort [11-13, 20, 29].

In grounded clinical terms, a lower threshold (for example, $p_t = 0.30-0.40$) means that the team is willing to start planning for most patients in order to miss as few potentially responsive patients as possible; this may be appropriate when bed pressure is modest and staffing allows broader coordination. A higher threshold (for example, $p_t = 0.60-0.70$) means that the team chooses to concentrate effort on fewer patients with higher predicted probabilities of improvement; this may be more realistic during bed shortage or personnel constraints. Figure 7 summarizes this workflow in a way that mirrors daily clinical operations (Figure 7 near here).

4-3. BI as the Primary Stratifier and FOIS as a Threshold-Adjacent Modifier

An important clinical insight from the combined interpretation of Figures 5 and 6 is that

transfer-time risk stratification in PAC-eligible stroke patients may follow a two-step logic rather than a single-variable rule. The boxplots showed that BI alone already produced clear coarse separation across baseline mRS strata, whereas FOIS alone showed substantial overlap and weaker discrimination. This suggests that BI captures the main structural signal of recovery readiness at PAC transfer. At the same time, the combined BI+FOIS model preserved the BI-driven pattern and placed the mRS 4 group closer to the threshold-adjacent zone, implying that FOIS adds value not by replacing BI but by refining classification in borderline patients.

The final-model BI×FOIS heatmap further strengthens this interpretation. Once age and acute-care LOS were fixed at clinically typical values and previous stroke status was specified, the 0.51 contour behaved like a visible bedside planning boundary. BI moved patients across this boundary most strongly, whereas FOIS shifted probability more subtly along the margin. Thus, FOIS should not be framed as unimportant simply because its adjusted odds ratio attenuated in the multivariable model; rather, its practical importance lies in assisting threshold-adjacent decisions, especially when teams must decide whether patients already accepted for PAC warrant earlier bed requests, document preparation, family counseling, and inter-unit coordination. Figure 5 should be interpreted as an exploratory reduced-model comparison rather than as an independent re-derivation of the final-model DCA threshold.

4-4. Capacity-Adaptive Threshold Policy

A practical implication is that threshold selection can be adapted to local resource

availability. When PAC beds and coordination capacity are relatively available, lower thresholds may be preferred to preserve sensitivity; when resources are constrained, higher thresholds may be more appropriate to concentrate effort on fewer, higher-probability patients. This interpretation is aligned with the underlying decision-analytic logic of threshold probability and net benefit in DCA [11-13, 20, 29].

4-5. Limitations and Future Research

This study has several limitations. First, it was a retrospective analysis from a single hospital system and included only patients who actually entered PAC. As such, the model should not be generalized to all acute stroke admissions or used to infer PAC eligibility. Second, although we performed internal validation using a train-test split, 5-fold and 10-fold cross-validation, and bootstrap-based DCA correction, no external validation cohort was available. Current methodological guidance emphasizes that external validation is essential before routine implementation in new settings [30]. Third, the candidate predictors were limited to routinely collected retrospective variables. Future prospective work could incorporate additional nursing, caregiver, rehabilitation-intensity, and system-throughput variables. More flexible machine-learning methods may also be explored in future studies, but any apparent gains should be judged against calibration, interpretability, and external validity requirements rather than discrimination alone [9, 10, 14, 30].

5. Conclusion

Among stroke patients already selected for PAC, the final model showed that DCA can translate routinely available transfer-time variables into a clinically usable planning threshold rather than a purely statistical score. The main innovation of this study is that BI×FOIS surface visualized the DCA-supported threshold of 0.51 as an interpretable bedside boundary. Within this framework, BI provided the main first-line stratification signal, whereas FOIS added practical value by refining decisions for patients near the threshold-adjacent margin. This shifts the model's role from predicting outcome alone to helping teams decide which already-PAC-eligible patients should receive earlier bed requests, documentation, family counseling, and inter-unit coordination when real-world capacity is constrained.

Ethics statement

The study protocol was approved by the Institutional Review Board (IRB) of Changhua Christian Hospital (CCH) (Approval No. #241005), encompassing research conducted at both CCH and Hanming Affiliated Christian Hospital. Due to the retrospective nature of the study and the use of de-identified datasets to ensure patient privacy, the requirement for informed consent was formally waived by the IRB. The study was conducted following the principles of the Declaration of Helsinki.

