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A laboratory-less nomogram predicting survival rates for hospice patients with advanced cancer

Haopeng Li[1†], Xiaofeng Chen[1†], Xubin Jing[1], Chaofen Wu[2], Yicheng Zeng[3], Muqing Wang[4], Weilong Zeng[5], Shaohui Zhang[1], Xueqiang Xu[1] and Xianbin Cai[1*]

Abstract

Introduction Cancer is the leading cause of death globally(1). According to the WHO's 2020 Global Cancer Report(2), China represented 23.7% of new cancer cases and 30.2% of cancer-related deaths worldwide in 2020. From 2015 to 2020, cancer cases made up 18.4% of the global total. Recent statistics show that in China, malignant tumors accounted for 23.91% of all deaths, with both incidence and mortality rates on the rise. Hospice patients in China often lack the measurement of laboratory indicators, which poses difficulties in their survival prediction. This is because almost all current survival prediction models include laboratory parameters. This study established a lab-free prediction model with an accuracy of approximately 73%-75% to predict the survival rates of patients at 30 days, 45 days, and 60 days. An online version has also been developed for wide applications.

Materials and methods We conducted a retrospective analysis of data from patients who received hospice care between January 2008 and December 2018. A total of 4,229 patients were divided into a training set (70%) and a test set (30%). The training group was used to develop the nomogram and a web-based calculator using the least absolute shrinkage and selection operator (LASSO) technique. The test group was used to validate the nomogram, using metrics such as the area under the receiver operating characteristic curve, calibration curve, and decision curve analysis.

Results Our analysis included 4,299 patients, with 3,163 in the training group and 1,066 in the test group. Using the LASSO algorithm, we identified eight predictors, namely quality of life, Karnofsky performance score, gender, pain duration, anorexia, abdominal distention, tachypnea, and edema. A nomogram with an online version was constructed to predict survival rates at 30, 45, and 60 days for hospice patients with advanced cancer. In the test set, the area under the curve (AUC) values were 0.7538, 0.7342, and 0.7324 for 30-day, 45-day, and 60-day survival, respectively. The nomogram demonstrated excellent calibration, and the decision curve analysis (DCA) showed a significant clinical net benefit.

Conclusion This study developed a laboratory-free nomogram and a web-based calculator for accurately predicting survival in hospice patients with terminal cancer.

[†]Haopeng Li and Xiaofeng Chen were co-first authors and contributed equally to this work.

*Correspondence:
Xianbin Cai
cxbin1@qq.com
Full list of author information is available at the end of the article

Keywords Prognosis, Clinical Decision-Making, Cancer pain, Palliative care

Background

Globally, cancer is the leading cause of death [1]. According to the World Health Organization's 2020 Global Cancer Report, China accounted for 23.7% of new cancer cases in 2020, with 30.2% of the world's total deaths attributed to the country [2]. From 2015 to 2020, cancer cases accounted for 18.4% of the global total [2]. The latest epidemiological statistics on malignant tumors in China reveal that deaths from malignant tumors accounted for 23.91% of all deaths, and both incidence and mortality rates are increasing [3].

Most cancer deaths occur between the ages of 60 and 74 [4]. Rather than dying in the hospital, elderly cancer patients often choose to die at home [5]. Hospice care which is also known as end-of-life care is provided to improve the quality of life for patients and enable them to pass away with dignity. It encompasses medical, spiritual, and psychological support for cancer patients and their families. Hospice care involves healthcare professionals working collaboratively with patients and their families to provide the comfort and care they need [6].

Given that treatment no longer controls the disease process and hospice care aims to ensure the highest possible quality of life, it is crucial to be able to predict survival time. Such predictions can help clinicians, patients, and their families make informed decisions regarding palliative systemic therapies, palliative procedures, artificial nutrition or hydration, and other aspects of care [7]. Research suggests that earlier decision-making by patients leads to improved quality of life and death and reduces costs in the final week of life [8]. Clinician prediction of survival (CPS) is often inaccurate, and uncertainty about prognosis diminishes the quality of doctor-patient communication, potentially resulting in more aggressive hospice care [9–11], Consequently, objective prediction tools with high accuracy are vital in hospice care.

Various methods have been proposed for predicting the survival rate of patients with advanced cancer, including CPS, GPS (Glasgow Prognostic Score), PPS (Palliative Performance Scale), PPI (Palliative Prognostic Index), and PaP (Palliative Prognostic Score). These models combine clinical and biomarker parameters [12]. Zhou LJ et al. created the Chinese Prognostic Scale (ChPS), but its accuracy rate was unsatisfactory [13]. To enhance the efficiency of the ChPS, Cui J developed a new-ChPS Scale in 2014. However, the sample size of the new scale was slightly inadequate, and the accuracy rate in predicting survival was not specified [14].

Hospice care, unlike palliative care, focuses solely on symptom relief and end-of-life support [6], This often means that follow-up blood tests or imaging examinations are not performed. Most of the prediction methods mentioned above rely on these diagnostic techniques. Therefore, it is necessary to construct a lab-free survival prediction model specifically for advanced cancer patients receiving hospice care.

