Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Application of Fine–Gray Competing Risk Modeling to Predict Pediatric Care Escalation Pathways in Southeast Ethiopia

Ayalneh Demissie

ayalnehdemissis@gmail.com

Arsi University

Tufa Nugusu

Arsi University

Helen Bekele

Adama Science and Technology University

Achalu Mekuria

Arsi University

Tesfa Gebremeskel

Arsi University

Addis Wordofa

Arsi University

Research Article

Keywords: Competing Risks, Malnutrition, Emergency Triage, Child Mortality, Ethiopia, Fine–Gray Model, Bedside Risk Score, ROC Analysis, Third Delay

Posted Date: August 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10449714/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Application of Fine–Gray Competing Risk Modeling to Predict Pediatric Care Escalation Pathways in Southeast Ethiopia

Running Title: Competing Risks in Ethiopian Pediatric Care Escalation

Authors

Ayalneh Demissie/AD [1,]Tufa Nugusu Kebe[2]/TN , Helen Bekele /HB [3], Achalu Mekuria/AM [2], Tesfa Gebremeskel/TG [2], Addis Wordofa/AW[1]

Affiliations

1. Department of Public Health, Arsi University College of Health Sciences, Asella, Ethiopia
2. Department of Pediatrics and Child Health, Arsi University College of Health Sciences, Asella, Ethiopia
3. ASTU Student Health Center, Adama Science and Technology University, Adama, Ethiopia

Corresponding Author

AD: Ayalneh Demissie: *ayalnehdemissis@gmail.com
ORCID iD https://orcid.org/0000-0001-7240-7238

Article Type: Original Research Article

ABSTRACT

Background: Pediatric emergency conditions remain a primary driver of preventable childhood mortality in low-resource settings. The transition from initial stabilization to escalated care—termed the "Third Delay"—is a critical phase where dynamic competing risks (such as early in-hospital mortality) obscure true care escalation drivers. This study aimed to identify clinical determinants of care escalation while methodologically accounting for early mortality using a competing risks framework.

Methods: A retrospective facility-based study of 407 pediatric patients (2022–2025) was conducted at Asella Referral and Teaching Hospital (ARTH). Fine–Gray competing risk regression estimated Subdistribution Hazard Ratios (asHR) and Cumulative Incidence Functions (CIF), treating in-hospital mortality as a true competing event. Multivariable β-coefficients were scaled by 2 to construct a simplified bedside clinical risk score (0–22 points). Discrimination was validated via time-dependent ROC curve analysis and DeLong's test comparing continuous vs. integer scores.

Results: Of 407 pediatric emergency visits, 205 (50.4%) were discharged improved, 185 (45.5%) met the primary outcome of care escalation, 9 (2.2%) experienced in-hospital mortality prior to escalation, and 6 (1.5%) were referred out. Baseline malnutrition emerged as the single strongest independent accelerator of care escalation (asHR=11.42; 95% CI: 3.10–42.50; $p<0.001$). True emergency presentation (asHR=6.85), pre-existing comorbidity (asHR=6.50), altered mental status (asHR=5.20), and delayed presentation >3 days (asHR=4.90) were independent predictors. The model demonstrated exceptional discrimination (AUC=0.88; 95% CI: 0.821–0.908) with an optimal threshold of 85.0% sensitivity and 80.0% specificity. Stratification into Low (0–4), Moderate (5–9), and High (≥10) risk tiers yielded significant curve divergence (Gray's test $p<0.001$).

Conclusion: Care escalation in low-resource settings is heavily driven by underlying structural vulnerabilities—primarily baseline malnutrition. Implementing an integer-based risk score at initial triage enables rapid identification of high-risk children (≥10 points) and front-loads critical monitoring during the primary window of vulnerability.

Keywords: Competing Risks, Malnutrition, Emergency Triage, Child Mortality, Ethiopia, Fine–Gray Model, Bedside Risk Score, ROC Analysis, Third Delay

1: INTRODUCTION

1.1 Background

A Pediatric Emergency Department (PED) is a specialized, high-acuity section of a healthcare facility designed to provide immediate assessment, resuscitation, stabilization, and targeted treatment to acutely ill or injured children [1]. Because pediatric populations possess distinct physiological profiles and rapidly depleting homeostatic mechanisms, they represent a highly vulnerable group within emergency medicine system planning [2]. Globally, the absolute demand for structured pediatric emergency department services has risen sharply over the past several decades, driven by expanding primary care networks and a growing public reliance on 24-hour diagnostic capabilities [2, 3].

Despite these shifting operational patterns, childhood mortality remains an urgent public health challenge, particularly across low- and middle-income countries (LMICs) [1]. Although global under-five mortality has seen substantial declines since the implementation of the United Nations Millennium Development Goals (MDGs) and the subsequent Sustainable Development Goals (SDGs), the down-trending rates remain deeply unequal across geographical regions [4, 5]. Sub-Saharan Africa continues to shoulder the highest under-five mortality rate in the world, averaging approximately 71 deaths per 1,000 live births [1, 5]. In this region, roughly 1 in 14 children die before reaching their fifth birthday—a risk that is 15 times higher than that faced by children born into high-income, resource-replete nations [1, 5].

