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ORIGINAL RESEARCH

Patient-level, Temporal, and Dynamic Operational Indicators of Emergency Department Prolonged Length of Stay: A Retrospective Cohort Study

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Abstract: Introduction: Emergency department length of stay (ED-LOS) is a key indicator of crowding and care quality. This study aimed to identify patient-level, temporal, and real-time operational predictors of prolonged ED-LOS.
Methods: We conducted a retrospective cohort study using routinely collected data from all ED visits at Foch Hospital, France, between January and November 2025. Prolonged ED-LOS was defined as ED-LOS >8 hours. Data were split chronologically into a training period from January to September and a held-out test period from October to November. Three logistic regression models were evaluated: Model 1 included patient-level and temporal variables; Model 2 additionally included dynamic congestion indicators; and Model 3 further included early process delays. **Results:** Among 41,818 ED visits, 41,431 were included in the final analytic sample. Overall, 8,119 (19.6%) visits had ED-LOS >8 hours. In the test set, Model 1 showed good discrimination (area under the receiver operating characteristic curve (AUC): 0.752, 95% confidence interval (CI): 0.740 – 0.766), which improved modestly after adding dynamic congestion variables in Model 2 (AUC: 0.761, 95% CI: 0.749 – 0.775). Model 3 achieved the best performance (AUC: 0.804 (95% CI: 0.793 – 0.815); Brier score: 0.127 (95% CI: 0.122 – 0.132)). Older age, triage acuity level 3 (classification infirmière des malades aux urgences: CIMU), weekend arrival, dynamic congestion at arrival, and early process delays were the main predictors of prolonged ED-LOS. **Conclusion:** Based on the findings, older age, intermediate triage acuity, weekend arrival, dynamic congestion at arrival, and early process delays were the independent predictors of prolonged ED stay. The addition of dynamic congestion variables improved prediction beyond patient-level and temporal characteristics, while the strongest performance was achieved after incorporating early delays to triage and physician assessment.

Keywords: Emergency departments; Length of stay; Crowding; Prediction methods, machine; Logistic regression

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1. Introduction

Emergency department (ED) crowding is a persistent challenge for healthcare systems worldwide, reflecting a mismatch between patient demand, available clinical resources, and downstream hospital capacity (1, 2). It has been associated with delayed care, poorer quality of treatment, increased costs, and adverse clinical outcomes (3), including higher inpatient mortality and prolonged hospital stays (4).
Emergency department length of stay (ED-LOS) is a widely used indicator of ED performance because it integrates multiple stages of care, from triage to disposition. Prolonged ED-LOS may reflect operational inefficiencies, diagnostic or staffing constraints, bed shortages, or downstream hospital bottlenecks (5, 6). The burden of prolonged stay is not evenly distributed across patients; older individuals and intermediate-acuity patients are particularly vulnerable, while low-acuity patients may experience delayed access to care or leave without being seen (7).
Predicting prolonged ED stays remains challenging because ED congestion is a dynamic and multifactorial process involving input, throughput, and output constraints (1, 2, 8). Traditional indicators based on aggregated metrics may fail to capture the real-time operational state of the department, and prediction models that do not incorporate dynamic congestion indicators may underestimate risk during periods of operational strain.
Recent studies have explored statistical and machine-learning approaches to predict ED length of stay, but systematic reviews highlight substantial heterogeneity in model design and validation strategies, and many models rely on internal validation methods that may overestimate performance when temporal variation is present (9). For operational deployment, temporal validation is therefore essential to ensure generalizability to future patients.
In addition, a key challenge is balancing predictive performance with interpretability. While machine-learning methods may capture nonlinear relationships and complex interactions between patient characteristics and operational conditions (10), interpretable models remain critical for clinical governance and quality improvement. Logistic regres-

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sion models enriched with dynamic congestion variables may provide a pragmatic compromise between interpretability and operational relevance.
This study aimed to identify patient-level, temporal, and dynamic operational predictors of prolonged ED length of stay using routinely collected timestamp data from a large emergency department cohort.

2. Methods

2.1. Study design and setting

We conducted a retrospective cohort (operational modeling) study using routinely collected data from all visits to the ED of Foch Hospital, France, between January 1 and November 30, 2025. The patient-level, temporal, and dynamic operational predictors of prolonged ED-LOS were identified using multivariate regression analysis models.
The study was approved by the Foch IRB: IRB00012437 (approval number: 26–02-03) on 01 April 2026.