The least absolute shrinkage and selection operator (LASSO) method can be used to build a simple model with a limited number of predictors without compromising predictive accuracy [15]. Using data from the largest hospice unit in Eastern Guangdong, our team applied the LASSO method to construct separate survival prediction models for lung and gastrointestinal cancers [16, 17]. These models were presented in the form of laboratory-free nomograms. However, the range of cancer types encountered in hospice patients extends beyond lung and gastrointestinal cancers, and the previous models have limitations in their application. Therefore, we expanded the disease types, sample size, and improved the modeling method to construct a laboratory-free nomogram for all cancer types. Additionally, we developed a web calculator version to enhance its practicality.

Method

Study population

The study population was selected from the Hospice Unit department at The First Affiliated Hospital of Shantou University Medical College. The participants included patients who had been diagnosed with cancer between January 2008 and December 2018 and had a projected survival of less than six months. This study was approved by the Ethics Committee of The First Affiliated Hospital of Shantou University Medical College (approval number: B-2022–293). Due to the retrospective nature of the study, informed consent was not obtained. A total of 28 variables were included in the analysis and based on the 10 events per variable (EPV) principle, it was determined that there should be a minimum of 280 positive events.

Patient and public involvement

Patient and public involvement were not included in this study, as it was a retrospective cohort study that did not involve direct participation or input from patients or the public.

Data collection

Baseline data, including gender, age, area of residence, education level, understanding of the illness, smoking or drinking history, history of hypertension or diabetes, and past analgesic treatment, were collected from the patients' case records upon admission. Additional data on cancer, including carcinoma type, metastasis, previous treatment regimen, pain duration, accompanying

symptoms, quality of life (QOL) scale, Karnofsky Performance Scale (KPS), numeric rating scale (NRS) score, and analgesic treatment, were also collected. The variable classifications include the following three types: 1. Categorical variables: These variables include diagnosis type, status, gender, area, whether symptoms such as constipation, weight lose, insomnia, anorexia, nausea, vomiting, abdominal distention, tachypnea, and edema exist, whether radiotherapy, chemotherapy, and operation were received, and whether the tumor has metastasized. 2. Numerical variables: These variables include time (days) and age. 3. Ordinal variables: These variables include education level, understanding of disease, duration of illness, plan of analgesic treatment, quality of life (QOL), Karnofsky Performance Status (KPS), pain score (NRS), whether hypertension or diabetes is present, and whether the individual smokes or drinks alcohol.

The QOL scale, developed by Dr. Sun Yan and based on widely used international scales, assesses various aspects such as appetite, energy, attitude toward treatment, sleep, family relationships, fatigue, work relationships, pain, perception of cancer, daily activities, treatment side effects, and facial expressions. Each option is scored on a range of 1–5, resulting in a total score of 60 [18]. The KPS was used to assess patients' performance status, with a higher score indicating better health status [19]. The scale was translated into Chinese for the convenience of patients and staff. The NRS was used to assess the patients' level of pain, with scores ranging from 0–3, 4–6, and 7–10 indicating mild, moderate, and severe pain, respectively [20].

The optimal cutoff points for the QOL and KPS scores were determined using X-tile 3.6.1 software (Yale University, New Haven, CT, USA) [21]. Survival time was measured by counting the days from registration to the occurrence of an event (death or service interruption) during the first follow-up conducted by two qualified doctors.

Data analysis

The patients were randomly divided into two groups: a training group and a test group, with a ratio of 3:1. Missing data in each group were imputed using the multiple imputation algorithm [22]. Variables with more than 20% missing data or cases which lost outcome events were excluded. A total of 4,229 cases were included in the analyses. Continuous variables with a normal distribution were compared using the student t-test and presented as mean (± standard deviation), while continuous variables with a skewed distribution were compared using the Mann–Whitney U test and presented as median (interquartile range (IQR)). Categorical variables were compared using chi-square tests and presented as frequency (proportion).

The Kaplan–Meier curve with a risk table was used to display and compare the survival trends of the two groups. In 1996, Robert Tibshirani proposed the least absolute shrinkage and selection operator regression algorithm (LASSO) [23], which simultaneously performs variable selection and penalization to zero out coefficients of unimportant variables while retaining important ones, thus avoiding overfitting and underfitting. LASSO was applied in this study to establish a Cox proportional hazard regression model for survival analysis. After identifying the most representative variables through LASSO, these variables were used to construct a Cox model. In order to facilitate the practical use of the model, a nomogram was developed to estimate survival rates at 30, 45, and 60 days. Nomograms have the ability to transform a complex model into a single score and can be widely used for cancer prognosis [24].

The performance of the model was assessed using calibration curves with 1,000 bootstrap resamples and the area under the receiver operating characteristic curve (AUC). Additionally, decision curve analysis (DCA) was applied to evaluate the clinical benefit of the model by comparing the net benefit to default strategies, such as treating all patients or no patients [25].