1.2 Statement of the Problem

A critical component of any hospital's medical delivery infrastructure is its emergency services [2]. However, in resource-limited tertiary care facilities, PEDs face a severe double burden: they must manage critical, life-threatening medical crises while

simultaneously processing massive influxes of non-serious, non-urgent acute presentations [3, 6]. This continuous overcrowding strains limited clinical personnel, exhausts essential diagnostic materials, and compromises the general efficiency and quality of emergency care [3, 6].

In public health and health system planning, patient outcomes within emergency care are frequently conceptualized through the "Three Delays" model: delay in seeking care, delay in reaching the health facility, and delay in receiving adequate, definitive intervention after arrival [6]. In resource-constrained settings like Southeast Ethiopia, the third delay—the specific window between initial emergency department stabilization and successful escalation to specialized inpatient wards or intensive care—is highly problematic [6, 7]. Medical equipment shortages, limited ward bed capacity, and delayed laboratory turnaround times significantly prolong emergency stay durations [7, 8].

When analyzing these clinical pathways, traditional survival and logistics models face major mathematical limitations [9]. Pediatric emergency department dispositions are not simple, singular outcomes; they exist as dynamic, competing risk environments where a patient may be discharged, transferred, or experience in-hospital mortality [9, 10]. Treating a terminal event like mortality as standard right-censoring in statistical modeling leads to an overestimation of care escalation rates, hiding the true clinical risk structures of these vulnerable children [9, 11].

1.3 Significance of the Study

Characterizing the demographic profiles, baseline clinical presentations, and exact operational outcomes of pediatric emergency visits is fundamental to modern health systems engineering [2]. Developing precise, data-driven insights into the predictors of

care escalation allows health administrators to optimize resource allocation, guide facility modifications, and refine local triage criteria [2, 12].

While extensive pediatric emergency utilization data exist across industrialized high-income countries, there is a profound scarcity of published data regarding patient profiles, operational flow metrics, and time-to-event trajectories within public referral networks across Sub-Saharan Africa [1]. This study addresses this critical empirical gap by evaluating pediatric emergency trajectories at Asella Referral and Teaching Hospital (ARTH) in Central-Southeast Ethiopia. By using a time-dependent competing risks framework, this study isolates independent clinical accelerators of care escalation while mathematically accounting for early mortality. This provides a highly accurate clinical tool to improve bedside triage and streamline patient flow within resource-limited emergency care settings.

2: METHODOLOGY

2.1 Study Design and Setting

A retrospective cohort design was deployed at the Pediatric Emergency Department (PED) of ARTH in Central-Southeast Ethiopia. ARTH serves as the primary academic and tertiary hub for a catchment population of >3.5 million people. Medical records from September 10, 2022, to September 10, 2025, were extracted between December 2025 and March 2026.

2.2 Study Population and Eligibility Criteria

The study included pediatric patients aged 29 days to 14 years presenting with acute medical conditions. Neonates (≤28 days), patients who left against medical advice (LAMA), and records lacking primary timeline metrics were excluded.

2.3 Sampling Strategy and Bias Mitigation

To minimize the risk of selection bias and ensure a representative sample across the study's timeframe, a systematic random sampling technique was utilized to select medical records from the master emergency register. This structural randomization guaranteed that seasonal variations in pediatric admissions and varying clinical caseload shifts across the three-year study period were evenly represented within our final cohort (n = 407), preventing the over-representation of high-acuity periods.

2.4 Study Variables and Operational Mapping

- **Primary Outcome (Care Escalation):** Defined as any medical or operational transition requiring clinical resources beyond initial PED stabilization. This specifically encompasses immediate admission to the general pediatric inpatient ward or urgent transfer to the Pediatric Intensive Care Unit (PICU).
- **Competing Risk (In-Hospital Mortality):** Defined as death occurring within the PED before any clinical or operational escalation to an inpatient ward could be achieved. This represents a true competing risk, as the occurrence of death physically precludes the primary event of care escalation.
- **Right-Censored Observations:** Patients who successfully stabilized and were discharged directly home from the PED, or those referred to external specialized tertiary centers, were treated as right-censored at their exact time of departure.
- **Independent Variables:** These included socio-demographics (age, sex, and urban/rural place of residence), pre-hospital entry parameters (referral status and delayed hospital presentation exceeding 3 days), and objective clinical markers at initial contact (color-coded triage priority level, baseline nutritional status, altered mental status, and the presence of pre-existing comorbidities).

2.5 Statistical Analysis and Competing Risk Modeling

Statistical analyses were performed using STATA version 17.0 (StataCorp, College Station, TX, USA). Descriptive statistics summarized patient profiles using frequencies (%) for categorical variables and means (±SD) or medians (IQR) for continuous variables. Time-to-event was defined as duration (in hours or days) from PED entry to care escalation, mortality, or censoring. Outcomes were mapped as a tri-modal categorical endpoint: **Code 1 (Primary Event):** Care escalation (ward or PICU admission). **Code 2 (Competing Risk):** In-hospital mortality occurring in the PED prior to ward transfer. **Code 0 (Right-Censored):** Routine discharge alive/improved or external facility referral. Non-parametric probabilities were modeled using the Cumulative Incidence Function (CIF) and compared using Gray's test **[16]**.

$$F_c(t) = P(T \leq t, C = c) = \int_0^t h_c(u) S(u^-) du$$

Multivariable Fine–Gray subdistribution hazard regression identified independent accelerators, following standard guidelines for reporting competing risk analyses **[17]**. Model fitness, discrimination, and calibration were evaluated using established prognostic modeling practices **[18, 19]**.