2.2. Participants

Each record corresponded to a single ED visit and included, when available, the arrival timestamp, triage timestamp, first physician contact delay, ED departure timestamp, triage acuity level (classification infirmière des malades aux urgences (CIMU) range from 1–6), age, calendar information, and ED disposition, including left without being seen/treated (LWBS).
Visits were excluded if ED-LOS could not be calculated because of missing, incoherent, or invalid arrival/departure timestamps; if age or CIMU triage acuity was missing; or if the operational trajectory was implausible, including negative durations or ED-LOS exceeding 7 days. For the post-triage model, visits were additionally excluded when triage delay or time to first physician contact was missing or inconsistent. LWBS visits were retained when ED-LOS was valid and were excluded only in sensitivity analyses.

2.3. Data gathering

Data were extracted retrospectively from the emergency department information system of Foch Hospital. The extraction included all ED visits recorded between January 1 and November 30, 2025. For each visit, routinely collected administrative, temporal, and operational variables were retrieved, including age, ED arrival timestamp, triage timestamp, first physician contact timestamp or delay, ED departure timestamp, CIMU triage acuity level, calendar information, ED disposition, and left-without-being-seen/treated status when available.
Emergency department length of stay was calculated as the time elapsed between ED arrival and ED departure. Early process delays were derived from timestamp data and included arrival-to-triage delay and time to first physician contact. Calendar variables were derived from the arrival timestamp and included hour of arrival, day of week, weekend status, night arrival, peak daytime arrival, and month of arrival.
Dynamic congestion indicators were computed at the time of ED arrival to characterize the real-time operational state of the department. These indicators included the number of recent arrivals during the previous 60, 120, and 240 minutes, ED occupancy at arrival, the number of patients waiting for physician assessment, and post-physician occupancy. These variables were used to capture input pressure, waiting burden, and downstream operational load.
Data cleaning was performed before statistical analysis. Visits with missing or invalid ED-LOS, missing age, or missing CIMU triage acuity were excluded from the final analytic sample. Invalid ED-LOS included missing or incoherent arrival/departure timestamps, negative durations, and implausible ED stays exceeding 7 days. For models incorporating early process delays, visits were additionally required to have valid triage delay and time to first physician contact. All analyses were conducted on pseudonymized data.

2.4. Definitions and outcomes

The primary outcome was prolonged emergency department length of stay (ED-LOS), defined as ED-LOS >8 hours.

2.5. Statistical analysis

Continuous variables were summarized as medians with interquartile ranges (IQRs), and categorical variables as counts and percentages. To avoid information leakage and preserve temporal validity, data were split chronologically into a training period from January 1 to September 30, 2025, and a held-out test period from October 1 to November 30, 2025. All models were developed in the training set and evaluated in the test set.
Multivariable logistic regression was the primary modeling approach. Three models were specified a priori. Model 1 included patient-level and temporal predictors: age, triage acuity, hour and month of arrival, day of week, weekend status, night arrival, and peak daytime arrival. Age was modeled per 10-year increase, CIMU 4 was the reference category, and cyclic sine/cosine terms were used for hour and month. Model 2 additionally included dynamic congestion variables at arrival: recent arrivals over the previous 60, 120, and 240 minutes, ED occupancy, waiting-for-physician count, and post-physician occupancy. Model 3 further included early process delays, namely triage delay and time to first physician contact, and was interpreted as a post-triage operational model rather than a pure arrival-time prediction model.
Model performance was assessed in the held-out test set using area under the receiver operating characteristic curve (AUC), average precision, Brier score, sensitivity, specificity, positive predictive value, and negative predictive value. Classification metrics were calculated at the threshold maximizing Youden's index. Calibration was assessed graphically using calibration plots across predicted-risk deciles. Adjusted odds ratios (ORs) with 95% confidence intervals (CIs) were reported, and two-sided p-values <0.05 were considered sta-

tistically significant. Analyses were performed in Python using pandas, NumPy, scikit-learn, statsmodels, and matplotlib.

2.6. Prediction time points

Two prediction time points were considered. Models 1 and 2 were arrival-based models, using information available at or immediately around ED arrival, including patient age, triage acuity, calendar variables, and dynamic congestion indicators computed at arrival. Model 3 was defined as a post-triage operational model because it additionally incorporated triage delay and time to first physician contact, which become available only after the initial phase of the ED trajectory. Therefore, Model 3 was interpreted as an early in-process risk stratification model rather than a pure arrival-time prediction model.

2.7. Handling of missing data

The primary analysis was conducted as a complete-case analysis for visits with valid ED-LOS, age, and CIMU triage acuity. For Model 3, visits were additionally required to have non-missing triage delay and time to first physician contact. The number of observations included in each model was reported separately. No multiple imputation was performed because missingness primarily reflected unavailable timestamps or incomplete operational trajectories rather than missing baseline covariates. Sensitivity analyses excluding patients who left without being seen or treated were planned when disposition information was available.

