

ORIGINAL ARTICLE

Predictors of Emergency Department Utilization Among Advanced Cancer Patients: Machine Learning Model Development and Internal Validation

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ABSTRACT

Background: In 2022, nearly 20 million people worldwide were living with cancer, projected to rise to 28.4 million by 2040. Advanced cancer patients experience multidimensional suffering while navigating fragmented healthcare systems, contributing to high costs and poor outcomes. Current palliative care referral tools focus on prognosis rather than predicting healthcare utilization needs. This study developed and internally validated machine learning models to predict subsequent Emergency Department utilization, with the ultimate goal of creating practical clinical tools to support proactive care decisions and early palliative care integration.

Methods: This retrospective cohort study with machine learning model development analyzed electronic medical records of advanced cancer patients referred to palliative care at Pathum Thani Hospital between January 2024 and June 2025. The study employed logistic regression with a machine learning development process to predict emergency care utilization. Performance was evaluated using AUROC, accuracy, calibration metrics, and DCA.

Results: Backward Elimination showed potential predictors for three-month subsequent emergency care utilization, including elderly status, malnutrition, presence of dyspnea, previous three-month hospitalization, functional status (PPS), adequate strong opioid prescribing, and ACP documentation. The internally validated model demonstrated moderate discriminative ability, accuracy, high specificity, and high calibration (low Brier score) with a low potential for overfitting between validation and test sets. Nevertheless, the model had low sensitivity, indicating it is more appropriate for a rule-in than a rule-out approach. The DCA showed net benefit over the treat-all and treat-no strategies at the harm-benefit treatment threshold probability > 10%.

Conclusion: This predictive tool enables proactive interventions, especially for emergency advanced care planning for patients most likely to require emergency services. However, this study requires ongoing development since it is limited to a single site and demonstrates low sensitivity. Further work is needed to establish external validation and assess real-world impact.

Keywords: palliative care, machine learning, healthcare utilization, Palliative Performance Scale, advanced care planning

นิพนธ์ต้นฉบับ

ปัจจัยการกำนวยการใช้บริการห้องฉุกเฉินในผู้ป่วยโรคมะเร็งระยะท้าย : การพัฒนาโมเดลแมชชีนเลิร์นนิ่งและความเที่ยงตรงภายใน

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บทคัดย่อ

ที่มา: ในปี พ.ศ. 2565 ประชากรประมาณ 20 ล้านคนทั่วโลกป่วยด้วยโรคมะเร็ง และ ถูกคาดการณ์ว่าจะเพิ่มขึ้นเป็น 28.4 ล้านคน ในปี พ.ศ. 2583 ซึ่งผู้ป่วยมะเร็งระยะท้ายทั่วโลกต้องเผชิญกับความทุกข์ทรมานในหลากหลายมิติ ในขณะที่ระบบการดูแลสุขภาพแบบแยกส่วนนำมาสู่ค่าใช้จ่ายในการดูแลสุขภาพที่สูงและผลลัพธ์ที่ไม่พึงประสงค์ ปัจจุบันเครื่องมือในการช่วยตัดสินใจในการส่งต่อผู้ป่วยเพื่อให้ได้รับการดูแลแบบประคับประคองในปัจจุบันมุ่งเน้นที่การทำนายพยากรณ์โรค มากกว่าการทำนายความต้องการใช้บริการสุขภาพ การศึกษานี้มีวัตถุประสงค์เพื่อพัฒนาและตรวจสอบความเที่ยงตรงภายในของโมเดลแมชชีนเลิร์นนิ่ง เพื่อทำนายการใช้บริการห้องฉุกเฉิน โดยมีเป้าหมายท้ายที่สุดเพื่อสร้างเครื่องมือทางคลินิกเพื่อสนับสนุนการดูแลเชิงรุก และ บูรณาการการดูแลแบบประคับประคองตั้งแต่ช่วงต้นที่ได้รับการวินิจฉัย