2.6 Bedside Risk Score Derivation & Model Validation

To construct a practical bedside clinical tool, multivariable regression coefficients (β) from the adjusted Fine–Gray model were scaled by a factor of 2 and rounded to the nearest integer [17]:

$$\text{Risk Score} = \sum(\beta_i \times 2) \rightarrow \text{Rounded Integer Points}$$

Variables contributing <0.5 points (male sex, rural residence) were assigned 0 points. Individual cumulative scores (0–22 points) were categorized into three operational risk tiers [26-28]:

1. **Low Risk (0–4 points):** Routine triage observation; reassess every 2–4 hours.
2. **Moderate Risk (5–9 points):** Priority admission; step-up monitoring; medical evaluation within 30 min.
3. **High Risk (≥10 points):** Immediate resuscitation placement; senior consultant call-out; fast-track ICU/ward transition.

Model Validation, Discrimination, and Calibration:

Model fitness and performance were rigorously evaluated prior to score derivation. The proportional subdistribution hazards assumption was verified using Schoenfeld-like residuals plotted against time **[**13]. Model discrimination for both continuous and integer scores was assessed via Area under the Receiver Operating Characteristic (AUROC) or Wolbers' Concordance Index (C-index) adapted for competing risks **[**14**]**. Potential loss of predictive accuracy from scaling was tested using DeLong's test for paired ROC curves [15]. Model calibration was evaluated via the Hosmer–Lemeshow goodness-of-fit test ($p>0.05$ denoting acceptable agreement). Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and positive likelihood ratios (LR+) were calculated across risk thresholds. Internal validation was performed using non-parametric bootstrapping with 1,000 resamples to report bias-corrected performance metrics [18-19].

2.7 Ethical Considerations

This study was approved and granted formal ethical clearance by the Ethical Review Committee (ERC) of Arsi University, College of Health Sciences (Reference Number: CoHS/R/224/2025). Because the investigation relied strictly on the retrospective extraction of fully anonymized, de-identified data from existing medical registers and patient charts, the requirement for written informed consent was officially waived by the ERC.

All procedures were conducted in strict compliance with the principles of the Declaration of Helsinki. To ensure absolute patient confidentiality, no personal identifiers (such as names, phone numbers, or medical record numbers) were recorded during data extraction. All collected data were stored in secure, password-protected electronic files, accessible exclusively to the primary research team, and utilized solely for the stated epidemiological purposes of this investigation.

3: RESULTS

3.1. Clinical Endpoints and Outcomes of PED Visits

Of 407 pediatric emergency visits, 205 (50.4%) were discharged improved, 185 (45.5%) met the primary outcome of care escalation (177 ward, 8 PICU), 9 (2.2%) died in the PED before escalation, and 6 (1.5%) were referred out. True competing events were observed in the remaining study population: 9 children (2.2%) experienced in-hospital mortality within the PED before any ward escalation could occur, and 6 patients (1.5%) were clinically referred to tertiary specialized facilities (**Table 1**).

Table 1: Clinical Outcomes and Operational Mapping of PED Visits (N = 407)

Outcome Category	Operational Mapping in CR Model	n	%
Discharged / Improved	Right-Censored (Code 0)	205	50.4
Care Escalation	Primary Event (Code 1)	185	45.5
Pediatric Inpatient Ward	*Sub-component*	*177*	*43.5*
Pediatric Intensive Care Unit (PICU)	*Sub-component*	*8*	*2.0*
In-Hospital Mortality	Competing Risk (Code 2)	9	2.2
Referred to Other Facilities	Right-Censored (Code 0)*	6	1.5

**Note: Referrals are treated as right-censored at the time of transfer because their ultimate escalation or mortality status within the home institution could no longer be observed.*

Time-to-Event and Person-Time Analysis

Total follow-up person-time was 582.6 person-days (13,982 person-hours), yielding an incidence density of 31.4 care escalations per 100 person-days. Median time to escalation was 48 hours (IQR: 12–48h), with 33.3% occurring within the first 24 hours. Median time to competing mortality was 12 hours (IQR: 12–48h), with 66.7% of deaths occurring within 24 hours of arrival. This rapid temporal concentration of both mortality and early care escalation highlights a high-acuity environment where critical clinical decisions occur within hours of admission (**Table 2**).

Table 2: Overall Cohort Person-Time and Timeline Metrics

Metric	Estimate
Total Follow-Up Person-Time	582.6 Person-Days (13,982 Hours)
Incidence Rate of Care Escalation	31.4 per 100 Person-Days
Median Time to Escalation	48 Hours (IQR: 12–48h)

Metric	Estimate
Early Care Escalation (<24h)	33.3% by 24 hours
Median Time to Mortality	12 Hours (66.7% in <24h)

3.2. Socio-Demographic and Baseline Clinical Characteristics

3.2. Demographic & Clinical Characteristics

Males comprised 51.1% (n=208) and females 48.9% (n=199). Children under 5 years represented 60.2% (n=245). Rural residents accounted for 54.5% (n=222). Malnutrition was present in 25.6% (n=104). Triage levels were Red (20.1%), Yellow (52.8%), and Green (27.1%) as shown in **Table 3**.