491 **Consent for publication**

492 Written informed consent was waived by patients for publication of this retrospective cohort
493 study.

494

495 **Competing interests**

496 The authors declare that they have no competing interests.

497

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500

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503

504 **Data availability statement**

505 The data that support the findings of this study are available from the corresponding author,
506 upon reasonable request. The data are not publicly available due to restrictions containing
507 information that could compromise the privacy of research participants and institutional
508 clinical data policies.

509

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602 **Tables**603 **Table 1. Baseline characteristics of the PAC cohort according to marked mRS improvement status**

Variable	mRS non-improved (n=297)	mRS improved (n=313)	<i>P</i> -value	Effect size
<i>Demographics</i>				
Age, year	68.04 (12.83)	61.83 (13.60)	<0.001	Cohen's d = -0.47
Sex, male	174 (58.6)	201 (64.2)	0.179	OR = 1.27 (0.92-1.76); V = 0.06
Obesity	75 (25.3)	90 (28.8)	0.378	OR = 1.19 (0.83-1.71); V = 0.04
Smoking	78 (26.3)	92 (29.4)	0.440	OR = 1.17 (0.82-1.67); V = 0.03
<i>Medical history</i>				
Hypertension	257 (86.5)	255 (81.5)	0.111	OR = 0.68 (0.44-1.06); V = 0.07
Diabetes	106 (35.7)	112 (35.8)	0.952	OR = 1.00 (0.72-1.40); V = 0.00
Hyperlipidemia	191 (64.3)	175 (55.9)	0.042	OR = 0.70 (0.51-0.97); V = 0.09
Heart disease	74 (24.9)	50 (16.0)	0.008	OR = 0.57 (0.38-0.86); V = 0.11
Previous stroke	82 (27.6)	47 (15.0)	<0.001	OR = 0.46 (0.31-0.69); V = 0.15
<i>Clinical Course</i>				
Stroke Subtype			0.026	Cramer's V = 0.09
Ischemia stroke	205 (69.0)	189 (60.4)		
Hemorrhage stroke	92 (31.0)	124 (39.6)		
tPA	28 (9.4)	23 (7.3)	0.435	OR = 0.76 (0.43-1.36); V = 0.04
EVT	26 (8.8)	23 (7.3)	0.624	OR = 0.83 (0.46-1.48); V = 0.03
Acute care LOS, days	20.05 (7.09)	18.41 (7.00)	0.003	Cohen's d = -0.23
PAC LOS, days	45.21 (25.84)	49.58 (23.19)	0.016	Cohen's d = 0.18
<i>Functional Scores at Admission</i>				
mRS	3.82 (0.38)	3.84 (0.37)	0.690	Cohen's d = 0.03

Barthel Index	40.71 (15.72)	48.29 (14.63)	<0.001	Cohen's d = 0.50
FOIS	5.75 (1.78)	6.36 (1.43)	<0.001	Cohen's d = 0.38
<i>Functional Scores at Discharge</i>				
mRS	3.83 (0.40)	2.66 (0.55)	<0.001	Cohen's d = -2.42
Barthel Index	59.74 (15.82)	81.98 (12.11)	<0.001	Cohen's d = 1.58
FOIS	6.35 (1.29)	6.88 (0.49)	<0.001	Cohen's d = 0.55

604

605 *Note. Data are presented as mean (SD) or n (%). P-values were derived from independent-samples t tests or Mann-Whitney U tests for continuous*
606 *variables and chi-square or Fisher exact tests for categorical variables, as appropriate. Effect sizes are reported to support clinical interpretation*
607 *beyond sample-size-driven statistical significance: Cohen's d is shown for continuous variables, whereas odds ratios (ORs) with 95% confidence*
608 *intervals and Cramer's V are shown for binary categorical variables. mRS improvement was defined as mRS at PAC discharge minus mRS at PAC*
609 *transfer < 0. Abbreviations: BI, Barthel Index; FOIS, Functional Oral Intake Scale; LOS, length of stay; mRS, modified Rankin Scale; PAC, post-*
610 *acute care.*

611

612

613

614 **Table 2. Univariable and multivariable logistic regression for marked mRS improvement status**