Data analysis was conducted using R (Version 4.2.1, R Foundation, Vienna, Austria) and various R packages including 'survminer', 'VIM', 'tableone', 'glmnet', 'ggplot2', 'rms', 'ggDCA', 'survival', 'timeROC', and 'mice'. All hypothesis tests used a significance level of 0.05 and were two-sided.

Result

Baseline clinical characteristic

The analysis included 4,229 patients. According to the random allocation principle, 1,066 patients were assigned to the test set, while 3,163 patients were assigned to the training set, ensuring equal baselines between the two groups (Table 1). The median survival time for all patients was 44 days, and the median age was 61 years. The three most common types of cancer were lung, liver, and colorectal cancer. The patient population consisted of 2,701 males (64%) and 1,528 females (36%). Approximately 71% of the patients came from urban areas, and the majority (85%) had received primary education or higher. Only 45% of the patients had a comprehensive understanding of their illness. Metastasis was present in approximately 83% of the patients. In terms of therapy, 36% underwent surgery, 39% received chemotherapy, and 18% received radiotherapy. Most patients had received previous analgesic treatment, with only 18% reporting ineffective pain

Table 1 Baseline characteristics

Variable	Overall, $N=4,229$[1]	Test set, $N=1,066$[1]	Training set, $N=3,163$[1]		*p*-value[2]
Diagnosis type					0.4
Lung Cancer	1,183 (28%)	294 (28%)	889 (28%)		
Esophageal Cancer	408 (9.6%)	98 (9.2%)	310 (9.8%)		
Gastric Cancer	337 (8.0%)	101 (9.5%)	236 (7.5%)		
Colorectal Cancer	462 (11%)	123 (12%)	339 (11%)		
Liver Cancer	506 (12%)	120 (11%)	386 (12%)		
Gallbladder Cancer	40 (0.9%)	9 (0.8%)	31 (1.0%)		
Pancreatic Cancer	120 (2.8%)	30 (2.8%)	90 (2.8%)		
Breast Cancer	246 (5.8%)	61 (5.7%)	185 (5.8%)		
Ovary Cancer	42 (1.0%)	8 (0.8%)	34 (1.1%)		
Uterine Cancer	116 (2.7%)	20 (1.9%)	96 (3.0%)		
Urinary Cancer	168 (4.0%)	51 (4.8%)	117 (3.7%)		
Head and Neck Cancer	279 (6.6%)	68 (6.4%)	211 (6.7%)		
Hematological Cancer	43 (1.0%)	12 (1.1%)	31 (1.0%)		
Others	279 (6.6%)	71 (6.7%)	208 (6.6%)		
Time (days)	44 (20, 86)	44 (22, 86)	43 (20, 86)		0.3
Status					0.4
Censor	344 (8.1%)	93 (8.7%)	251 (7.9%)		
Dead	3,885 (92%)	973 (91%)	2,912 (92%)		
Gender					0.2
Female	1,528 (36%)	369 (35%)	1,159 (37%)		
Male	2,701 (64%)	697 (65%)	2,004 (63%)		
Age	61 (53, 71)	61 (53, 71)	61 (53, 70)		>0.9
Area					0.7
Rural	1,216 (29%)	302 (28%)	914 (29%)		
Urban	3,013 (71%)	764 (72%)	2,249 (71%)		
Education					0.4
Illiteracy	633 (15%)	142 (13%)	491 (16%)		
Primary School	2,047 (48%)	526 (49%)	1,521 (48%)		
Middle School	982 (23%)	261 (24%)	721 (23%)		
High School	453 (11%)	110 (10%)	343 (11%)		
High School Above	114 (2.7%)	27 (2.5%)	87 (2.8%)		
Understanding				0.5	
Complete Ignorance	2,322 (55%)	570 (53%)	1,752 (55%)		
Partial Understanding	647 (15%)	172 (16%)	475 (15%)		
Full Understanding	1,260 (30%)	324 (30%)	936 (30%)		
Metastasis	3,494 (83%)	876 (82%)	2,618 (83%)		0.7
Operation	1,537 (36%)	367 (34%)	1,170 (37%)		0.13
Chemotherapy	1,653 (39%)	422 (40%)	1,231 (39%)		0.7
Radiotherapy	763 (18%)	203 (19%)	560 (18%)		0.3
Duration					0.8
<1 Month	810 (19%)	204 (19%)	606 (19%)		
1-6 months	2,804 (66%)	708 (66%)	2,096 (66%)		
6-12 months	439 (10%)	105 (9.8%)	334 (11%)		
>12 months	176 (4.2%)	49 (4.6%)	127 (4.0%)		
Analgesic treatment					0.3
None	773 (18%)	207 (19%)	566 (18%)		
NSAIDS	635 (15%)	144 (14%)	491 (16%)		
Weak Opioids	1,415 (33%)	349 (33%)	1,066 (34%)		

Table 1 (continued)