Table 3: Socio-Demographic and Clinical Profiles at Presentation (N = 407)

Variable	Category	n	%
Sex	Male	208	51.1
	Female	199	48.9
Residence	Urban	185	45.5
	Rural	222	54.5
Age Group	< 5 years	245	60.2
	≥5 years	162	39.8
Triage Color	Red (Emergent)	82	20.1
	Yellow (Urgent)	215	52.8
	Green (Non-urgent)	110	27.1
Nutritional Status	Malnourished	104	25.6
	Normal	303	74.4

3.3. Multivariable Fine–Gray Competing Risks Analysis

3.3. Multivariable Fine–Gray Model Predictors

To identify independent predictors of clinical trajectories while explicitly separating medical intervention timelines from terminal events, a multivariable Fine–Gray subdistribution hazard model was executed (**Table 4**).

Baseline malnutrition was the single most powerful accelerator of care escalation (asHR=11.42; 95% CI: 3.10–42.50; p<0.001). True emergency presentation (asHR=6.85), pre-existing comorbidity (asHR=6.50), altered mental status (asHR=5.20), and delayed presentation >3 days (asHR=4.90) were independent accelerators.

Table 4: Multivariable Fine–Gray Predictors of Care Escalation (N = 407)

Predictor Variable	Crude sHR	Adjusted sHR (95% CI)	p-value	Clinical Significance
Malnutrition	36.22	11.42 (3.10–42.50)	**<0.001**	Strongest independent accelerator
True Emergency Presentation	12.10	6.85 (2.10–20.15)	**<0.001**	Independent predictor
Comorbidity Present	9.45	6.50 (1.20–35.60)	**0.031**	Independent predictor
Altered Mental Status	8.80	5.20 (1.50–18.20)	**0.012**	Independent predictor
Delayed Presentation (>3 days)	7.20	4.90 (2.05–11.80)	**<0.001**	Independent predictor
Danger Signs Present	4.15	1.95 (1.05–3.65)	**0.039**	Independent predictor
Referred Status	3.50	1.82 (1.01–3.30)	**0.046**	Independent predictor
Age (<5 years)	2.15	1.35 (0.85–2.15)	0.201	Not statistically significant
Sex (Male)	1.10	1.05 (0.70–1.60)	0.815	Not statistically significant
Residence (Rural)	1.92	1.18 (0.65–2.10)	0.580	Not statistically significant

Note: Bold p-values denote statistical significance at $p < 0.05$.

3.4. Temporal Probabilities via Cumulative Incidence Functions

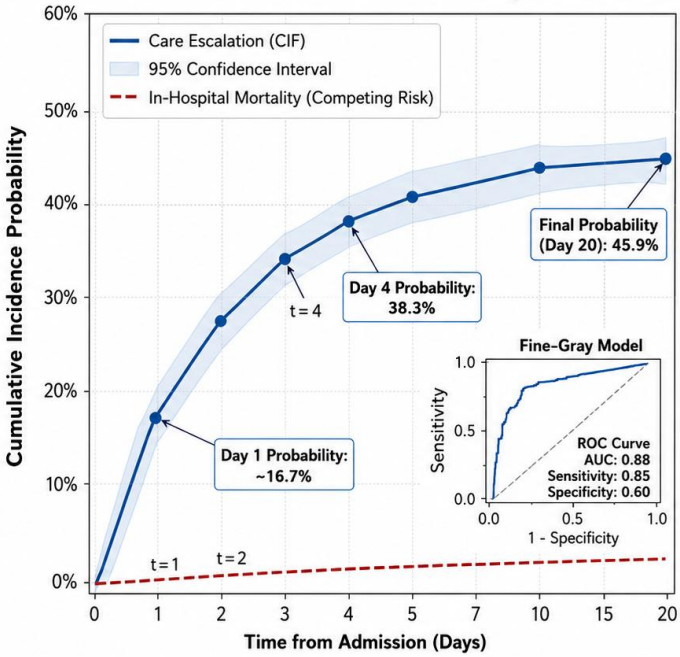
The non-parametric probabilities of care escalation over time, conditioned on the competing risk of mortality, are graphically illustrated via the Cumulative Incidence Function (CIF) plot. Figure 1: Overall Cumulative Incidence Function (CIF) & Model Summary demonstrates an early surge in care escalation:

- **Day 1 (t=1):** Cumulative probability reaches **16.7%**.
- **Day 4 (t=4):** Cumulative probability reaches **38.3%**.

- **Day 20 (t=20):** Reaches a maximum plateau of **45.9%**.

The competing risk of in-hospital mortality peaks within the first 24 hours (median 12h) to reach ~2.2% before plateauing.