Variable	Univariate analysis			Multivariate analysis		
	OR	(95% CI)	P-value	aOR	(95% CI)	P-value
Age, year	0.965	(0.953–0.977)	<0.001	0.969	(0.955–0.984)	<0.001
Sex, male	1.269	(0.915–1.759)	0.153	NA		NA
Obesity	1.195	(0.835–1.710)	0.331	NA		NA
Smoking	1.169	(0.820–1.667)	0.389	NA		NA
Hypertension	0.684	(0.441–1.061)	0.090	NA		NA
Diabetes	1.004	(0.721–1.398)	0.981	NA		NA
Hyperlipidemia	0.704	(0.508–0.975)	0.035	NA		NA
Heart disease	0.573	(0.384–0.855)	0.006	NA		NA
Previous stroke	0.463	(0.310–0.692)	<0.001	0.470	(0.289–0.765)	0.002
Stroke Subtype_ Ischemia stroke	0.684	(0.490–0.956)	0.026	NA		NA
tPA	0.762	(0.428–1.355)	0.355	NA		NA
EVT	0.827	(0.461–1.484)	0.524	NA		NA
Acute care LOS, days	0.967	(0.946–0.990)	0.004	0.978	(0.952–1.006)	0.122
PAC LOS, days	1.007	(1.001–1.014)	0.029	NA		NA
mRS	1.090	(0.714–1.666)	0.689	NA		NA
Barthel Index	1.034	(1.022–1.046)	<0.001	1.029	(1.015–1.043)	<0.001
FOIS	1.267	(1.142–1.405)	<0.001	1.077	(0.945–1.227)	0.267

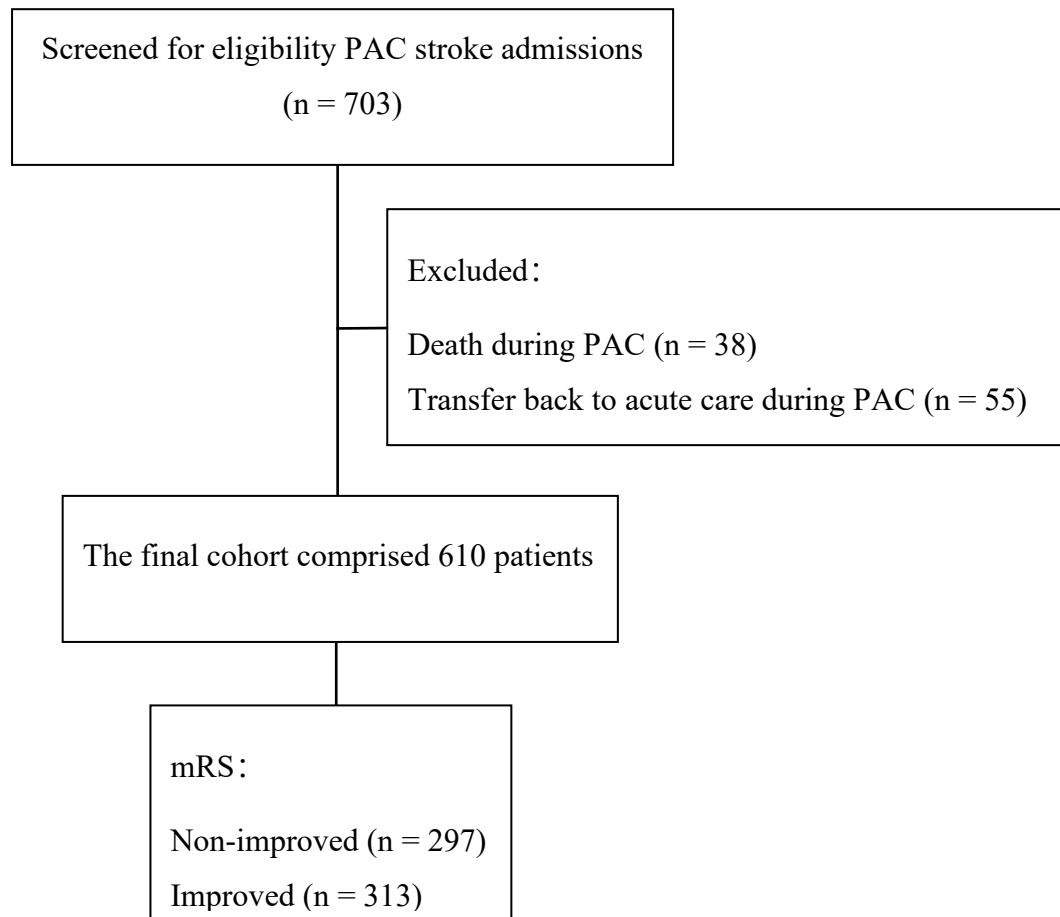
615

616 *Note. OR and aOR are shown with 95% confidence intervals. The exact feature-selection pipeline was as follows: variables were first screened*