Variable	Overall, $N=4,229$[1]	Test set, $N=1,066$[1]	Training set, $N=3,163$[1]	*p*-value[2]
Strong Opioids	1,406 (33%)	366 (34%)	1,040 (33%)	
Effect				0.6
Bad	777 (18%)	209 (20%)	568 (18%)	
Average	603 (14%)	147 (14%)	456 (14%)	
Good	2,318 (55%)	572 (54%)	1,746 (55%)	
Excellent	531 (13%)	138 (13%)	393 (12%)	
Constipation	1,942 (46%)	488 (46%)	1,454 (46%)	> 0.9
Weight Lose	3,757 (89%)	951 (89%)	2,806 (89%)	0.7
Insomnia	2,205 (52%)	562 (53%)	1,643 (52%)	0.7
Anorexia	3,435 (81%)	876 (82%)	2,559 (81%)	0.4
Nausea	1,035 (24%)	273 (26%)	762 (24%)	0.3
Vomiting	1,012 (24%)	263 (25%)	749 (24%)	0.5
Abdominal distention	803 (19%)	211 (20%)	592 (19%)	0.4
Tachypnea	1,364 (32%)	320 (30%)	1,044 (33%)	0.071
Edema	676 (16%)	161 (15%)	515 (16%)	0.4
QOL				0.2
< = 31	1,836 (43%)	445 (42%)	1,391 (44%)	
> 31	2,393 (57%)	621 (58%)	1,772 (56%)	
NRS				0.3
< = 3	421 (10.0%)	117 (11%)	304 (9.6%)	
4–6	2,234 (53%)	547 (51%)	1,687 (53%)	
> = 7	1,574 (37%)	402 (38%)	1,172 (37%)	
KPS				0.8
< = 30	1,248 (30%)	317 (30%)	931 (29%)	
40	1,816 (43%)	463 (43%)	1,353 (43%)	
> = 50	1,165 (28%)	286 (27%)	879 (28%)	
Hypertension	664 (16%)	167 (16%)	497 (16%)	> 0.9
Diabetes	398 (9.4%)	106 (9.9%)	292 (9.2%)	0.5
Smoke	761 (18%)	199 (19%)	562 (18%)	0.5
Drink	298 (7.0%)	73 (6.8%)	225 (7.1%)	0.8

[1] Median (IQR); n (%)

[2] Wilcoxon rank sum test; Pearson's Chi-squared test

relief. The overall survival function is presented in the risk table (Supplemental Fig. 1).

The best cut-off points for Karnofsky Performance Scale (KPS) and Quality of Life (QOL) scores were determined using X-tile 3.6.1 software (Yale University, New Haven, CT, USA). KPS scores were divided into three groups: 30 or less, 40, and 50 or more. QOL scores were categorized into two levels: 31 or less, and greater than 31. As shown in Supplementary Fig. 3, the selected cut-off values provide the greatest differentiation among various groups, hence these cut-off values are used.

Feature selection and construction of nomogram

The LASSO algorithm was employed for feature selection using all available variables in the training set. In LASSO regression with 10-fold cross-validation, the optimal λ value was found to be 0.063, corresponding to log (λ) = -2.770 following the one standard error. Based on the optimal log (λ) from the LASSO method, eight predictive factors with nonzero coefficients were selected. These factors included QOL, KPS, gender, duration of pain, presence of anorexia, abdominal distention, tachypnea, and edema (Fig. 1).

Multivariate analyses, incorporating all the aforementioned variables, were conducted using a Cox proportional hazards regression model to identify independent predictors. As shown in Supplemental Table 1, all eight variables were found to be independent predictors of survival days. According to the Hazard Ratio shown in Supplemental Table 1, KPS was the