วัตถุประสงค์และวิธีการ: การศึกษาแบบย้อนหลัง ร่วมกับการพัฒนาโมเดลแมชชีนเลิร์นนิ่ง โดยวิเคราะห์ข้อมูลจากเวชระเบียนอิเล็กทรอนิกส์ของผู้ป่วยมะเร็งระยะท้ายที่ได้รับการส่งปรึกษาการดูแลแบบประคับประคองที่โรงพยาบาลปทุมธานี ระหว่าง มกราคม พ.ศ. 2567 ถึง มิถุนายน พ.ศ. 2568 โดยการศึกษาได้มีการนำโมเดลการถดถอยโลจิสติกส์ มาเข้าสู่กระบวนการพัฒนาโมเดลแมชชีนเลิร์นนิ่ง เพื่อทำนายการใช้บริการห้องฉุกเฉิน รายงานผลการศึกษากับพื้นที่ได้กราฟลักษณะการทำงานของตัวรับ ความแม่นยำ ตัวชี้วัดความสอดคล้องของความน่าจะเป็นที่ทำนายกับผลลัพธ์จริง และการวิเคราะห์เส้นโค้งการตัดสินใจ

ผลการศึกษา: จากการคัดเลือกตัวแปรแบบถดถอยหลัง พบตัวแปรทำนายที่ส่งผลต่อการใช้บริการห้องฉุกเฉินใน 3 เดือนข้างหน้า ได้แก่ ผู้สูงอายุ, ทุพโภชนาการ, มีอาการหายใจเหนื่อย, นอนโรงพยาบาลใน 3 เดือนที่ผ่านมา, ความสามารถในการช่วยเหลือตนเอง, ได้รับยาแก้ปวดกลุ่มมอร์ฟีน, การบันทึกการวางแผนการดูแลล่วงหน้า โดยโมเดลซึ่งได้รับการตรวจสอบความเที่ยงตรงภายใน แสดงความสามารถในการจำแนก และ ความแม่นยำระดับปานกลาง ร่วมกับความจำเพาะและความสอดคล้องระหว่างค่าความเสี่ยงที่ทำนายและเหตุการณ์จริงที่สูง อย่างไรก็ตามโมเดลที่พัฒนาขึ้นมีความไวที่ต่ำ บ่งบอกว่าเหมาะต่อการยืนยันเข้า มากกว่า การตัดออก การวิเคราะห์เส้นโค้งการตัดสินใจแสดงถึงผลประโยชน์สุทธิเหนือกลยุทธ์การนำไปใช้กับผู้ป่วยทุกราย และ การไม่นำไปใช้เลย ที่เกณฑ์ มากกว่าร้อยละ 10 ของความน่าจะเป็นที่หากผู้ป่วยเป็นโรคจริงจะทำให้การรักษาคุ่มค่าระหว่างความเสี่ยงและประโยชน์

สรุป: เครื่องมือนี้เหมาะต่อการยืนยันผู้ป่วยที่มีความเสี่ยงสูง เครื่องมือในการทำนายนี้ช่วยส่งเสริมการดูแลเชิงรุกโดยเฉพาะการวางแผนการดูแลล่วงหน้าในส่วนของการฉุกเฉิน ในผู้ป่วยที่มีความเสี่ยงสูงที่อาจจะมาใช้บริการห้องฉุกเฉิน อย่างไรก็ตามการศึกษานี้ยังต้องการพัฒนาต่อเนื่องจากการศึกษาที่สถานที่เดียวและยังมีความไวที่ต่ำ นอกจากนี้ยังต้องการการทดสอบความเที่ยงตรงภายนอกและประเมินผลกระทบต่อประชากรจริง

คำสำคัญ: การดูแลแบบประคับประคอง แมชชีนเลิร์นนิ่ง การใช้บริการสุขภาพ คณะนสมรรถนะสำหรับผู้ป่วยระยะประคับประคอง การวางแผนการดูแลล่วงหน้า

