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Original Research Article

Cost-saving prediction model of transfer to palliative care for terminal cancer patients in a Japanese general hospital

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ABSTRACT

Background: Although medical costs need to be controlled, there are no easily applicable cost prediction models of transfer to palliative care (PC) for terminal cancer patients.
Objective: Construct a cost-saving prediction model based on terminal cancer patients' data at hospital admission.
Study design: Retrospective cohort study.
Setting: A Japanese general hospital.
Patients: A total of 139 stage IV cancer patients transferred to PC, who died during hospitalization from April 2014 to March 2019.
Main outcome measure: Patients were divided into higher (59) and lower (80) total medical costs per day after transfer to PC. We compared demographics, cancer type, medical history, and laboratory results between the groups. Stepwise logistic regression analysis was used for model development and area under the curve (AUC) calculation.
Results: A cost-saving prediction model (AUC = 0.78, 95% CI: 0.70, 0.85) with a total score of 13 points was constructed as follows: 2 points each for age ≤ 74 years, creatinine ≥ 0.68 mg/dL, and lactate dehydrogenase ≤ 188 IU/L; 3 points for hemoglobin ≤ 8.8 g/dL; and 4 points for potassium ≤ 3.3 mEq/L.
Conclusion: Our model contains five predictors easily available in clinical settings and exhibited good predictive ability.

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KEYWORDS
cost-saving; palliative care; terminal cancer; prediction model; health economics; end-of-life

Introduction

Palliative care (PC) has been shown to improve the quality of life (QOL) of cancer patients and their families [1,2]. Previous studies of economic aspects have found that PC could lead to cost-savings in the treatment of terminal cancer patients [3–6]. It has been reported that 44.1% of cancer patients actively trade off care costs, duration, and QOL when deciding between life-extending treatment and PC [7]. However, transferring terminal cancer patients to the palliative care unit (PCU) is uncommon in Japan. In fiscal year 2018, the percentage of cancer patients who died in PCUs was 13.9%, whereas the percentage in other units (e.g., the intensive care unit) was 69.4% [8].

Many countries, including Japan, are facing increasing medical costs [9]. Total Japanese medical costs in fiscal year 2018 reached a record high of 43 trillion JPY, almost double the cost reported in fiscal year 1990 [10]. As in other medical fields, incorporating the concept of cost-saving into advanced cancer treatment policies is necessary to maintain national fiscal health while respecting the feelings and wishes of patients and their families.

To promote appropriate allocation of medical resources, patient classifications need to consider the most important determinants of resource consumption [11]. In addition, there is no significant cost-saving effect of PC for terminal cancer patients when PC interventions are not provided early after hospital admission [4]. Some factors have been reported to be associated with the cost of PC during hospitalization, such as Karnofsky performance status (KPS) scores [12,13]; however, there are no cost-saving prediction models of transfer to PC for cancer patients at end-of-life during hospitalization that can be easily applied in the clinical settings based on objective data on hospital admission (e.g., laboratory test data), without subjective assessments of the doctor or patient.

Therefore, we aimed to construct a cost-saving prediction model based on terminal cancer patients'

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objective data on hospital admission to allow medical staff to assess at an early stage whether transfer to PC could lead to cost-savings.

Materials and methods

Data sources and setting

We conducted a retrospective cohort study using the database from St. Luke's International Hospital in Tokyo, Japan. The PC department does not perform direct cancer therapy (e.g., chemotherapy) in this hospital. Instead, other usual care (UC) departments, for example, the medical oncology department, perform such therapies. To compare costs for terminal cancer patients, hospitalization data were divided into two periods for each patient: before (pre-PC) and after (post-PC) transfer to the PC department.

Cost data were gathered from the hospital's cost accounting system, HOPE/X-W (Fujitsu Limited, Japan). Other data were collected from the hospital's computerized medical records system, HOPE/EGMAIN-GX (Fujitsu Limited, Japan).

The study complied with the Declaration of Helsinki and the Ethical Guidelines for Medical and Health Research Involving Human Subjects [14], carried out by the opt-out method. The study protocol was approved by the research ethics board at St. Luke's International University (Receipt number: 20-R021) and by the Graduate School of Pharmaceutical Sciences, University of Tokyo (Receipt number: 2–9). We did not obtain individual patients' informed consent because it is not required for encoded administrative health data.