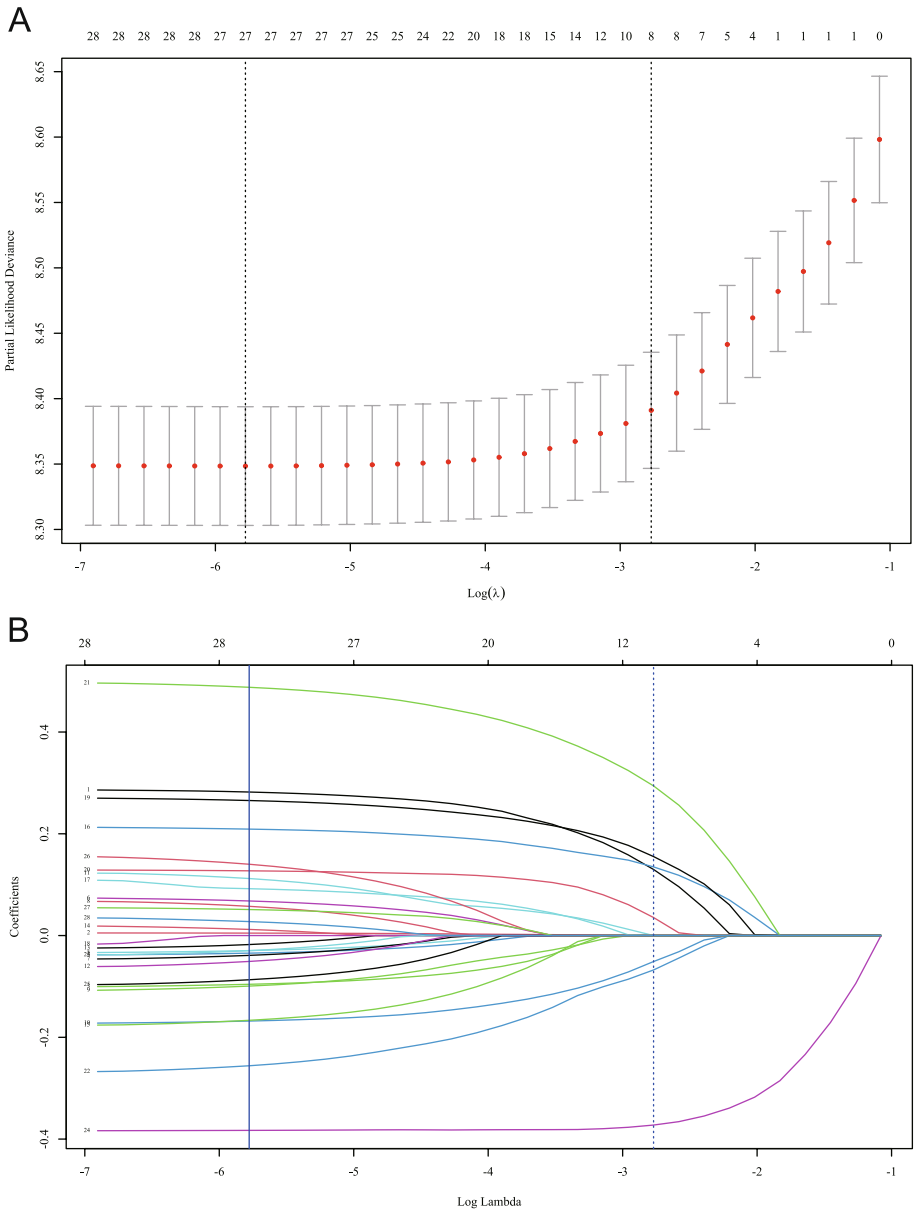

Fig. 1 Construction of a predictive model from the 28 prognostic factors. A: 8 prognostic factors were selected using LASSO Cox regression analysis. The two dotted vertical lines were drawn at the optimal scores by minimum criteria and 1-s.e. criteria

most protective factor, while edema was the most significant risk factor for survival days. Based on the cox hazards regression model and its coefficients, a nomogram was constructed (Fig. 2).

The nomogram enables clinicians to calculate the scores of the indicators and sum them up to obtain a total point. This total point can then be used to determine the probability of survival by aligning it with the axis of total points and the axis of survival probability.

Validation and performance evaluation of nomogram

Through survival analysis of the samples in this cohort, we found that the median survival time is approximately 45 days (Supplementary Fig. 1). Due to the short survival period of hospice care patients, we set the observation time to 1 month and used the median death time as the interval midpoint, thus selecting 30 days, 45 days, and 60 days as time points. The receiver operating characteristic (ROC) curve analysis was utilized to evaluate