617 using univariable logistic regression with $p < 0.25$ as the candidate-entry threshold; candidate variables were then reviewed for clinical
618 interpretability, availability at the PAC transfer time point, potential post-baseline leakage, and collinearity using correlation inspection and
619 variance inflation factors. AIC-guided backward elimination was used as a selection aid, but the final prespecified multivariable model retained
620 age, Barthel Index, previous stroke, acute-care LOS, and FOIS because these variables were transfer-time available and clinically actionable.
621 Abbreviations: aOR, adjusted odds ratio; BI, Barthel Index; FOIS, Functional Oral Intake Scale; LOS, length of stay; mRS, modified Rankin Scale;
622 OR, odds ratio; PAC, post-acute care.

Figure Legends

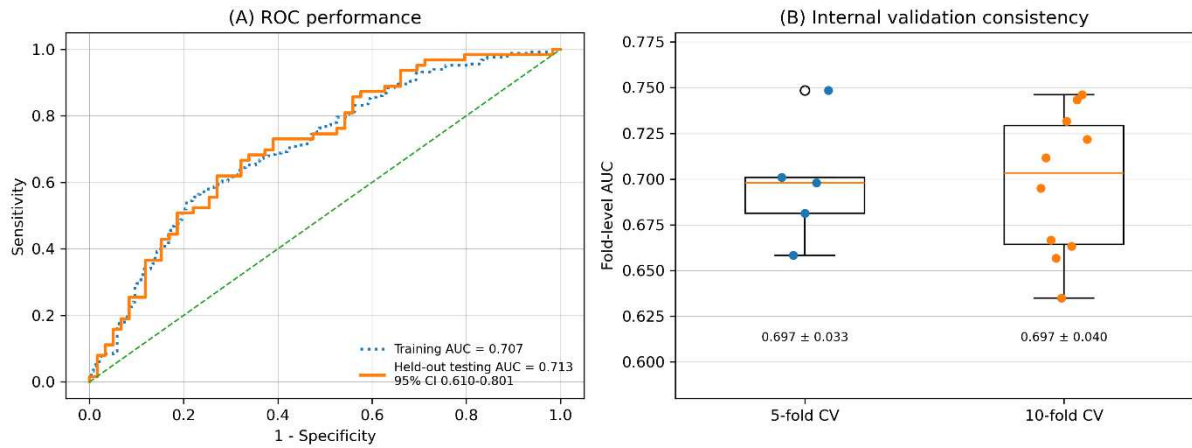
Figure 1. Participant screening and inclusion flow for the PAC-only stroke cohort



Legend. Flow diagram of patient selection. mRS improvement was defined as mRS at PAC discharge minus mRS at PAC admission < 0 . Abbreviations: mRS, modified Rankin Scale; PAC, post-acute care.