Introduction

Based on the current situation, it was found that in 2022, there were nearly 20 million cancer patients worldwide. A study predicts that by 2040, the number of cancer patients globally will increase to 28.4 million, an increase of approximately 50.00%. In Thailand, there were 180,000 new cancer patients in 2022, and it is predicted that this number may increase by 50.00% by 2045.¹⁻³

Patients with late-stage cancer face complex suffering—physical, psychological, social, and spiritual, in addition to declining physical function. They also must contend with a fragmented health-care system, which leads to subsequent public health economic problems.⁴⁻⁷

The World Health Organization (WHO) defines palliative care as an approach to improve the quality of life of patients with life-threatening and incurable diseases, including cancer, as well as the quality of life of their families. In 2024, the American Society of Clinical Oncology (ASCO) recommended that integrated care, combining conventional treatment with palliative care from the early stages of a terminal cancer diagnosis, can help alleviate suffering, improve quality of life, and reduce life-prolonging treatments.^{8,9}

A major obstacle to palliative care is that patients are often referred to a palliative care team only in the final stages of life. This results in inadequate management of physical discomfort, causing suffering for both the patient and their family. It also leads to a dependency on the healthcare system and high healthcare costs.¹⁰⁻¹³

The systematic review found mortality prediction as the most frequent use of machine learning in palliative care. Other existing non-machine learning prediction tools for terminally ill cancer patients primarily focus on prognosis and life expectancy based on functional status measures like the Palliative Performance Scale (PPS). Current referral criteria include the surprise question, gold standard framework (GSF), and Supportive and Palliative Care Indicator Tools (SPICT), but these tools cannot clearly predict acute care utilization patterns or emergency service needs. As these consultations are naturally time-consuming and do not scale well when it comes to identifying people in need of palliative care in the broader population beyond the tertiary hospital setting, it makes sense to search for automated alternatives.¹⁴⁻¹⁷

This study developed internally validated machine learning models to predict subsequent Emergency Department (ED) utilization. The ultimate goal is to deploy this model as a clinical decision support tool to enable proactive care and ensure the timely integration of early palliative care.

Methods

Study design and setting

This study was designed as a retrospective cohort investigation with the development of machine learning models, conducted in accordance with the TRIPOD-AI reporting guidelines. The setting included palliative care outpatient clinics, the ED, and inpatient wards at Pathum Thani Hospital. The study period extended from January 1, 2024, to June 30, 2025. Ethical approval was obtained from the Pathum Thani Hospital Ethics Committee (EC-PTH A133-68, August 8, 2025).

The Palliative Care Department at Pathum Thani Hospital provides care for patients diagnosed with incurable serious illnesses, regardless of their functional status or symptom burden. At every visit, cancer patients undergo an initial assessment of their PPS and symptom burden (via the Edmonton Symptom Assessment Scale; ESAS) by palliative care nurses at the triage station. Subsequently, these assessments are re-evaluated, and ACP is documented in the medical records by palliative care specialists following a clinical consultation.

Participants

Inclusion criteria

1. Age ≥ 18 years
2. Advanced cancer diagnosis with documentation including cancer origin, disease stage, and laboratory or imaging confirmation
3. Referred for palliative care consultation with a recorded referral date
4. Decision-making capacity at referral (no severe psychiatric illness or dementia)
5. Complete baseline and follow-up data, including PPS, symptoms, and healthcare utilization records

Exclusion criteria

1. Incomplete key variable data (initial PPS score, referral date, cancer origin)
2. Failed to attend palliative care appointments
3. Previous palliative care referral before the study period

Predictors and outcome measures

Candidate predictors

- Demographics: age, sex, BMI, healthcare coverage
- Clinical characteristics: early referral (PPS score > 50), cancer origin, comorbidities (diabetes mellitus, cardiovascular disease, chronic kidney disease)
- Treatment factors: concurrent anticancer therapy, strong opioid prescriptions
- Symptom burden: pain, dyspnea, confusion, bleeding, number of symptoms (the patients were assessed using the ESAS by a palliative specialist or nurse, and the results were recorded in the electronic medical record.)
- Previous healthcare utilization: ED visit within three months before palliative care consultation
- Care planning: advanced care planning (ACP) documentation (data were obtained from electronic medical records documented by palliative care specialists.)