3. Results

3.1. Study population and outcome distribution

A total of 41,818 emergency department visits were recorded during the study period. After exclusion of visits with missing or invalid emergency department length of stay, age, or CIMU triage acuity, the final analytic sample included 41,431 visits. The dataset was split chronologically into a training set from January 1 to September 30, 2025, and a held-out test set from October 1 to November 30, 2025. The training set included 33,375 visits, and the held-out test set included 8,056 visits. Overall, 8,119 (19.6%) visits had an ED-LOS more than 8 hours. In the held-out test set 1,553 (19.3%) visits met the primary endpoint of ED-LOS >8 hours. This proportion was consistent with the previously described October–November validation period, in which prolonged stays remained frequent and ED-LOS displayed a markedly right-skewed distribution.

3.2. Descriptive patterns of prolonged ED stay

Table 1 compares the baseline characteristics of studied ED visits between cases with and without ED-LOS > 8 hours. Patients with ED-LOS >8 hours were generally older and more frequently belonged to intermediate acuity groups. In particular, prolonged stays were more common among patients classified as CIMU 2–4, whereas low-acuity patients classified as CIMU 5–6 had a lower probability of ED-LOS >8 hours. However, low-acuity groups may represent a different quality issue, particularly because previous descriptive analyses showed higher proportions of leaving without being seen among CIMU 5–6 patients. Temporal patterns also suggested that prolonged ED stay was not solely determined by arrival volume. Weekend arrival was associated with increased risk of prolonged ED stay, whereas night arrival was not significantly associated with the outcome after adjustment. These findings suggest that hospital-wide operating conditions, downstream capacity, and cumulative congestion may contribute to prolonged ED stay beyond patient inflow alone.

3.3. Independent predictors of ED-LOS > 8 hours

Based on the multivariate regression analysis (table 2, figure 1), the independent predictors of ED-LOS > 8 hours were age, per 10-year increase (odds: 1.26. 95%CI: 1.24-1.28), CIMU 3 acuity (odds: 1.69 95%CI: 1.57-1.82), weekend arrival (odds: 1.56 95%CI: 1.46-1.67), and peak daytime arrival (odds: 0.87 95%CI: 0.81-0.93).

In the adjusted patient-and-temporal model, older age was strongly associated with prolonged ED stay. Each 10-year increase in age was associated with a 26% increase in the odds of ED-LOS >8 hours.

Triage acuity was also strongly associated with prolonged ED stay. Compared with CIMU 4, CIMU 3 was associated with substantially higher odds of ED-LOS >8 hours, whereas CIMU 5 and CIMU 6 were associated with markedly lower odds. CIMU 2 was associated with a modest increase in risk, while CIMU 1 was associated with lower odds than CIMU 4.

Weekend arrival was independently associated with prolonged ED stay, with an adjusted odds ratio of 1.56. Night arrival was not significantly associated with the outcome after adjustment. Peak daytime arrival was associated with slightly lower adjusted odds, suggesting that prolonged stay was not simply explained by higher daytime arrival intensity.

3.4. Screening performance characteristics of models

In the held-out test set, Model 1 showed good discrimination for prolonged ED stay, with an AUC of 0.752 (95% CI: 0.740 – 0.766) and a Brier score of 0.137 (95% CI: 0.133 – 0.142). Adding dynamic congestion variables in Model 2 modestly improved performance, with an AUC of 0.761 (95% CI: 0.749 – 0.775), an average precision of 0.411 (95% CI: 0.388 – 0.437), and a Brier score of 0.135 (95% CI: 0.130 – 0.140) (Figure 2). The best performance was observed for Model 3, which incorporated early process delays, with an AUC of 0.804 (95% CI: 0.793 – 0.815), an average precision of 0.532 (95% CI: 0.504 – 0.558), and a Brier score of 0.127 (95% CI: 0.122 – 0.132). At the optimal probability threshold, Model 3 achieved a sensitivity of 0.736 (95% CI: 0.713 – 0.757), specificity of 0.719 (95% CI: 0.707 – 0.730), positive predictive value of 0.398 (95% CI:

0.380 – 0.416), and negative predictive value of 0.915 (95% CI: 0.907 – 0.923) (Figure 3). This indicates that the post-triage model was particularly useful for ruling out prolonged stay among patients at low predicted risk (Table 3).

3.5. Added value of dynamic congestion variables

The addition of dynamic congestion variables improved prediction beyond patient-level and temporal characteristics. Although the improvement in AUC was modest, from 0.752 to 0.761, average precision increased from 0.379 to 0.411, suggesting better identification of visits at high risk of prolonged stay. This finding indicates that prolonged ED stay is not determined only by clinical acuity or time of arrival. The operational state of the department at the moment of arrival, including recent arrival volume, ED occupancy, the number of patients waiting for physician assessment, and post-physician occupancy, contributed additional predictive information. This result is consistent with the interpretation that ED congestion is a dynamic, state-dependent process rather than a simple linear function of arrival volume.