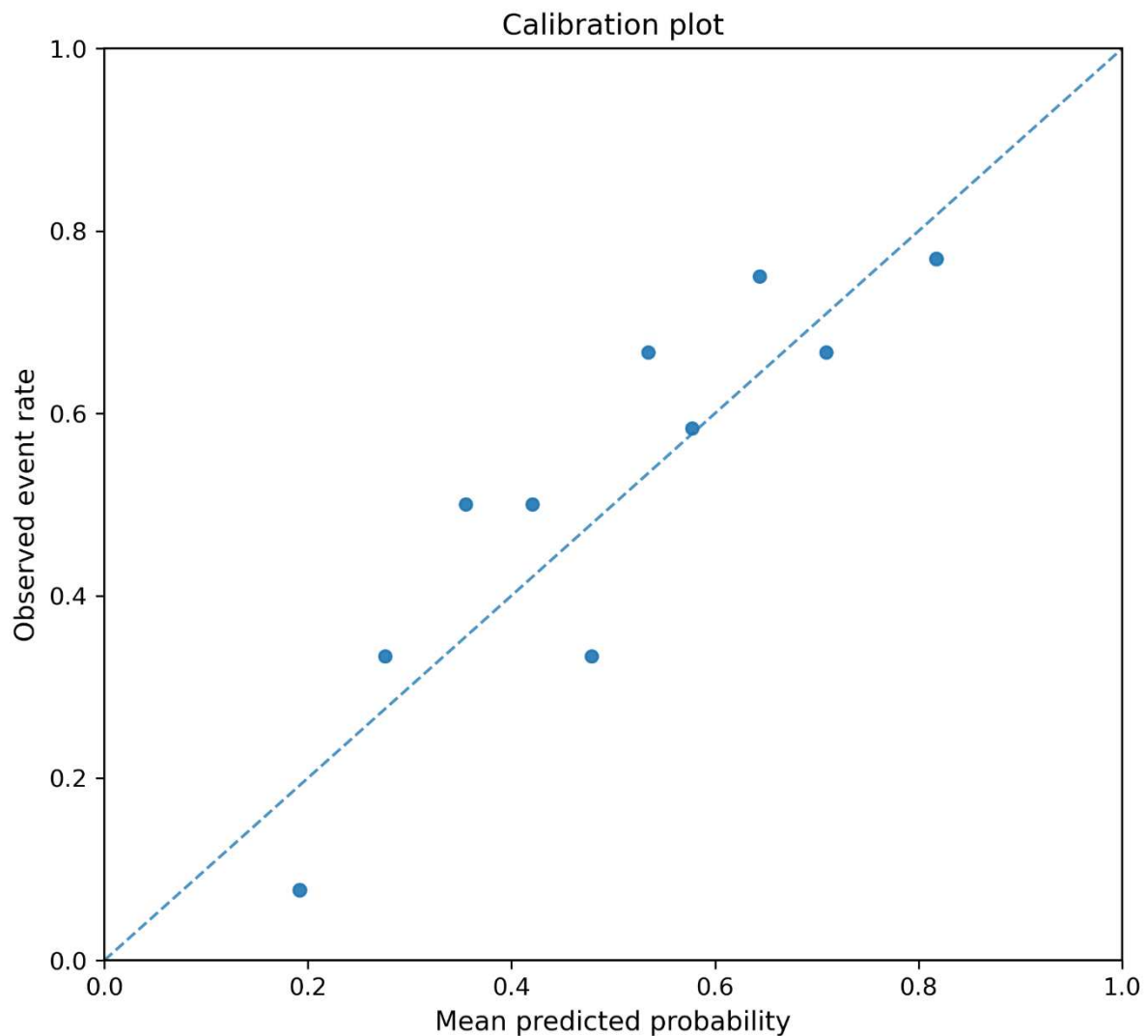
Figure 2. Receiver operating characteristic performance and internal-validation