Response variables

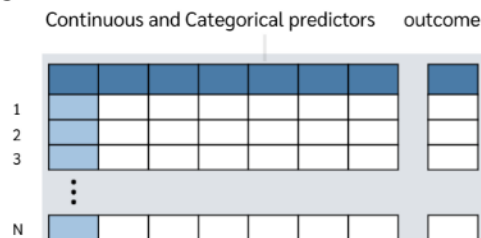
- Subsequent ED visits within three months after palliative care consultation

Machine learning model development (Figure 1)

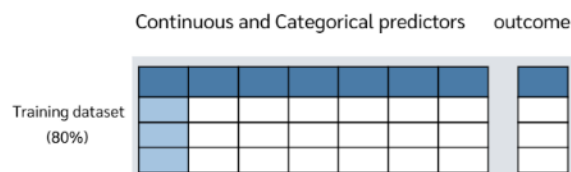
Missing values for body mass index (BMI), which accounted for less than 20.00% in both groups, were addressed using mean imputation. To address data imbalance, SMOTE (Synthetic Minority Over-sampling Technique) was applied to simulate the minority class, which consisted of patients who subsequently visited the ED. This approach helps mitigate the risk of the model developing bias toward the majority class.

The dataset was partitioned into an 80.00% training set and a 20.00% test set. Backward elimination was used for feature selection by gradually removing each predictor that had the highest p-value (least significant) in the regression model. A logistic regression model with ten-fold cross-validation was used without hyperparameter tuning to avoid overfitting. The model was trained using candidate predictors identified as significant through backward elimination feature selection. Model performance was evaluated using the area under the receiver operating characteristic curve (AUROC), accuracy, sensitivity, specificity, precision, F1 score, and Brier score for the

Data Pre-processing



80 : 20 Stratified random sampling



Training process

- Training dataset +
1. Feature Selection by Backward Elimination
 2. Logistic Regression with Selected Feature

Internal Validation : 10-fold cross validation

Testing process

Testing dataset + Trained Logistic Regression
Evaluation : Accuracy, Area Under Receiver Operative Characteristic Curve (AUROC), Sensitivity, Specificity, F1 score, Precision score

Figure 1. Machine learning development process

testing dataset. Clinical utility was assessed with decision curve analysis (DCA).

For model interpretability, coefficient levels were used to weight feature importance for each predictor. DCA was used for evaluating the clinical utility and net benefit of the predictive model across a range of clinical risk thresholds.

Software

Data analysis performed using Python 3.10 with numpy, pandas, scipy, pingouin, statsmodels, and scikit-learn packages.

Results

Participant characteristics

A total of 265 participants were included (88.30% of the eligible population). Mean age was 66.78 years (SD: 12.52), with 55.47% male participants. Median PPS was 60 (IQR: 50-70), and 147 patients (55.47%) were referred early (PPS > 50). The most common cancer origins were colorectal (26.03%), head and neck (12.83%), hepatocellular (10.94%), and lung (10.56%). Diabetes mellitus was the most frequent comorbidity (18.11%), and 57.35% received no anticancer therapy (Table 1).