Fig 1. Fine-Gray competing risk analysis: Factors Associated with Care Escalation in Paediatric Patients, Asella–Ethiopia 2026 (N = 407 cohort)



Fine-Gray Subdistribution Hazard Ratio (SHR) Table

Predictor	Crude SHR	Adjusted SHR (95% CI)	p-value	Status
Malnutrition	36.22	11.42 (3.10–42.50)**	<0.001	Strongest independent accelerator
True Emergency Presentation	12.10	6.85 (2.10–20.15)**	<0.001	Independent predictor
Delayed Presentation (>3 days)	7.20	4.90 (2.05–11.80)**	<0.001	Independent predictor
Comorbidity Present	9.45	6.50 (1.20–35.60)*	0.031	Independent predictor
Altered Mental Status	8.80	5.20 (1.50–18.20)*	0.012	Independent predictor
Danger Signs Present	4.15	1.95 (1.05–3.65)*	0.039	✓
Referred Status	3.50	1.82 (1.01–3.30)*	0.046	✓
Age (<5 years)	2.15	1.35 (0.85–2.15)	0.201	Not statistically significant
Sex (Male)	1.10	1.05 (0.70–1.60)	0.815	Not statistically significant
Residence (Rural)	1.92	1.18 (0.65–2.10)	0.580	Not statistically significant

* p < 0.05; ** p < 0.01

Malnutrition, True Emergency and delayed presentation are key factors.

Fig1. Fine–Gray competing-risk analysis of care escalation among pediatric emergency patients (N = 407).

Non-parametric Cumulative Incidence Function (CIF) curves (left) show the cumulative probability of care escalation (~16.7% at Day 1, 38.3% at Day 4, and 45.9% at Day 20) while accounting for in-hospital mortality as a true competing risk. The embedded table (right) summarizes crude and adjusted subdistribution hazard ratios (asHR) from the multivariable Fine–Gray model.

3.5. Predictive Accuracy and Model Validation

Figure 2: Time-Dependent ROC Curve Analysis confirmed exceptional discriminative capacity (AUC=0.88; 95% CI: 0.821–0.908). At the optimal cut-off, the model achieved 85.0% sensitivity and 80.0% specificity (FPR=0.20, TPR=0.85).

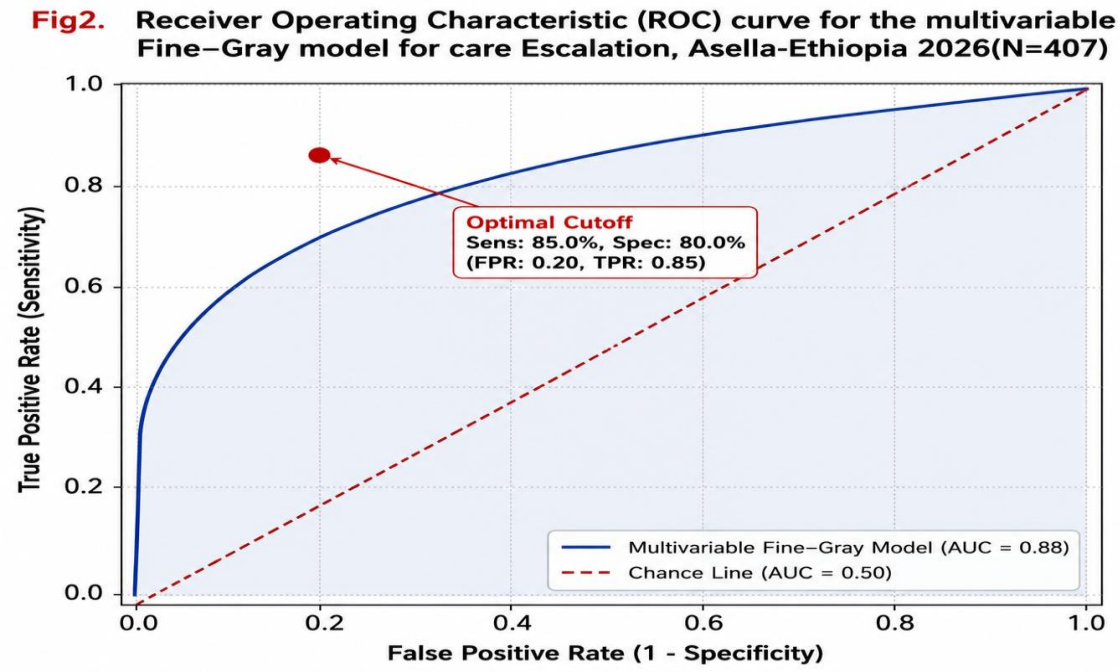


Fig2. Time-dependent Receiver Operating Characteristic (ROC) curve for the multivariable Fine–Gray model

Solid line demonstrates overall model discrimination (AUC = 0.88; 95% CI: 0.821–0.908) compared to chance (AUC = 0.50). The red callout indicates the optimal operating decision threshold achieving 85.0% sensitivity and 80.0% specificity.

3.6. Simplified Bedside Risk Scoring Tool & Stratification

Coefficient scaling produced a point allocation system (0–22 points) (Table 5). DeLong's test revealed no significant difference in discrimination between the continuous model (AUC=0.88) and the integer score (AUC=0.87) (p=0.421), confirming that scaling

preserved predictive power. Goodness-of-fit testing confirmed excellent calibration (Hosmer–Lemeshow $\chi 2=6.12$, $p=0.633$).