3.6. Added value of early process delays

The strongest improvement in predictive performance was observed when early process delays were included. Model 3, which incorporated triage delay and time to first physician contact, achieved an AUC of 0.804, compared with 0.761 for Model 2.

This result suggests that early delays during the ED trajectory are strong operational markers of subsequent prolonged stay. In particular, delayed access to first physician assessment may capture both immediate crowding and broader downstream constraints. Although Model 3 is not a pure arrival-time prediction model, it may have substantial operational value for early risk stratification after triage or after initial waiting time has accumulated.

4. Discussion

In this study, nearly one in five patients experienced an ED-LOS exceeding 8 hours. Prolonged stay was predictable using routinely available clinical, temporal, and operational variables. Age, CIMU acuity, and calendar-time predictors showed good discrimination, while dynamic congestion indicators added incremental value. The best performance was observed after incorporating early process delays, suggesting that delayed early progression is a strong marker of subsequent prolonged stay. These findings indicate that prolonged ED stay is not randomly distributed but concentrated among patients with identifiable clinical and organizational profiles. It is shaped not only by patient acuity or arrival timing but also by the real-time operational state of the department. Early delays, particularly delayed access to physician assessment, may therefore function as warning signals of later prolonged stay, consistent with the dynamic interaction between input, throughput, and output constraints that characterizes ED crowding (11, 12).

Older age was independently associated with prolonged ED stay, with a 26% increase in the odds of ED-LOS >8 hours per 10-year increase. This finding is consistent with previous studies showing that older adults experience longer ED stays and more complex care trajectories, partly reflecting frailty, multimorbidity, and higher diagnostic and admission needs (13-15). Triage acuity also played a key role. Compared with CIMU 4, CIMU 3 showed the highest adjusted odds of prolonged stay, suggesting that intermediate-acuity patients may be particularly vulnerable to operational delays. These patients often require diagnostic work-up and monitoring but may not benefit from the rapid prioritization pathways reserved for the most critical cases. Prior studies have similarly shown that ED-LOS depends not only on severity but also on diagnostic complexity and disposition processes (6, 16).

Patients with low acuity (CIMU 5–6) had lower odds of prolonged stay, but this should not be interpreted as absence of crowding-related risk. Instead, low-acuity patients may be more likely to experience long waiting times or to leave without being seen during periods of congestion. Previous research suggests that prolonged ED-LOS and leaving without being seen may represent two related manifestations of access constraints within crowded ED systems (17-19).

Weekend arrival was independently associated with prolonged ED stay, suggesting that delays are not driven solely by patient inflow or triage processes but also by hospital-wide organizational constraints. Weekend periods may involve reduced diagnostic and specialist availability, slower discharge processes, and limited bed turnover, all of which can delay disposition decisions.

This interpretation aligns with the input–throughput–output model of ED crowding, in which output constraints, particularly inpatient bed availability and boarding, are major drivers of prolonged ED stays (11, 12). Previous studies have shown that delayed bed placement is associated with increased crowding, longer ED stays, and adverse outcome (20, 21). Accordingly, the weekend effect observed in this study likely reflects broader hospital-flow constraints rather than isolated ED staffing differences. In contrast, night arrival was not independently associated with prolonged ED stay after adjustment. Although staffing may be lower at night, reduced arrival volume may offset this effect, whereas weekend periods may capture more persistent structural slowdowns in hospital operations.

The inclusion of dynamic congestion variables resulted in a modest improvement in AUC but a clearer gain in average precision, an important metric for imbalanced outcomes such as ED-LOS >8 hours. This suggests that real-time operational indicators improve identification of high-risk patients beyond traditional patient and temporal characteristics.

The congestion variables used—recent arrivals, ED occupancy, waiting-for-physician count, and post-physician occupancy—capture complementary dimensions of ED load, reflecting input pressure, overall system burden, and upstream and downstream bottlenecks. This multidimensional representation of ED state is operationally meaningful, as similar arrival volumes may correspond to very different congestion conditions.

These findings are consistent with prior studies showing that crowding is a dynamic, state-dependent process rather than a simple function of patient volume, and that capacity and flow indicators improve prediction of operational outcomes such as delayed care and leaving without being seen (17, 22). Together, these results support the integration of real-time congestion metrics into ED monitoring and early warning systems.

The largest improvement in performance was observed after adding early process delays, with the post-triage model achieving an AUC of 0.804 compared with 0.761 for the arrival-based model. Rather than representing causal determinants, triage delay and time to first physician contact likely function as early operational markers of an ED trajectory that is already becoming delayed, reflecting combined effects of workload, staffing, and downstream constraints.

From an operational perspective, arrival-based models support early risk estimation, whereas post-triage models may be more actionable for real-time monitoring and escalation. The high negative predictive value observed in the post-triage model suggests potential usefulness for identifying patients unlikely to experience prolonged stay, allowing teams to focus resources on higher-risk cases.