Feature selection and model interpretability

The logistic regression model, derived through backward elimination, identified seven independent predictors for a subsequent ED visit. Four

factors were associated with a significantly increased risk of subsequent ED visits. Elderly patients (odds ratio [OR], 2.89; 95%CI, 1.56–5.36; $p = 0.001$) carried the highest risk, contributing +3 weighted points to the scoring system. Malnutrition (BMI < 18.5) and dyspnea were also strong risk factors, with ORs of 2.05 (95%CI, 1.08–3.89; $p = 0.028$) and 2.31 (95%CI, 1.34–3.98; $p = 0.003$), respectively, each contributing +2 points. Previous Hospitalization was also independently associated with increased risk (OR, 2.45; 95%CI, 1.42–4.24; $p = 0.001$), adding +2 weighted points. Conversely, three factors were found to be significantly protective against subsequent ED visits. ACP documentation demonstrated the strongest protective effect (OR, 0.37; 95%CI, 0.22–0.64; $p < 0.001$), corresponding to a -3 point reduction in risk. both early referral (OR, 0.45; 95%CI, 0.27–0.77; $p = 0.003$) and Strong Opioid Prescribing (Background with Breakthrough dose) (OR, 0.48; 95%CI, 0.28–0.84; $p = 0.010$) were also protective, each reducing the risk score by -2 points. All identified predictors were statistically significant ($p < 0.05$). (Table 2)

Model performance summary

The final logistic regression model demonstrated moderate discriminative ability, with the AUROC measured at 0.659 (validation set: 95%CI, 0.600–0.716) and 0.726 (test set: 95%CI, 0.582–0.854). Overall Accuracy remained consistent