consistency of the prespecified multivariable model



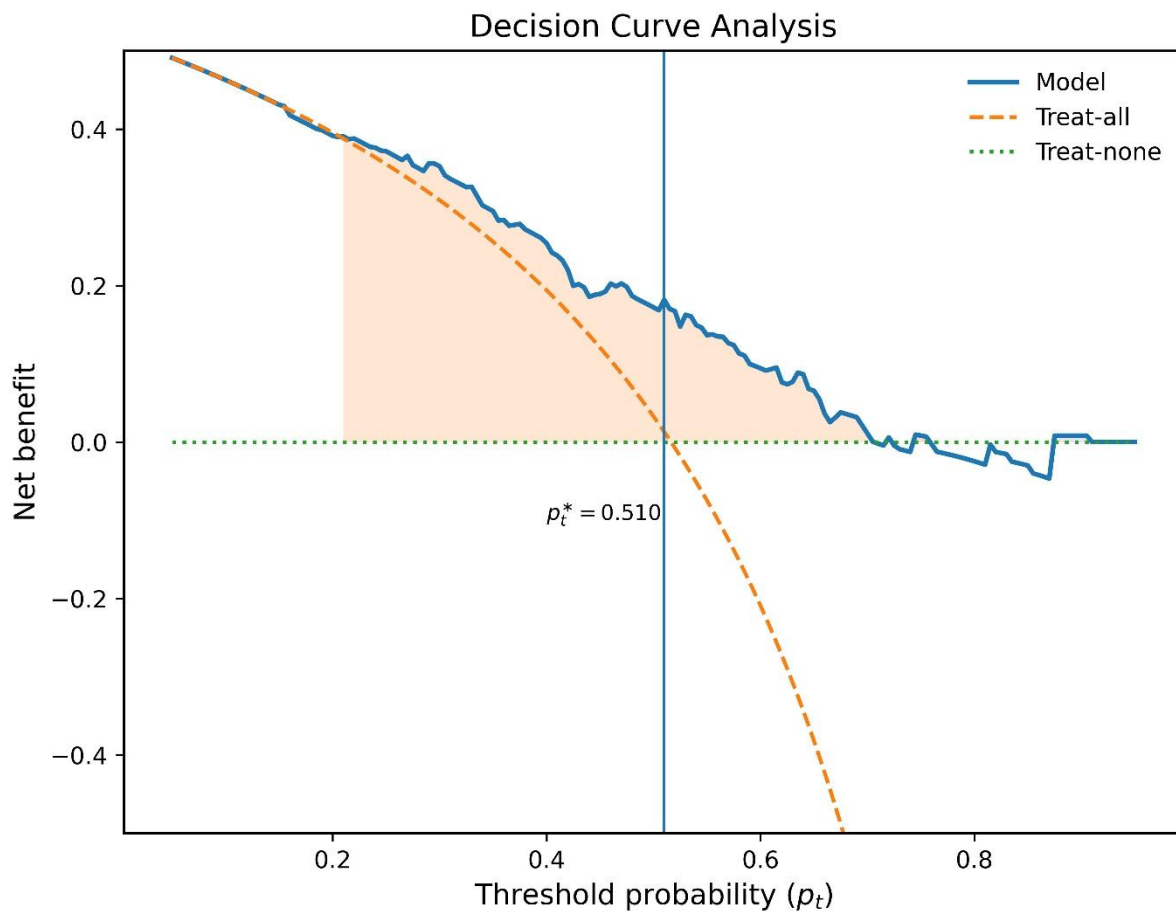
Legend. Panel A shows receiver operating characteristic (ROC) performance for the prespecified multivariable logistic regression model in the training set and held-out test set. The training AUC was 0.707, and the held-out test AUC was 0.713 with a bootstrap 95% CI of 0.610-0.801. Panel B compares fold-level AUC distributions from stratified 5-fold and 10-fold cross-validation in the training set, with seed fixed at 20260126. The 5-fold CV AUC was 0.697 ± 0.033, and the 10-fold CV AUC was 0.697 ± 0.040, supporting consistency of model discrimination across internal-validation strategies. Abbreviations: AUC, area under the ROC curve; CV, cross-validation; ROC, receiver operating characteristic.

Figure 3. Calibration plot of predicted probability for marked mRS improvement



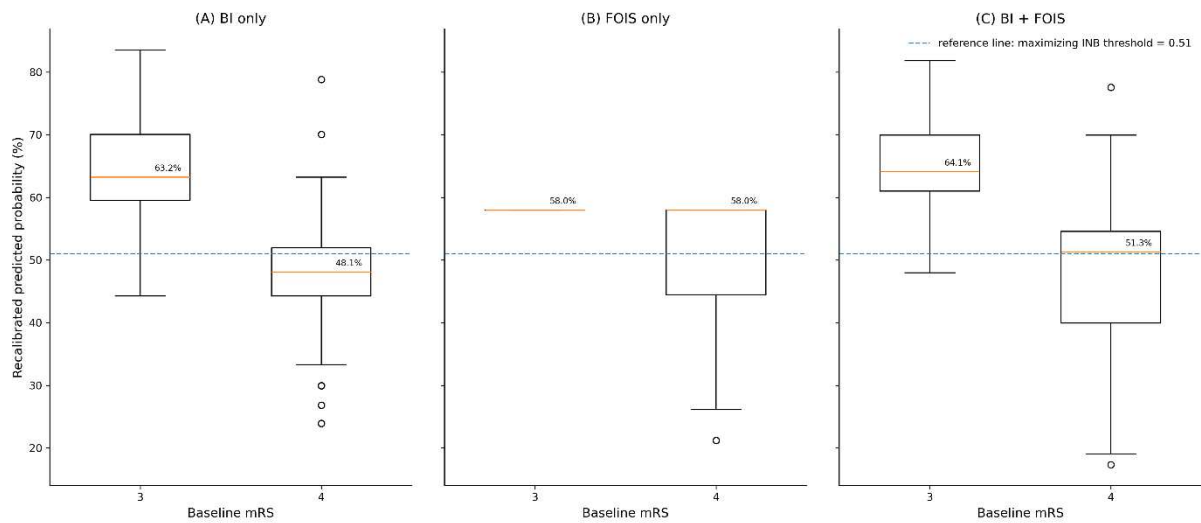
Legend. Decile-based calibration plot for the held-out test set. The x-axis shows mean predicted probability within each decile, and the y-axis shows the corresponding observed event rate. The 45-degree line represents perfect calibration. Calibration was additionally summarized by the recalibration intercept and slope, the Hosmer–Lemeshow test, and the Brier score. Abbreviations: mRS, modified Rankin Scale.