Importantly, many ED-LOS prediction models incorporate downstream variables unavailable at the time of decision-making (9). By explicitly distinguishing arrival-based from post-triage prediction, the present study clarifies the operational timing of prediction and reduces the risk of overinterpreting models that rely on late-stage information.

Model performance should be interpreted in relation to operational use. Although discrimination was good, particularly for Model 3, prediction of prolonged ED-LOS remains challenging because patient flow depends on both clinical characteristics and evolving system-level constraints. This is consistent with systematic reviews highlighting heterogeneity and methodological limitations in ED-LOS prediction studies (9). A key strength of the present study is the use of a strict chronological split, which better reflects real-world deployment than random train-test approaches and accounts for temporal variation in ED operations. Another strength is the focus on interpretable models. While machine-learning methods can improve prediction by capturing nonlinear relationships (23, 24), interpretability remains essential for clinical governance and quality improvement. In this context, logistic regression models incorporating dynamic congestion indicators provide a practical balance between predictive performance and operational usefulness.

These findings have practical implications for ED quality improvement. Prolonged ED-LOS should be viewed as an operational phenotype rather than a single homogeneous outcome. For older and intermediate-acuity patients, prolonged stay may reflect diagnostic complexity and downstream admission constraints, whereas for low-acuity patients the main risk may be delayed access to care or leaving without being seen. Quality dashboards should therefore integrate ED-LOS thresholds with time-to-physician and LWBS indicators, stratified by acuity. Dynamic congestion variables should also be incorporated into routine monitoring. Static indicators such as daily attendance or median waiting time may fail to detect high-risk operational states, whereas real-time measures such as occupancy and waiting burden provide earlier signals of system stress.

Finally, the strong performance of the post-triage model suggests that early delays should trigger operational escalation. Delayed physician access may serve as an early warning sign of a prolonged-care trajectory, supporting interventions such as targeted reassessment, accelerated diagnostics, or proactive bed management. Previous studies indicate that front-end process redesign can improve timeliness, but sustained improvement requires addressing downstream capacity constraints (8, 25).

The clinical relevance of prolonged ED-LOS is supported by evidence linking ED crowding and delayed care to adverse outcomes, including reduced quality of care and increased mortality risk (1, 2, 12). However, the relationship between prolonged ED stay and mortality may be influenced by patient severity and admission pathways, suggesting that prolonged ED-LOS may function both as a risk exposure and as a marker of system pressure (5, 22). From a quality perspective, prolonged ED-LOS identifies patients exposed to extended periods in a high-demand environment where timely care and communication may be more difficult. Although the present study did not evaluate clinical outcomes, identifying patients at risk of prolonged stay provides a basis for future research linking operational risk prediction to patient safety and quality-of-care outcomes.

5. Limitations

This study used a large real-world dataset of routinely collected ED visits, included a temporally separated test period, and evaluated models at clinically meaningful prediction time points. Dynamic congestion variables captured the real-time operational state of the ED, and multiple performance metrics (AUC, average precision, Brier score, and classification measures) provided a comprehensive assessment of model performance. Several limitations should be acknowledged. This was a single-center study, and external validation is required before generalization to other hospitals. The analysis relied on routinely collected administrative and timestamp data, and some clinically relevant predictors (e.g., chief complaint, comorbidities, vital signs, or boarding duration) were unavailable. Model 3 incorporated early process delays and should be interpreted as early in-process risk stratification rather than arrival-time prediction. The study identified predictors of prolonged ED-LOS but did not evaluate whether model-guided interventions improve operational performance or patient outcomes. Complete-case analysis was used in this study. A total of 387 visits were excluded from the final analytic sample (41,431 of 41,818 visits included; 0.93% excluded) because of missing or invalid ED-LOS, age, or CIMU triage acuity. Given the very small proportion of exclusions, this data loss is unlikely to have materially changed the overall event rate or substantially reduced statistical precision. However, exclusion may still have introduced selection bias if missing or invalid records were concentrated during specific periods of crowding, among particular acuity groups, or among incomplete operational trajectories. In addition, Model 3 required available triage delay and time to first physician contact, and should therefore be interpreted as an early in-process model conditioned on timestamp availability.

6. Conclusions

In this temporally validated cohort of ED visits, prolonged ED-LOS was predictable using routinely available clinical, temporal, and operational variables. Older age, intermediate triage acuity, weekend arrival, dynamic congestion at arrival, and early process delays were the main predictors of prolonged stay. The addition of dynamic congestion variables improved prediction beyond patient-level and temporal characteristics, while the strongest performance was achieved after incorporating early delays to triage and physician assessment. These findings support the use of interpretable, operationally informed prediction models to identify patients at risk of prolonged ED stay and to guide real-time quality improvement in emergency care.