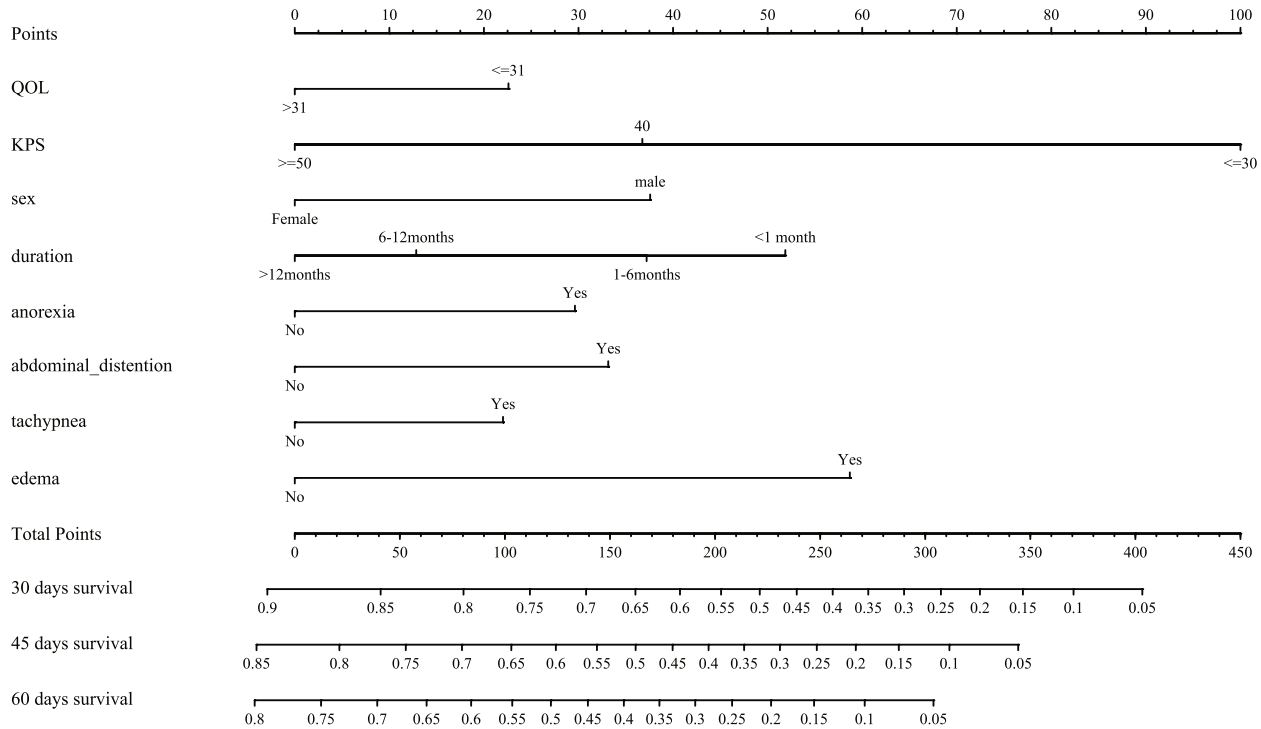

Fig. 2 Nomogram model for predicting 30-day, 45-day and 60-day overall survival (OS) in hospice care advanced cancer patients in the main training set

the performance of the nomogram on the test set (Supplemental Fig. 2). The AUC values were 0.7538 (0.7230–0.7845) at 30 days, 0.7342 (0.7040–0.7644) at 45 days, and 0.7324 (0.7014–0.7631) at 60 days, indicating good performance. The model demonstrated good calibration at 30 days, 45 days, and 60 days (Fig. 3). Moreover, the decision curve analysis (DCA) curves showed that the net benefit at 30 days, 45 days, and 60 days was superior across a broad threshold in both the training and test groups (Fig. 4), In this study, the significance of the Decision Curve Analysis (DCA) lies in evaluating whether interventions can bring benefits under specific mortality rates predicted by the model at particular time points. It is important to clarify that the expected mortality rate is not 100% at each time point.

Website of nomogram

A free and user-friendly web-based calculator of nomogram (https://lulingzero.shinyapps.io/SHHCP-NOMO/) was available online to help patients and physicians to calculate the survival probability of 30-, 45- and 60-day.

Discussion

There is considerable research on survival prognosis analyses of advanced cancer, with most predictive models incorporating both biological parameters and clinical symptoms such as PaP score and new-ChPS score [14, 26]. However, unlike palliative care, hospice care programs focus on helping terminally ill patients live each day to the fullest [6]. Therefore, measuring pain and clinical symptoms becomes crucial in hospice care, making previous models potentially unsuitable for patients receiving hospice care. Lingjun et al. developed a prognostic scale for advanced cancer that only included clinical symptoms and scales. However, traditional methods of choosing predictors may lead to challenges such as multiple collinearities and overfitting, which can limit the performance of the scale. By incorporating a penalized function, the LASSO algorithm can effectively penalize unimportant variables to zero while retaining the important ones [23]. This approach allows for the development of an effective and concise model, avoiding multiple collinearities and overfitting.

In this study, we constructed a nomogram based on the LASSO Cox regression model and developed an online version for convenient use by clinicians. The LASSO method selected eight variables, including QOL, KPS, gender, duration of pain, existence of anorexia, abdominal distention, tachypnea, and edema. We consider gender to be a significant prognostic factor for predicting the survival of hospice patients with advanced cancer. According to the 2020 cancer report published by the World Health