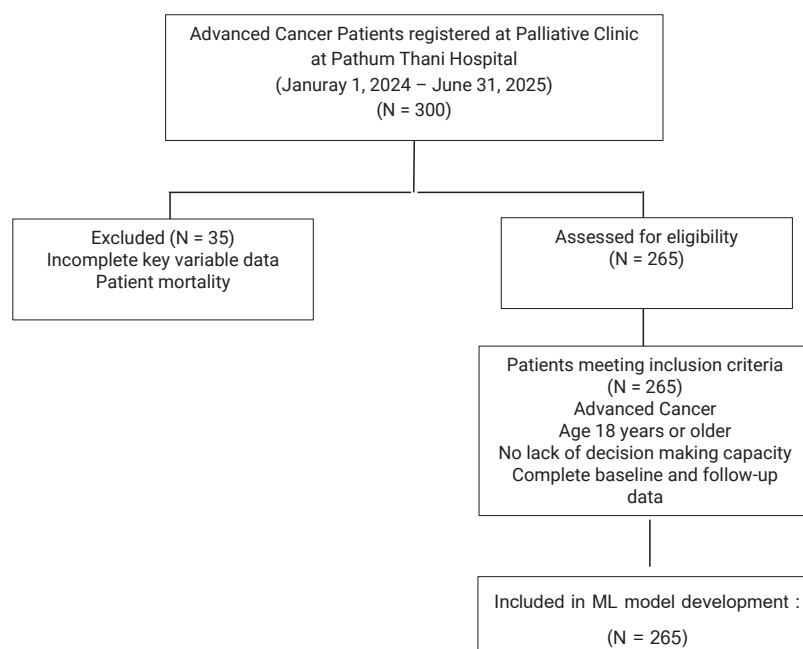


Figure 2. Flow diagram of the study

Table 1. Baseline characteristics of participants

Characteristic	Subsequent ED visit (N = 58)	Non-subsequent ED visit (N = 207)
PPS, Median (Q1, Q3)	55 (42.5, 70)	60 (50, 80)
PPS > 50, n (%)	29 (50.00)	89 (42.99)
Sex, n (%)	Male: 31 (53.44) Female: 27 (46.55)	Male: 116 (56.03) Female: 91 (43.96)
Age, mean (SD)	62.79 (11.48)	67.89 (12.59)
BMI, mean (SD)	19.66 (3.18)	20.43 (3.48)
Right to treatment, n (%)	Universal Health Coverage: 49 (84.48)	Universal Health Coverage: 184 (88.88)
Cancer origin, n (%)	Colorectal: 12 (20.68) Head and Neck: 5 (8.62) Hepatocellular: 10 (17.24) Lung: 10 (17.2) Prostate: 3 (5.17) Breast: 5 (8.62)	Colorectal: 57 (27.53) Head and Neck: 29 (14.00) Hepatocellular: 19 (9.17) Lung: 18 (8.69) Prostate: 24 (11.59) Breast: 15 (7.24)
Underlying diseases, n (%)	Diabetes mellitus: 12 (20.68) Chronic kidney disease: 5 (8.62) Cardiovascular disease: 4 (6.89)	Diabetes mellitus: 36 (17.39) Chronic kidney disease: 13 (6.28) Cardiovascular disease: 30 (1.44)
Anticancer therapy, n (%)	No specific treatment: 35 (60.34)	No specific treatment: 117 (56.52)
Symptoms, n (%)	Pain 44 (75.86) Dyspnea 23 (39.65) Confusion 2 (3.44)	Pain 154 (74.39) Dyspnea 68 (32.85) Confusion 18 (8.69)
Number of symptoms, n (%)	No 1 (1.72) One 22 (37.93) More than One 35 (60.34)	No 16 (7.72) One 70 (33.81) More than One 131 (63.28)
ACP documentation	30 (51.72)	141 (68.11)
Previous ED visit within 3 months	35 (60.34)	70 (33.81)
Previous Hospitalization within 3 months	41 (70.68)	111 (53.62)
Opioid prescription (background with breakthrough dose)	29 (50.00)	92 (44.44)

ED, Emergency Department; PPS, Palliative Performance Scale; BMI, body mass index; ACP, advanced care planning

Table 2. Independent predictors of further ED visit

Derived from Logistic Regression after backward elimination feature selection

Predictors	coefficient	OR (95%CI:)	p-value	Weighted points
Elderly (age ≥ 60)	1.060	2.89 (1.56-5.36)	0.001	+3
Malnutrition (BMI < 18.5)	0.718	2.05 (1.08-3.89)	0.028	+2
Dyspnea	0.836	2.31 (1.34-3.98)	0.003	+2
Previous hospitalization	0.897	2.45 (1.42-4.24)	0.001	+2
Functional status (PPS ≥ 50)	-0.797	0.45 (0.27-0.77)	0.003	-2
Strong opioid prescribing	-0.727	0.48 (0.28-0.84)	0.010	-2
(background with breakthrough dose)	-0.982	0.37 (0.22-0.64)	0.000	-3
ACP documentation				

ED, Emergency Department; PPS, Palliative Performance Scale; BMI, body mass index; ACP, advanced care planning

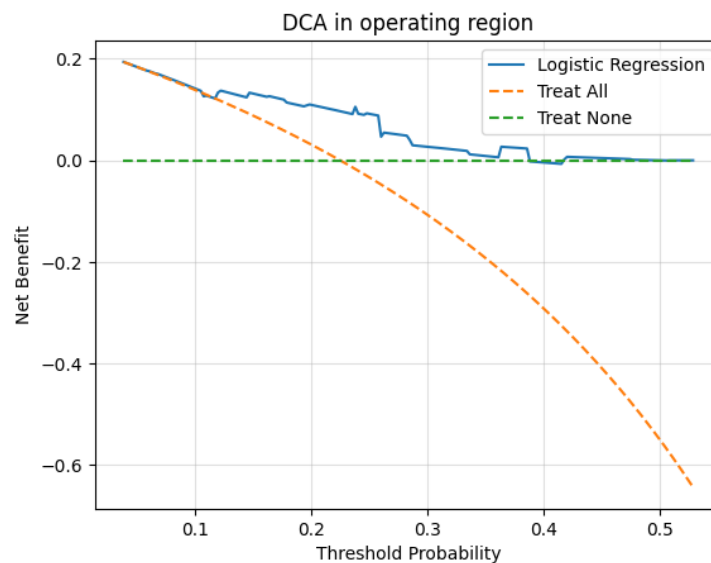
across both evaluation sets, measuring 0.743 in the validation set and 0.738 on the test set. The model exhibited high specificity (validation set: 0.857; Test set: 0.855), indicating a strong capacity to correctly identify patients who would not re-

quire a subsequent ED visit. However, the model showed limited ability to detect actual subsequent ED visits, as evidenced by a low sensitivity score of 0.328 (validation set) and 0.333 (test set). Given the moderate Precision (validation