7. Declarations

7.1. Acknowledgments

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7.2. Authors' contributions

Conceptualization, methodology, and software AV; writing – original draft preparation: AV. The author has read and agreed to the published version of the manuscript.

7.3. Funding/Support

The author declares that no funds, grants, or other support were received during the preparation of this manuscript.

7.4. Ethics Approval

The study was approved by the Foch IRB: IRB00012437 (approval number: 26–02-03) on 01 April 2026.

7.5. Consent to publish

Not applicable

7.6. Availability of data and material

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

7.7. Conflict of interest

The author has no relevant financial or non-financial interests to disclose.

7.8. Using artificial intelligence chatbots

None.

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Table 1: Performance Metrics of three machine learning models in predicting the risk of mortality following drowning

Variables	Total N=41,431	ED-LOS >8 h Yes (n=8,119)	ED-LOS ≤8 h No (n=33,312)	P value
Age (year)				
Median (IQR), years	49.0 (32.0–69.0)	65.0 (44.0–79.5)	46.0 (30.0–64.0)	<0.001
Arrival (hour)				
Median (IQR)	14.3 (10.7–18.2)	15.7 (11.7–18.9)	14.0 (10.4–17.9)	<0.001
Arrival-to-triage delay (minute)				
Median (IQR)	14.0 (10.0–20.0)	15.0 (11.0–21.0)	14.0 (10.0–19.0)	<0.001
Arrival-to-first physician contact				
Median (IQR)	91.0 (50.0–159.0)	155.0 (78.0–256.0)	81.0 (46.0–138.0)	<0.001
ED departure (hour)				
Median (IQR)	15.1 (8.8–18.7)	11.8 (5.7–17.3)	15.7 (10.2–19.0)	<0.001
Triage acuity level				
CIMU 1	504 (1.2)	91 (1.1)	413 (1.2)	<0.001
CIMU 2	5,565 (13.4)	1,482 (18.3)	4,083 (12.3)	
CIMU 3	6,019 (14.5)	2,135 (26.3)	3,884 (11.7)	
CIMU 4	14,785 (35.7)	3,514 (43.3)	11,271 (33.8)	
CIMU 5	11,335 (27.4)	785 (9.7)	10,550 (31.7)	
CIMU 6	3,223 (7.8)	112 (1.4)	3,111 (9.3)	
Calendar information				
Weekend arrival	10,654 (25.7)	2,452 (30.2)	8,202 (24.6)	<0.001
Night arrival	11,160 (26.9)	2,334 (28.7)	8,826 (26.5)	<0.001
Peak daytime arrival	25,722 (62.1)	4,600 (56.7)	21,122 (63.4)	<0.001
ED disposition				
Discharged home	30,353 (73.3)	4,464 (55.0)	25,889 (77.7)	<0.001
Hospitalized on site	6,059 (14.6)	2,869 (35.3)	3,190 (9.6)	
Redirected without care	1,935 (4.7)	18 (0.2)	1,917 (5.8)	
LWBT	1,464 (3.5)	154 (1.9)	1,310 (3.9)	
Transferred	805 (1.9)	508 (6.3)	297 (0.9)	
Referred*	216 (0.5)	17 (0.2)	199 (0.6)	
Handed over to authorities	203 (0.5)	2 (0.0)	201 (0.6)	
Left during care	178 (0.4)	43 (0.5)	135 (0.4)	
DAMA	128 (0.3)	28 (0.3)	100 (0.3)	
Returned home	53 (0.1)	0 (0.0)	53 (0.2)	
Returned#	18 (0.0)	10 (0.1)	8 (0.0)	
Absconded/eloped	15 (0.0)	5 (0.1)	10 (0.0)	
Died in the ED	4 (0.0)	1 (0.0)	3 (0.0)	

Data are presented as median (interquartile range (IQR)) or frequency (%).
Triage acuity was calculated based on classification infirmière des malades aux urgences (CIMU) range from 1–6);
LWBS: left without being seen/treated. *: referred to a specialist/general practitioner; #: Returned to nursing home/long-term care facility; DAMA: Discharged against medical advice; LWBT: Left without being seen/treated;
ED-LOS: Emergency department length of stay.

Table 2: Independent predictors of ED-LOS >8 hours in Model 1

Predictor	Adjusted OR	95% CI	P-value
Age (per 10-year increase)	1.26	1.24–1.28	< 0.001
CIMU 1 vs CIMU 4	0.60	0.44–0.80	0.001
CIMU 2 vs CIMU 4	1.15	1.06–1.25	0.001
CIMU 3 vs CIMU 4	1.69	1.57–1.82	< 0.001
CIMU 5 vs CIMU 4	0.29	0.27–0.32	< 0.001
CIMU 6 vs CIMU 4	0.14	0.11–0.17	< 0.001
Weekend arrival	1.56	1.46–1.67	< 0.001
Night arrival	1.07	0.97–1.17	0.191
Peak daytime arrival	0.87	0.81–0.93	< 0.001

ED: emergency department; ED-LOS: emergency department length of stay; OR: odds ratio; CI: confidence interval;
CIMU: classification infirmière des malades aux urgences (triage acuity scale).