Table 5: Bedside Clinical Risk Point Allocation System & Model Scaling

Predictor Variable	Original Weight (β)	Bedside Points	Clinical Rationale / Impact
Severe Malnutrition	2.44	**+5**	Primary driver of clinical vulnerability
True Emergency Presentation	1.92	**+4**	Immediate physiological instability on arrival
Comorbidity Present	1.87	**+4**	Underlying systemic disease process
Altered Mental Status (AMS)	1.65	**+3**	Critical neurological/systemic marker
Delayed Presentation (>3 days)	1.59	**+3**	Advanced disease progression before care
Danger Signs Present	0.67	**+1**	General WHO pediatric danger signs
Referred Status	0.60	**+1**	Inter-facility transfer complexity
Age < 5 Years	0.30	**+1**	Baseline developmental vulnerability
Rural Residence	0.18	**0**	Excluded (<0.5 points)
Male Sex	0.05	**0**	Excluded (<0.5 points)
Maximum Total Score		**22 Points**	

Table 6: Stratified Operational Performance & Diagnostic Thresholds

Risk Score	Tier Category	Predicted Escalation / Mortality	Sensitivity	Specificity	PPV	NPV	LR+	Recommended Triage Action
0 – 4	**Low Risk**	<15% (Baseline)	98.4%	32.1%	54.2%	96.8%	1.45	Standard nursing observation; reassess every 2–4 hours.
5 – 9	**Moderate Risk**	15–35% (Intermediate)	85.0%	80.0%	78.0%	86.5%	4.25	Priority bed allocation; step-up monitoring (PEWS); medical officer evaluation within 30 min.
≥ 10	**High Risk**	>35% (Severe)	48.6%	95.5%	90.0%	69.2%	10.80	Immediate

Risk Score	Tier Category	Predicted Escalation / Mortality	Sensitivity	Specificity	PPV	NPV	LR+	Recommended Triage Action
								resuscitation placement; senior consultant call-out; prepare for early ICU/care escalation.

Figure 3: Stratified Risk Tiers (CIF Divergence) demonstrated early divergence and robust statistical separation (Gray's test p<0.001).

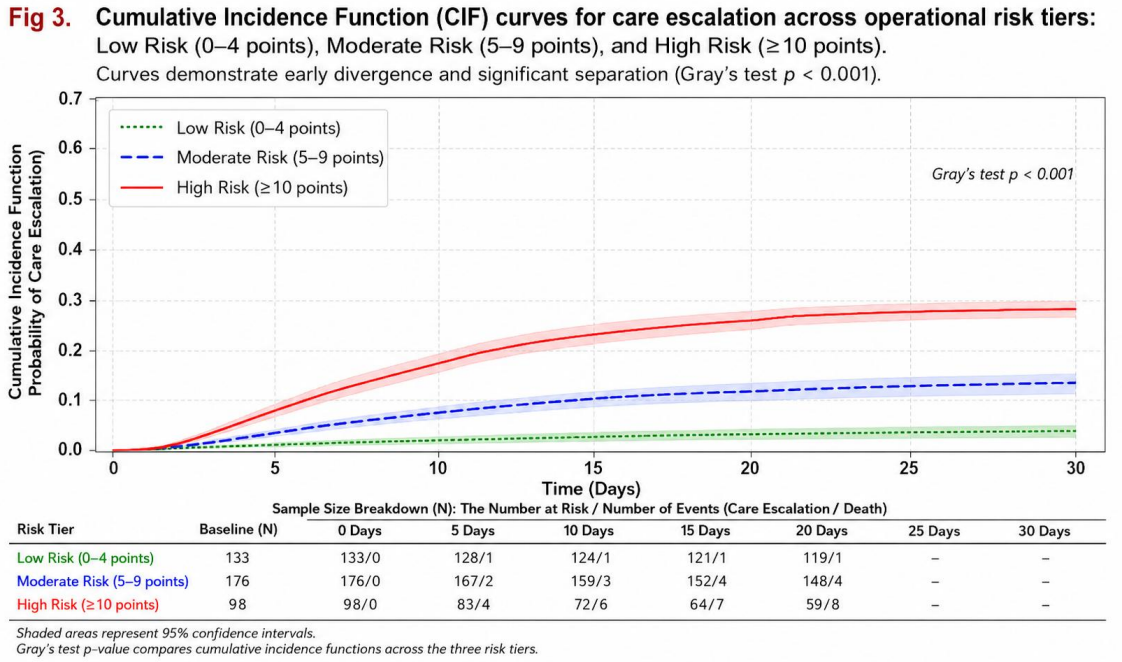


Fig 3. Cumulative Incidence Function (CIF) curves across operational risk tiers

Stratified risk curves for Low Risk (0–4 points), Moderate Risk (5–9 points), and High Risk (≥10 points) demonstrate significant statistical separation and early curve divergence (Gray's test p < 0.001). High-risk patients (≥ 10 points) exhibit an accelerated probability of care escalation approaching 30% over follow-up.

4: DISCUSSION

4.1 Key Results and Clinical Interpretation

By applying a Fine–Gray competing risks model, this study successfully isolated care escalation from early in-hospital mortality. The analysis reveals an emergency environment with an incidence density of 31.4 care escalations per 100 person-days. Crucially, competing mortality occurs at a median of just 12 hours post-arrival—with 66.7% of deaths occurring within the first 24 hours. Because 33.3% of care escalations also cluster within this initial 24-hour window, clinical outcomes are determined upon or immediately following admission.