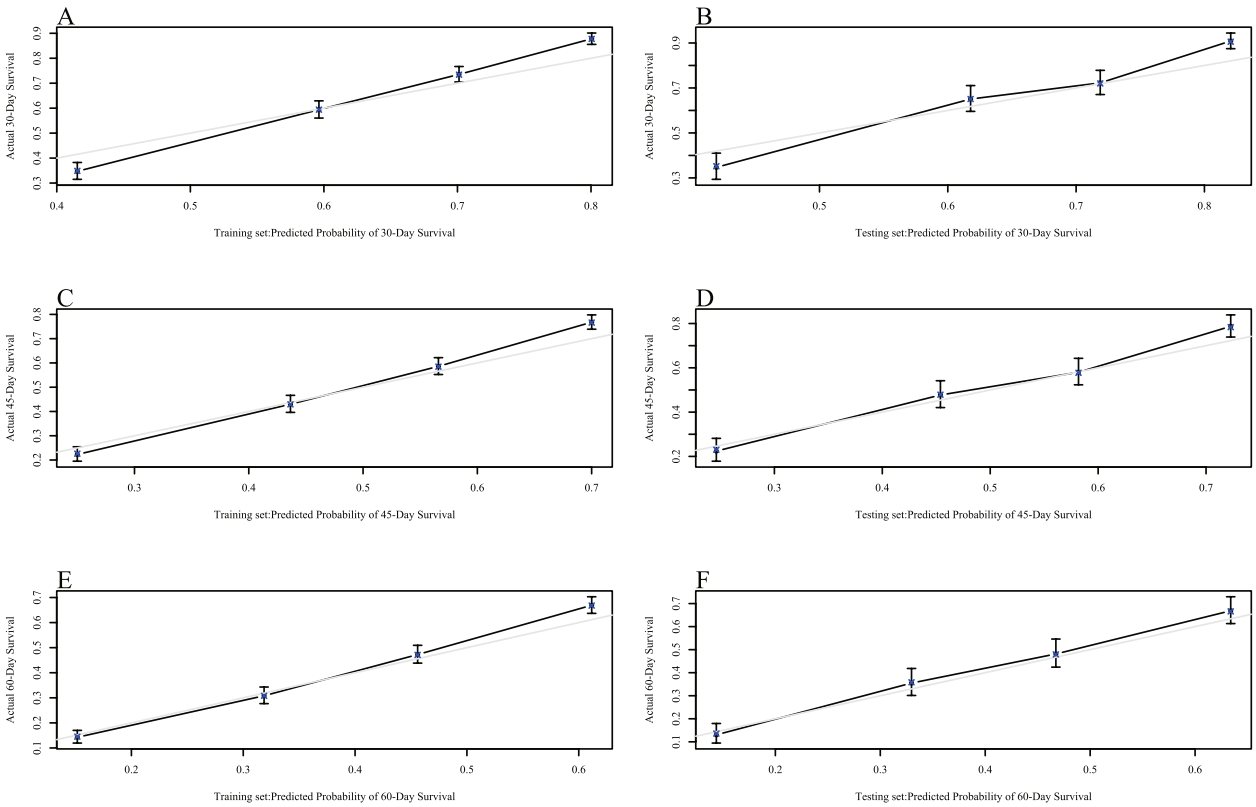

Fig. 3 Calibration curves for predicting overall survival rate by the nomogram in the training and test set. Calibration curves of the prognostic nomogram for 30-days overall survival (**A**), 45-days overall survival (**C**) and 60-days overall survival (**E**) in the training set; calibration curves for 30-days overall survival (**B**), 45-days overall survival (**D**), and 60-days overall survival (**F**) in the test set

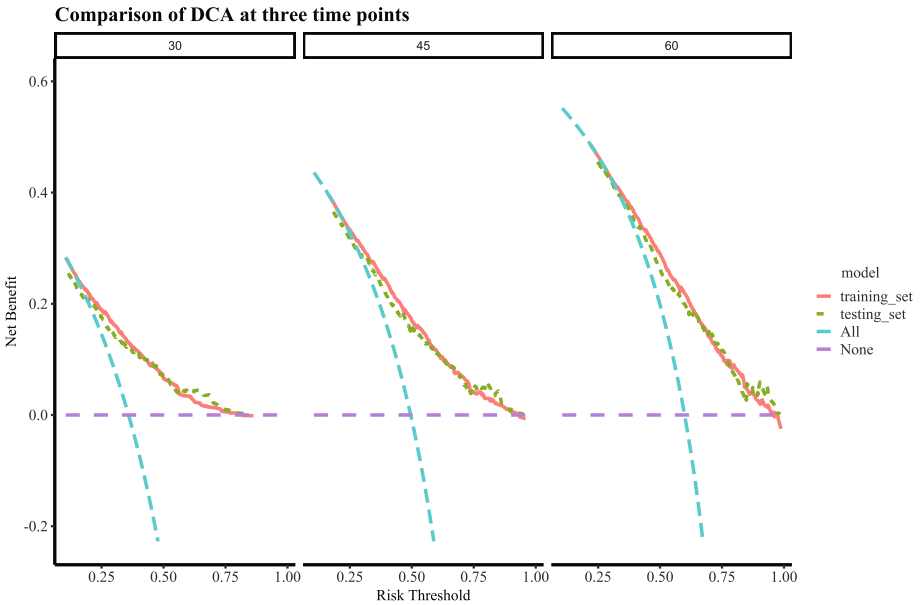

Fig. 4 The decision curves analysis curve of the nomogram of predicting 30-day, 45-day and 60-day overall survival (OS) in hospice care advanced cancer patients in the training and test set

Organization, the age-standardized incidence rate (120.8 vs. 84.2 per 100,000 people) and cumulative risk (12.59% vs. 8.86%) in the male population are both higher than those in the female population [27], suggesting that gender may play an important role in survival rates, The age-standardized incidence rate refers to the incidence rate adjusted for the population age structure, and cumulative risk refers to the probability of developing cancer over a lifetime. The KPS scale has been proven reliable for predicting survival in palliative care patients in Turkey [28]. Both KPS and QOL have been widely used in previous studies to predict survival rates and have shown certain predictive performance [13, 14, 29].

Notably, NRS was not included in the nomogram. Although pain was included in the new-ChPS scale, it had a lower *P*-value (< 0.01) in the univariate analysis results by the log-rank test, but a higher *P*-value (> 0.05) in the multivariate analysis using the Cox stepwise regression model [14]. This suggests the presence of an intermediary effect. Steele et al. found that baseline pain was not associated with the outcomes of patients with Stage IV Pancreatic Cancer, despite such an association being reported in newly diagnosed cases [30, 31]. However, in our model, QOL and pain duration were selected as predictors, as pain can greatly impact the quality of life [32], and a longer duration may correspond to a higher survival rate. These factors may mediate the relationship between survival prognosis and the degree of pain. Furthermore, anorexia, tachypnea, abdominal distention, and edema were also included in our model, as these clinical symptoms have been found to be related to survival duration [14, 33–35].