Table 3. Logistic regression model performance summary

Metric	Internal validation (mean $\pm$ 95%CI:)	Test set (mean $\pm$ 95%CI:)
AUROC	0.659 (0.600-0.716)	0.726 (0.582-0.854)
Accuracy	0.743 (0.701-0.795)	0.738 (0.637-0.838)
Sensitivity	0.328 (0.225-0.423)	0.333 (0.118-0.546)
Specificity	0.857 (0.809-0.907)	0.855 (0.766-0.937)
Precision	0.453 (0.286-0.616)	0.400 (0.143-0.650)
F1-score	0.366 (0.244-0.489)	0.364 (0.138-0.550)
Brier score	0.163 (0.144-0.183)	0.155 (0.112-0.201)

AUROC, area under the receiver operating characteristic curve

**Figure 3.** Decision curve analysis

set: 0.453, Test set: 0.400), the F1-score, which is the harmonic mean of precision and sensitivity, was moderate at 0.366 (validation set) and 0.364 (test set). The low Brier scores (validation set: 0.163; test set: 0.155) suggest that the model's probability predictions are well-calibrated and reliable. (Table 3)

Clinical utility analysis

The ML models demonstrated a net benefit in DCA (Figure 2) when compared to “treat all” and “treat none” strategies at a threshold probability of > 10%, which is clinically relevant for prevention and screening (as clinicians may intervene if the predicted risk is $\geq$ 10%) (Figure 3).

Discussion

The prediction model for emergency care utilization within three months among patients with advanced cancer demonstrated high specificity, indicating that it has potential for effectively identifying high-risk patients (rule-in) compared with

general screening approaches. However, despite the high specificity, the model showed low precision (positive predictive value) and F1 scores, suggesting that a considerable proportion of individuals predicted to be “high risk” did not actually experience the outcome, which may lead to unnecessary interventions. However, the intervention in this context is palliative care, which advanced cancer patients should receive according to standard treatment protocol. At the same time, the low sensitivity indicates that the model tends to miss some truly high-risk patients. Nevertheless, false negatives can be managed through other mechanisms, such as palliative care services in the ED.

Importantly, the model exhibited favorable calibration, as indicated by low Brier scores (< 0.17), suggesting that predicted probabilities closely matched observed outcomes. DCA further demonstrated that the model provides a positive net benefit compared with “treat all” or “treat none” strategies, particularly at clinically

relevant threshold probabilities above 10.00%. This supports the model's potential role in guiding targeted interventions, such as early symptom assessment or proactive ACP discussions for patients at elevated risk.

The findings of our study align with and extend prior research on healthcare utilization and symptom burden in advanced cancer patients referred to palliative care. Consistent with earlier studies, patients with poorer performance status, as indicated by a PPS of ≤ 50 , demonstrated higher rates of acute care utilization. Previous literature has repeatedly shown that advanced functional decline correlates with increased acute care utilization, underscoring the vulnerability of this population.^{18,19}

Our identification of dyspnea as a significant symptom associated with subsequent ED visits is also supported by prior investigations. Dyspnea is among the most distressing and frequent symptoms experienced by advanced cancer patients, often leading to urgent care needs. This symptom burden highlights critical clinical targets for early intervention.²⁰

Notably, the association between ACP and reduced ED visits after referral echoes previous findings demonstrating that ACP fosters goal-concordant care and decreases unnecessary or unwanted healthcare use. This supports ongoing advocacy for integration of ACP early in the trajectory of advanced illness, reinforcing its role as a critical component of comprehensive palliative care.^{21,22}