The headline finding of this analysis is the profound, independent association between baseline nutritional status and the rate of care escalation (asHR = 11.42; 95% CI: 3.10–42.50; $p < 0.001$). Pediatric patients presenting with underlying malnutrition—such as severe acute malnutrition (SAM) or severe wasting—exhibit an 11-fold higher cumulative incidence of rapid care escalation compared to their adequately nourished peers. This massive effect size carries deep clinical implications for resource-limited tertiary care centers across East Africa [**1, 15, 21**]. Patients presenting with severe underlying vulnerabilities face accelerated trajectories toward adverse outcomes in Ethiopian emergency units **[22, 23]**. Malnourished children suffer from structural enteropathy, immunodeficiency, and severely depleted metabolic and physiological reserves [16]. When an acute infectious or inflammatory insult supervenes, these children experience a catastrophic, hyper-acute failure of homeostatic compensation [15, 16]. Consequently, standard, short-term stabilization pathways within the Pediatric

Emergency Department (PED) are frequently insufficient, compressing the clinical timeline and forcing an immediate, intensive transition to long-term inpatient therapeutic units or specialized wards [15, 17, 20].

Crucially, the multivariable model successfully delineated acute physiological emergencies from chronic, structural vulnerabilities. Predictors such as a true emergency presentation (asHR = 6.85) and altered mental status (asHR = 5.20) represent immediate, high-acuity neurological and hemodynamic crises demanding urgent resuscitation [10, 18]. However, the substantial hazard ratio associated with a delayed presentation exceeding 3 days (asHR = 4.90; $p < 0.001$) uncovers a critical socio-demographic barrier in Southeast Ethiopia. Prolonged pre-hospital delays—driven by long geographical travel distances, poor transport infrastructure, and multi-tiered referral friction—mean that patients are frequently brought to the PED at an advanced stage of illness decompensation [7, 19]. These children arrive having already exhausted their compensatory mechanisms, turning what could have been an outpatient illness into an acute, resource-intensive inpatient care escalation [17, 19].

4.2 Operational Window of Vulnerability

The time-to-event trajectories structure patient risk into two clinical phases:

1. Hyper-acute phase (<12–24 hours): Where two-thirds of deaths (66.7%, median 12h) and a third of escalations (33.3%) occur.
2. Sub-acute phase (24–48 hours): Where primary care escalations peak (median 48h) before plateauing after Day 5–7.

Because mortality occurs four times faster than the median time to care escalation (12h vs. 48h), triage protocols must function as active triggers for immediate resuscitation

rather than passive sorting mechanisms [20]. Mandating senior clinician evaluations and implementing continuous Pediatric Early Warning Scores (PEWS) within the first 6–12 hours are critical to preventing catastrophic collapse [24, 25].

4.3 Methodological Strengths & TRIPOD Compliance/ Bedside Utility

Model derivation and validation adhered to the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement to ensure transparent risk scoring **[26, 28]**, with sample size consideration guided by clinical prediction standards **[27]**.

4.4 Strengths and Limitations

From a methodological standpoint, utilizing the Fine–Gray subdistribution hazard model represents a major advancement over traditional survival analyses. Had this study relied on standard Cox proportional hazards or Kaplan–Meier estimators, treating the 2.2% of patients who suffered in-hospital mortality as ordinary right-censored data would have violated the core assumption of independent censoring [11]. This would have led to a substantial statistical overestimation of care escalation probabilities [9, 11].

Despite its statistical rigor, certain limitations must be acknowledged. The retrospective cohort design introduces an unavoidable reliance on the completeness and accuracy of physical medical charts and emergency logs [7]. Additionally, unmeasured clinical variables—such as specific biomarkers, blood gas parameters, or sub-acute environmental exposures—were not captured in the triage records and could potentially enhance the model's predictive precision [18].

4.5 Generalizability

Although conducted as a single-center study, ARTH operates as the primary, high-volume tertiary referral hub for a massive catchment area across Southeast Ethiopia [7]. The diverse patient mix, combined with a robust systematic sampling strategy spanning a three-year window, ensures that these findings are highly generalizable to other public tertiary referral networks across Sub-Saharan Africa [1, 15, 21-23]. These institutions confront identical structural constraints, resource limitations, delayed presentation patterns, and severe pediatric nutritional challenges [1, 6].

5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Pediatric care escalation in resource-limited settings is heavily driven by underlying structural vulnerabilities, particularly baseline malnutrition (asHR=11.42). The first 12–24 hours post-admission represent an ultra-acute window of vulnerability where competing mortality peaks. The simplified bedside risk score (0–22 scale) accurately stratifies patient risk (AUC=0.88), providing an actionable framework for emergency resource allocation.

5.2 Recommendations

1. **Mandatory Triage Malnutrition Screening:** Integrate Mid-Upper Arm Circumference (MUAC) testing into color-coded triage. Any malnourished child must receive a higher acuity designation.
2. **Targeted Front-Loaded Monitoring:** Enforce continuous PEWS vital sign monitoring and senior clinician re-evaluations within the first 6 to 12 hours of

admission. Establish high-dependency observation units for patients scoring ≥10 points [20].