Table 3: Predictive performance of logistic regression models for ED-LOS >8 hours

Characteristics	Model		
	1	**2**	**3**
Test (number)	8,056	8,056	7,596
Events (number)	1,553	1,553	1,533
AUC	0.752	0.761	0.804
Average precision	0.379	0.411	0.532
Brier score	0.137	0.135	0.127
Optimal threshold	0.195	0.222	0.191
Sensitivity	0.750	0.669	0.736
Specificity	0.636	0.730	0.719
Positive predictive value	0.330	0.371	0.398
Negative predictive value	0.914	0.902	0.915

Model 1: patient + temporal variables; Model 2: + dynamic congestion variables; Model 3: + early process delays.
ED: emergency department; ED-LOS: emergency department length of stay; AUC: area under the receiver operating characteristic curve.

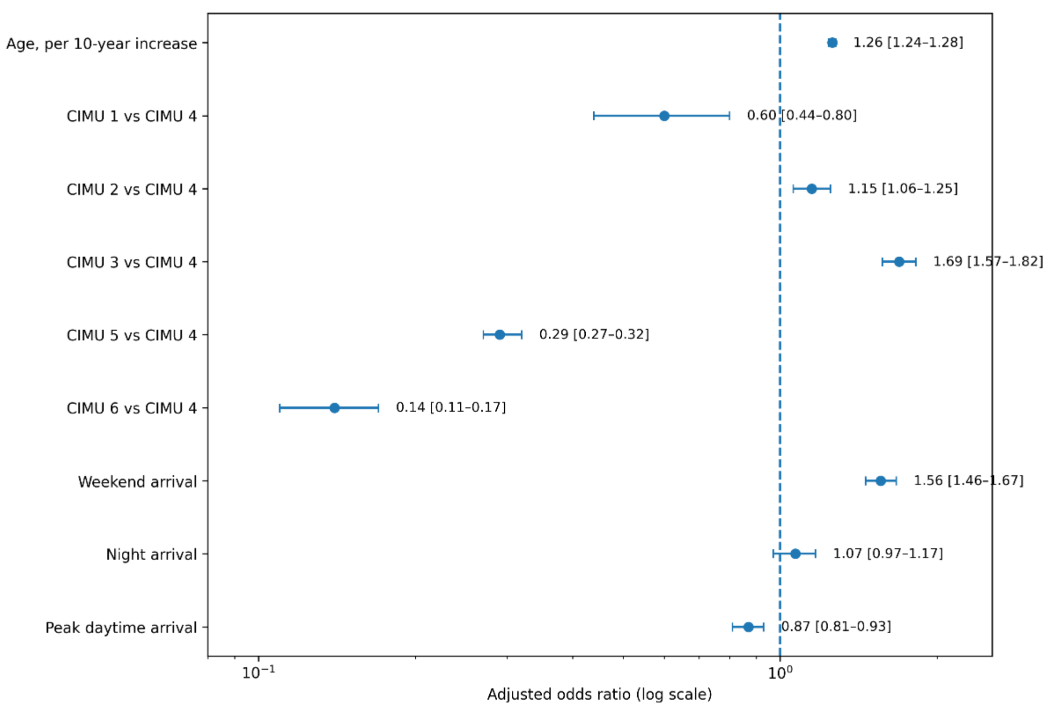

Figure 1: Adjusted predictors of prolonged emergency department length of stay. Forest plot showing adjusted odds ratios and 95% confidence intervals for the association between patient-level and temporal predictors and ED-LOS exceeding 8 hours in Model 1. Classification infirmière des malades aux urgences (CIMU) 4 was used as the reference category for triage acuity. Odds ratios greater than 1 indicate increased odds of prolonged stay.