This study provides both traditional epidemiological insights and advanced predictive modeling for emergency care utilization in advanced cancer patients. The statistical analysis confirmed that advanced age, malnutrition, history of recent prior hospitalization, functional status (PPS), a specific symptom (dyspnea), adequate symptom control through strong opioid prescribing, and ACP are critical determinants of emergency care utilization. The machine learning approach demonstrated that these traditional predictors can be enhanced through algorithmic modeling to create practical clinical tools.

This study had several limitations. The single-center, retrospective design may limit the generalizability of the findings and results in a relatively small sample size. This consequently led to a very limited number of cases available for the

test set, which may affect the robustness of the model evaluation. There is a potential for survivor bias among patients with low PPS scores. Model validation was performed internally only, highlighting the need for external validation before clinical implementation. There was no comparison between the group receiving background strong opioids combined with PRN doses and the group receiving either background strong opioids or PRN doses for breakthrough symptoms alone. Prospective multicenter validation and comparisons with more complex models (e.g., tree-based, ensemble, neural network models) may further refine predictive performance.

Additionally, the ultimate goal of this internal validation study was to establish a prediction tool that can support primary care physicians or other specialists in identifying advanced cancer patients who may need an emergency plan or ACP before palliative care emergencies occur, and to reduce unnecessary life-sustaining treatments or other interventions that do not align with patient values and may cause additional suffering.

Conclusions

This study developed and validated a practical logistic regression model that identifies key predictors of subsequent ED visits among palliative care patients, demonstrating modest discriminative ability but strong calibration, high specificity, and meaningful clinical utility. Elderly age, malnutrition, dyspnea, and recent hospitalization significantly increased the likelihood of ED revisits, while ACP documentation, early referral, and adequate opioid prescribing were strongly protective. Although sensitivity remained limited, the model's positive net benefit at clinically relevant thresholds supports its use as a targeted risk-stratification tool to guide proactive symptom management and care planning. Integrating this scoring system into routine practice may help clinicians identify patients who require palliative care, ultimately promoting more efficient resource utilization and improved patient-centered outcomes.

Future work should focus on external validation and prospective implementation of these predictive tools to realize their potential for improving care quality and reducing unnecessary healthcare utilization in advanced cancer populations.

Highlight

1. Screen High-Risk Patients in the Community: Primary care clinics should closely monitor advanced cancer patients who are elderly (Age ≥ 60 years), malnourished (BMI < 18.5), experiencing dyspnea, or have a history of hospitalization within 3 months, as these are key predictors of Emergency Department (ED) utilization.

2. Proactive ACP and Data Sharing: advanced care planning (ACP) documentation has the strongest protective effect against ED visits; therefore, primary care teams should initiate ACP discussions early and seamlessly share this data with tertiary hospitals to ensure goal-concordant crisis care.

3. Initiate early palliative referral: referring patients to palliative care pathways early while they still maintain good functional status (PPS ≥ 50) significantly reduces the likelihood of subsequent emergency healthcare utilization.

4. Optimize symptom management at home: Adequate strong opioid prescribing (combining background and breakthrough doses) effectively reduces ED visits, highlighting the need for primary care teams to aggressively manage pain and dyspnea within the community.

Author Contributions

The corresponding author was responsible for literature review, methodology design, data collection, data analysis and interpretation, machine learning model development, and manuscript writing. The author critically reviewed and revised the manuscript for intellectual content and approved the final version for submission.

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Ethics approval and consent to participate

This study was approved by the Ethics Committee of Pathum Thani Hospital (Ethics Committee Approval Code: EC-PTH A133-68, approval date: August 8, 2025). Informed consent was waived due to the retrospective nature of the study, and all patient data were anonymized before analysis.

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Data availability statement

The datasets analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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