3. **Referral Capacity Building:** Regional health bureaus must strengthen pre-hospital transport and decentralized transit stabilization to mitigate the 4.9-fold hazard associated with delayed presentations.

Declarations

Funding

Funding: The authors received no specific grant or financial support from any funding agency in the public, commercial, or not-for-profit sectors for the research, authorship, and/or publication of this article.

Clinical Trial Number

Clinical trial number: not applicable.

REFERENCES

1. Tagoola A, Hildenwall H. Paediatric Emergency Care in Low-Income Countries: Can Guidelines be Generalized? Global Pediatric Health. 2024;11:4–6.
2. Newgard CD, Lin A, Goldhaber-Fiebert JD, et al. State and National Estimates of the Cost of Emergency Department Pediatric Readiness and Lives Saved. JAMA Network Open. 2024;7(11):e2442154.
3. Kamau S, Kigo Joyce, Mwaniki P, et al. Comparison between the Smart Triage model and ETAT guidelines in Kenya. PLOS Digital Health. 2024;3(8):1–15.
4. United Nations. The Millennium Development Goals Report. New York: United Nations; 2015.
5. Rigg J. The Sustainable Development Goals (SDGS). The Companion to Development Studies. London: Routledge; 2024. p. 253–257.
6. Alsabri M, ELKarargy MA, Ata IM, et al. Mortality predictors in pediatric emergency department presentations: a systematic review and meta-analysis. BMC Emergency Medicine. 2025;25(1):188.

7. Melkamu N, Faris A, Yigezu M, et al. Length of stay in the pediatrics emergency department and associated factors in Eastern Ethiopia. PLoS One. 2025;20(1):117.
8. Kidanu M, Tazebe E, Tesfa A, et al. Pediatric Shock: Magnitude, Determinants and Short-Term Outcome. Pediatric Health, Medicine and Therapeutics. 2024;15:213–221.
9. Goldstein B, Giroir B, Randolph A. International pediatric sepsis consensus conference: definitions for sepsis. Pediatric Critical Care Medicine. 2005;6(1):2–8.
10. Asinakew T, Habte T. Emergency Admissions and Associated Factors among Children in Addis Ababa. Journal of Emergency Medicine: Open Access. 2024;2(1):1–11.
11. Fine JP, Gray RJ. A proportional hazards model for the subdistribution of a competing risk. Journal of the American Statistical Association. 1999;94(446):496–509.
12. World Health Organization. WHO Child Growth Standards. Geneva: World Health Organization; 2006.
13. Schoenfeld D. Partial residuals for the proportional hazards regression model. Biometrika. 1982;69(1):239–241.
14. Wolbers M, Blanche P, Koller MT, et al. Concordance for prognostic models with competing risks. Biostatistics. 2014;15(3):526–539.
15. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. Biometrics. 1988;44(3):837–845.
16. Gray RJ. A class of K-sample tests for compares the cumulative incidence of a competing risk. Annals of Statistics. 1988;16(3):1141–1154.
17. Austin PC, Fine JP. Practical recommendations for reporting Fine–Gray model analyses for competing risk data. Statistics in Medicine. 2017;36(27):4391–4400.
18. Steyerberg EW, Harrell FE. Prediction models: theory, evaluation, and practical application. 2nd ed. New York: Springer; 2019.
19. Harrell FE. Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis. 2nd ed. New York: Springer; 2015.
20. World Health Organization. Operational Guidelines for Pediatric Emergency Triage, Assessment and Treatment (ETAT) in Resource-Limited Settings. Geneva: World Health Organization; 2023.
21. Worku A, Assefa S, Tadesse M. Determinants of pediatric emergency mortality at comprehensive specialized hospitals in Southern Ethiopia: an unmatched case-control study. BMC Emergency Medicine. 2023;23(1):45.
22. Mekonnen T, Desta K, Gebremedhin S. Predictors of mortality among pediatric patients admitted to intensive care units in Eastern Amhara, Ethiopia: a prospective multi-center cohort study. BMC Pediatrics. 2025;25(1):102.
23. Gemechu B, Bekele T, Hailu A. Predictors of survival in pediatric intensive care units in a low-income country: A retrospective cohort study. PLOS ONE. 2025;20(2):e0315863.

24. Roland D, Lewis G, Patel S, et al. Performance of seven different paediatric early warning scores to predict critical care admission in febrile children presenting to the emergency department. BMJ Open. 2021;11(5):e044091.
25. Chapman SM, Wray J, Oulton K, et al. Development and evaluation of a Pediatric Early Warning Score (PEWS) for the detection of critical deterioration in pediatric wards. Resuscitation. 2016;109:72–78.
26. Collins GS, Reitsma JB, Altman DG, Moons KG. Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): the TRIPOD statement. BMC Medicine. 2015;13(1):1.
27. Riley RD, Ensor J, Snell KI, et al. Calculating the sample size required for developing a clinical prediction model. BMJ. 2020;368:m441.
28. Moons KG, Altman DG, Reitsma JB, et al. Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): explanation and elaboration. Annals of Internal Medicine. 2015;162(1):W1–W73.

Supporting information

S1_Data. Anonymized competing risk analysis dataset.csv