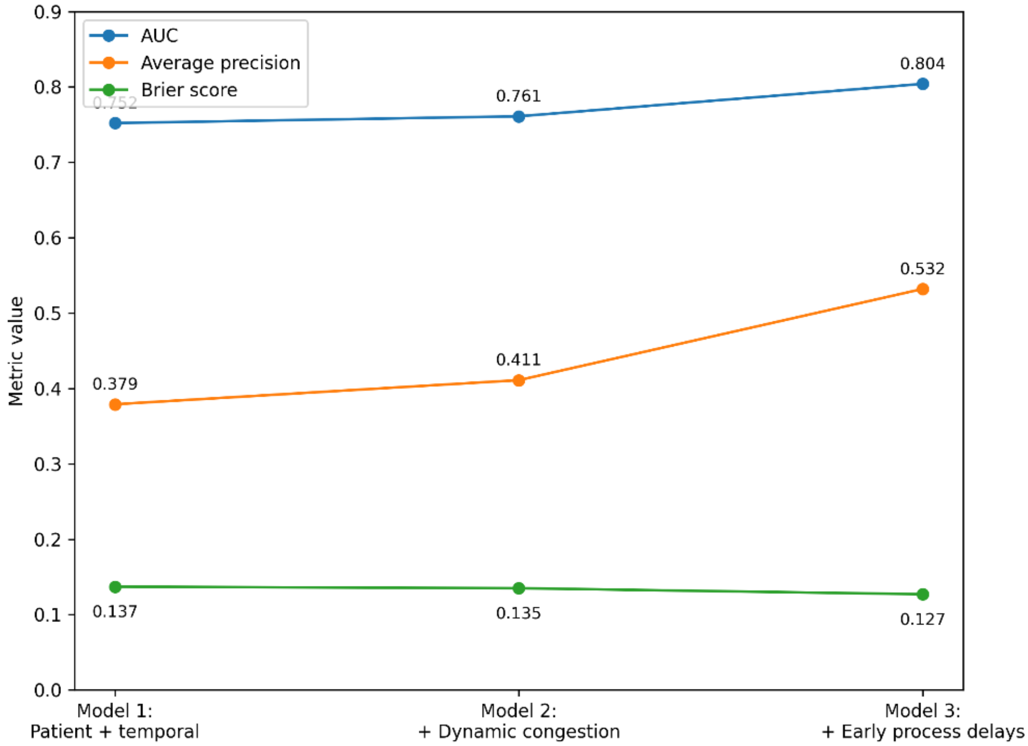

Figure 2: Predictive performance of the three logistic regression models. Summary comparison of the three main models for prediction of prolonged emergency department (ED) stay (>8 hours) in the held-out test set. Model 1 included patient-level and temporal variables, Model 2 additionally incorporated dynamic congestion variables, and Model 3 further incorporated early process delays. Model 3 showed the best overall performance.

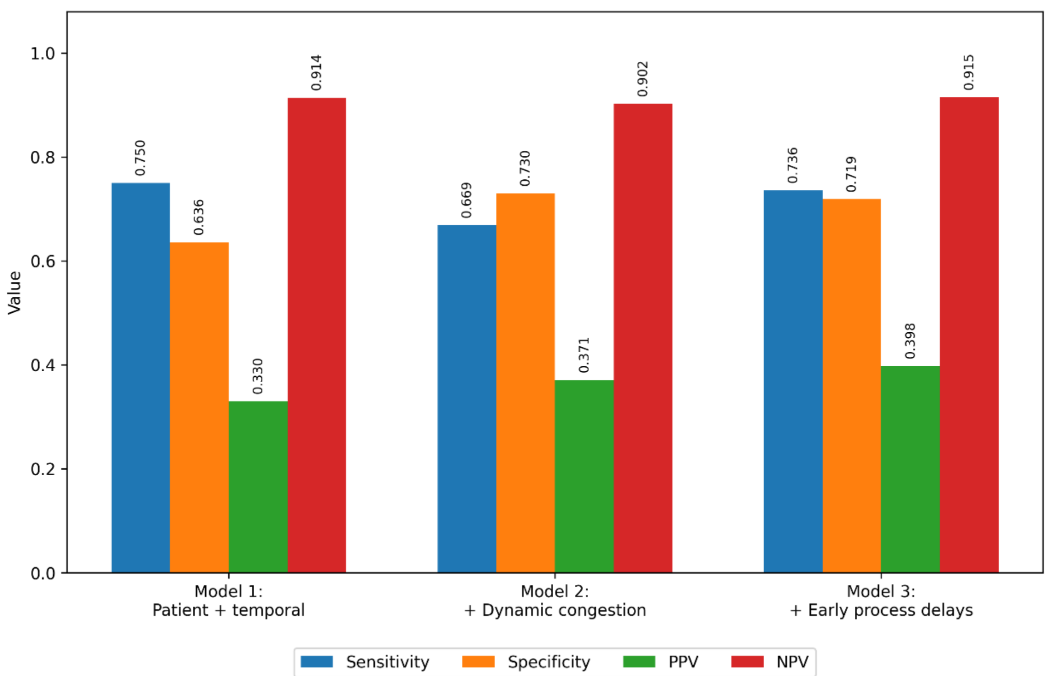

Figure 3: Classification performance metrics across models. Comparison of sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) for the three logistic regression models at their optimal classification thresholds. The post-triage model achieved the best balance between discrimination and classification performance.