Figure 4. Decision-curve analysis for threshold-based early transfer planning



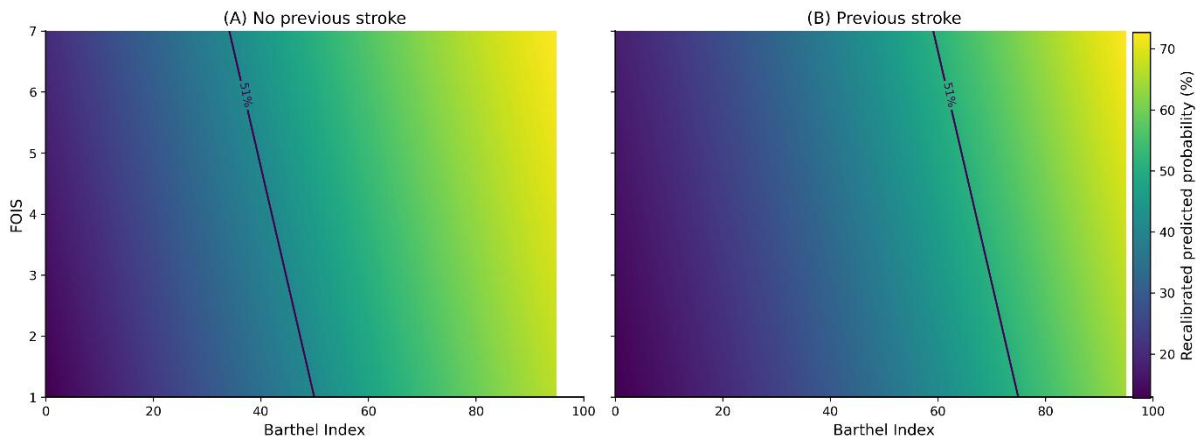
Legend. Decision-curve analysis comparing the model-based strategy with treat-all and treat-none strategies across threshold probabilities (p_t). Net benefit is plotted on the y-axis and threshold probability on the x-axis. The model-based policy was defined as triggering early transfer planning when the predicted probability of marked mRS improvement was greater than or equal to p_t . The principal range in which the model provided higher net benefit than default strategies was approximately $p_t = 0.21$ - 0.705 , with maximal incremental net benefit near $p_t^* = 0.510$. Abbreviations: DCA, decision-curve analysis; INB, incremental net benefit; mRS, modified Rankin Scale; p_t , threshold probability.

Figure 5. Test-set recalibrated predicted probabilities by baseline mRS



Legend. Boxplots show recalibrated predicted probabilities in the baseline mRS: BI only (panel A), FOIS only (panel B), and BI+FOIS (panel C). The horizontal dashed line at 0.51 is shown as a reference line corresponding to the threshold probability associated with maximal incremental net benefit in the final five-predictor model. Boxes indicate interquartile ranges, center lines indicate medians, whiskers indicate non-outlying ranges, and circles indicate outliers. Abbreviations: BI, Barthel Index; FOIS, Functional Oral Intake Scale; mRS, modified Rankin Scale; INB, incremental net benefit.