Compared to our team's previous models, the current model incorporates more parameters. It is worth mentioning that tachypnea, a new parameter included in the current model, has been suggested to be associated with survival [34, 35] The mechanism might involve advanced cancer-caused hypoalbuminemia leading to an increase in pleural and ascitic fluid, resulting in thoracic cavity compression. Additionally, due to the higher mortality rates of lung and gastrointestinal cancers in Chinese patients, most parameters from previous models for these cancers were also included. This is consistent with the predominance of patients with gastrointestinal and lung cancers among those who experienced the outcome event in this study. In the context of hospice care, the expected mortality rate of patients is typically close to 100% because the focus of care at this stage has shifted to symptom relief and improving quality of life. To prevent family members from misunderstanding the "net benefit" of the DCA as a life-extending benefit, it must be clarified that the "net benefit" in DCA refers to the clinical value of providing supportive care at specific predicted mortality rates at specific time points, rather than directly indicating the actual effect of extending life.

This model differs from currently widely used predictive tools (such as PPS, PPI, and PaP) in the following ways: 1. It does not require laboratory parameters; 2. The evaluation period is monthly; 3. It employs the LASSO method to construct the model, minimizing collinearity to the greatest extent. However, the commonality is that these models are all used to assess the survival rates of patients with advanced cancer.

There are several limitations in this study. First, the model was constructed using a retrospective database, which may introduce recall bias and data gaps. However, the study had a large sample size, and missing data were handled using multiple imputation. Second, the data were collected from a single center. Although the model was validated using cross-validation and a test set, external validation is still necessary. Third, the model's AUC, while acceptable, was not excellent since it only included clinical symptoms and scales as predictors. Considering the focus of hospice care and the financial status of the patients, a predictive model without biological factors may be more suitable. The decision curve analysis demonstrated good clinical utility.

To achieve better generality and assist clinicians, patients, and their families in making survival predictions, we developed a web-based survival predictive calculator, available at https://lulingzero.shinyapps.io/SHHCP-NOMO/. This platform aligns with the increasing use of smart devices and promotes the paperless approach.

Conclusion

In this study, we developed a nomogram for advanced cancer patients receiving hospice care, incorporating QOL, KPS, gender, duration of pain, existence of anorexia, abdominal distention, tachypnea, and edema. We also created a web-based calculator for predicting the survival rates at 30, 45, and 60 days. These methods can assist clinicians and patients in making more informed decisions, promoting the quality of life, and relieving the economic and psychological burdens.

Abbreviations

LASSO	Least Absolute Shrinkage and Selection Operator
AUC	Area Under the Curve
DCA	Decision Curve Analysis
CPS	Clinician Prediction of Survival
GPS	Glasgow Prognostic Score
PPS	Palliative Performance Scale
PPI	Palliative Prognostic Index
PaP	Palliative Prognostic Score
ChPS	Chinese Prognostic Scale
EPV	Events Per Variable
QOL	Quality Of Life
KPS	Karnofsky Performance Scale
NRS	Numeric Rating Scale

IQR Interquartile Range
ROC The Receiver Operating Characteristic Curve Analysis

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-025-22361-8.

Supplementary Material 1.
Supplementary Material 2.
Supplementary Material 3.
Supplementary Material 4.
Supplementary Material 5.

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Authors' contributions
Conceptualization, H.L. and X.C. ; methodology, X.C. and X.J. ; software, H.L. and Y.Z. ; validation, C.W. and M.W. ; investigation, S.Z. ; data curation, W.Z. and X.X. ; writing—original draft preparation, H.L. ; writing—review and editing, X.C. ; project administration, X.C. and X.J. ; funding acquisition, X.C. and X.J. . All authors have read and agreed to the published version of the manuscript.

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Data availability
The datasets generated and analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study was conducted in accordance with the Declaration of Helsinki, and approved the ethical review board of the First Hospital Affiliated of Shantou University Medical College (approval number: B-2022-293, date of approval: 2022-12-19). Requirement for informed consent was waived because the study was retrospective, and the identity of all patients remained undisclosed.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]Department of Gastroenterology, The First Affiliated Hospital of Shantou, University Medical College, Shantou, Guangdong, People's Republic of China. [2]Department of Pathology, The First Affiliated Hospital of Shantou University Medical College, Shantou, Guangdong, People's Republic of China. [3]Department of Gastroenterology, Puning People's Hospital, Jieyang 515300, China. [4]Department of Endoscopy Center, Shantou Central Hospital, 114 Waima Road, Shantou, Guangdong 515041, China. [5]Department of Gastroenterology, Yuebei People's Hospital, Shantou University Medical College, Shaoguan 512025, China.

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