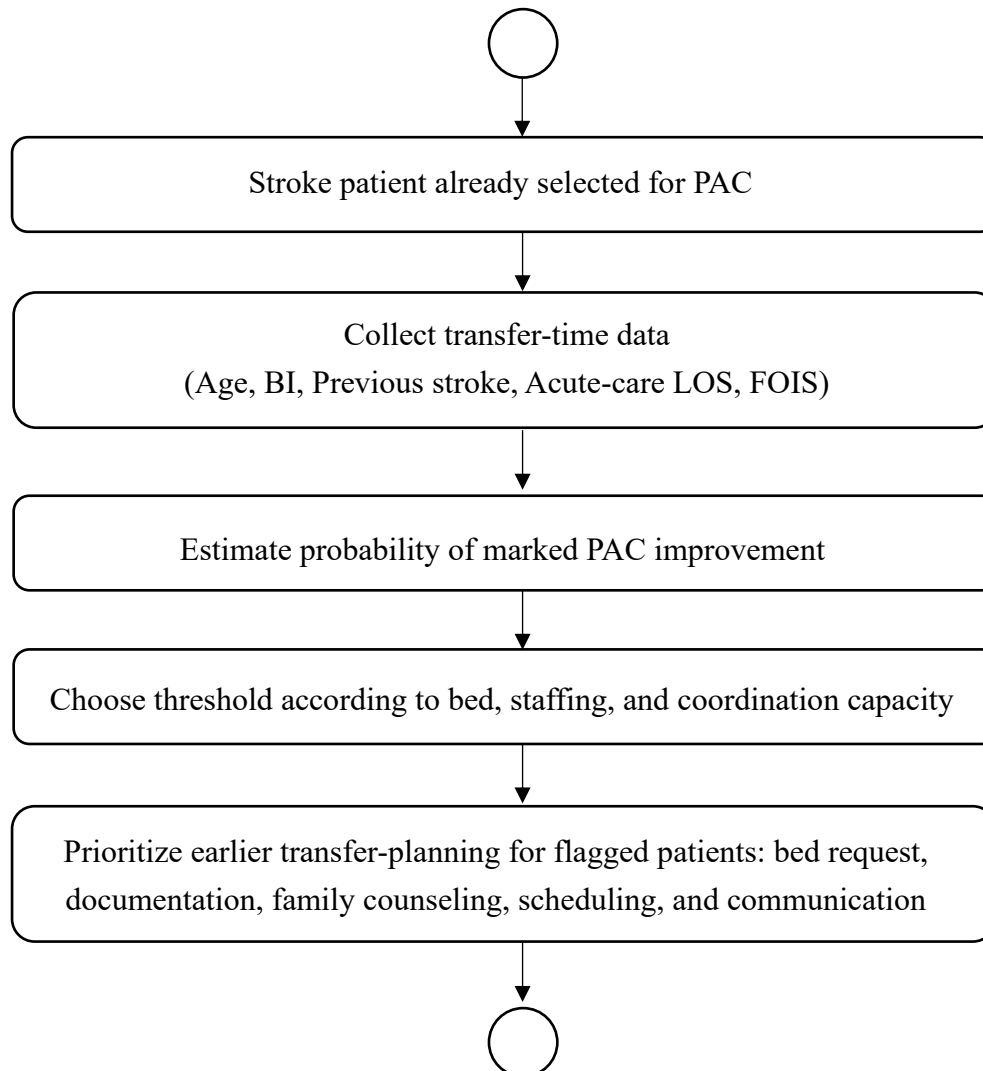
Figure 6. BI×FOIS probability surface with the 0.51 decision boundary



Legend. Heatmaps show conditional recalibrated predicted probabilities of marked functional improvement during the PAC episode from the final five-predictor model projected onto the BI×FOIS plane. Age and acute-care LOS were fixed at their test-set median values, and previous stroke status was specified as absent (panel A) or present (panel B). The contour labeled 51% indicates the threshold probability corresponding to maximal incremental net benefit in the decision-curve analysis. The figure is intended to visualize how the DCA-supported threshold maps onto clinically interpretable combinations of functional status and oral intake/swallowing status, rather than to serve as an additional decision-curve analysis.

Abbreviations: BI, Barthel Index; DCA, decision-curve analysis; FOIS, Functional Oral Intake Scale; LOS, length of stay; PAC, post-acute care.

Figure 7. Proposed clinical workflow for using transfer-time model output to prioritize early PAC transfer planning



Legend. Proposed bedside workflow for using the transfer-time model in routine practice. After a stroke patient has already been accepted as appropriate for PAC, the team enters immediately available transfer-time variables (Age, BI, previous stroke, acute-care LOS, and FOIS) to estimate the probability of marked functional improvement during the upcoming PAC episode. The team then chooses a threshold according to local bed availability, staffing, and

725 *coordination capacity. Patients whose predicted probability meets or exceeds the chosen*
726 *threshold are flagged for earlier transfer planning, including bed request, document*
727 *preparation, family counseling, scheduling, and inter-unit communication. Abbreviations: BI,*
728 *Barthel Index; FOIS, Functional Oral Intake Scale; LOS, length of stay; PAC, post-acute care.*
729

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryFigure1Bootstrapoptimismcorrecteddecisioncurveanalysis.png](#)