Sample

The inclusion criteria included patients aged 18 years or older, diagnosed with stage IV cancer before admission, who were transferred to PC during hospitalization, and subsequently died at St. Luke's International Hospital from April 2014 to March 2019. The exclusion criteria constituted patients who declined to participate, were transferred to PC more than once during their hospitalization, were transferred to PC on admission day, or who died of causes other than cancer. Patients with missing data were also excluded.

Candidate predictive factors

The aim of the study was to create a cost-saving prediction model that would generally apply in clinical settings on hospital admission. The following objective indicators were selected as candidate factors because terminal cancer patients might have difficulty communicating due to coma or dementia, and physicians' diagnostic criteria might vary by country or region. Data on the following clinical characteristics based on the date of admission were collected: age, sex, marital status, having at least one child, cancer type, medical history (history of chemotherapy, radiation therapy, and/or surgical intervention for cancer), and laboratory test data (albumin, alanine aminotransferase [ALT], aspartate aminotransferase [AST], blood urea nitrogen [BUN], chlorine [CL], creatinine [CRN], C-reactive protein [CRP], hemoglobin [HGB], potassium [K], lactate dehydrogenase [LDH], sodium [NA], platelets, and white blood cell count [WBC]) collected by routine blood draw. Regarding laboratory test data, since blood draw was performed only when clinically necessary and not daily in this hospital, we defined the first laboratory test data measured within the two days before and after admission as the laboratory test data on admission. Previous studies have shown that age [15,16], marital status [7,17,18], children living at home [19], and cancer type [7] predict the greater use of aggressive life-extending treatments such as chemotherapy, and that some laboratory test data are prognostic for terminal cancer patients [20–23]. Thus, these factors may also affect cost-saving. We posited that other variables (i.e., sex, medical history) would also be associated with cost-saving.

Costs

We measured the following pre-PC and post-PC costs: pharmacy (total cost of drugs), radiation therapy, surgery, medical supply, laboratory testing, diagnostic imaging, blood transfusion, rehabilitation, nursing, and other treatment (e.g., pressure ulcer care). We also calculated the total amount of these costs.

Pharmacy costs were based on Japanese drug prices. Nursing costs were calculated from total labor costs for nurses, including benefits and bonuses, divided by the total number of patients based on the number of hospitalized patients per day for each unit for each fiscal year. The other costs were estimated from Japanese medical fee points. We calculated costs per admission and per day. In this study, 100 JPY was equal to 1 USD. We divided patients into two groups: patients with higher (HC) and lower (LC) total costs per day for post-PC than pre-PC. That is, the group of patients with mean daily post-PC costs − pre-PC costs > 0 was

defined as the HC group and the group of patients with post-PC costs − pre-PC costs < 0 as the LC group.

Data analysis

We used the independent-samples t-test for continuous variables and the Fisher's exact test for categorical variables between HC and LC. Significance was set at $p < 0.05$. We also estimated the 95% confidence interval (CI) for continuous variables.

Regarding patient characteristics, continuous values were grouped to facilitate the development of prediction rules for clinical settings. Thus, we divided age and all laboratory test values into two groups, based on the Youden index [24]. Univariate analysis was performed to reveal relevant differences between HC and LC. All candidate predictors with $p < 0.1$ in the univariate analysis were included in a forward stepwise logistic regression model, with a criterion of $p < 0.05$ for final entry or removal. The predicted scores for each predictor were obtained based on the beta values in the final prediction model. A receiver operating characteristic (ROC) curve was then drawn, and the area under the curve (AUC) and LC rate based on the predicted scores were obtained [25]. If the prediction model had an AUC ≥ 0.7, it was considered to indicate good predictive ability [26]. For internal validation, a bootstrapping technique with 1000 iterations was used to simulate unbiased expected future performance [27]. All statistical analyses were conducted using JMP Pro version 15.2.0.

Results

Candidate predictive factors

A total of 155 patients were enrolled over five years. After excluding patients with missing laboratory test

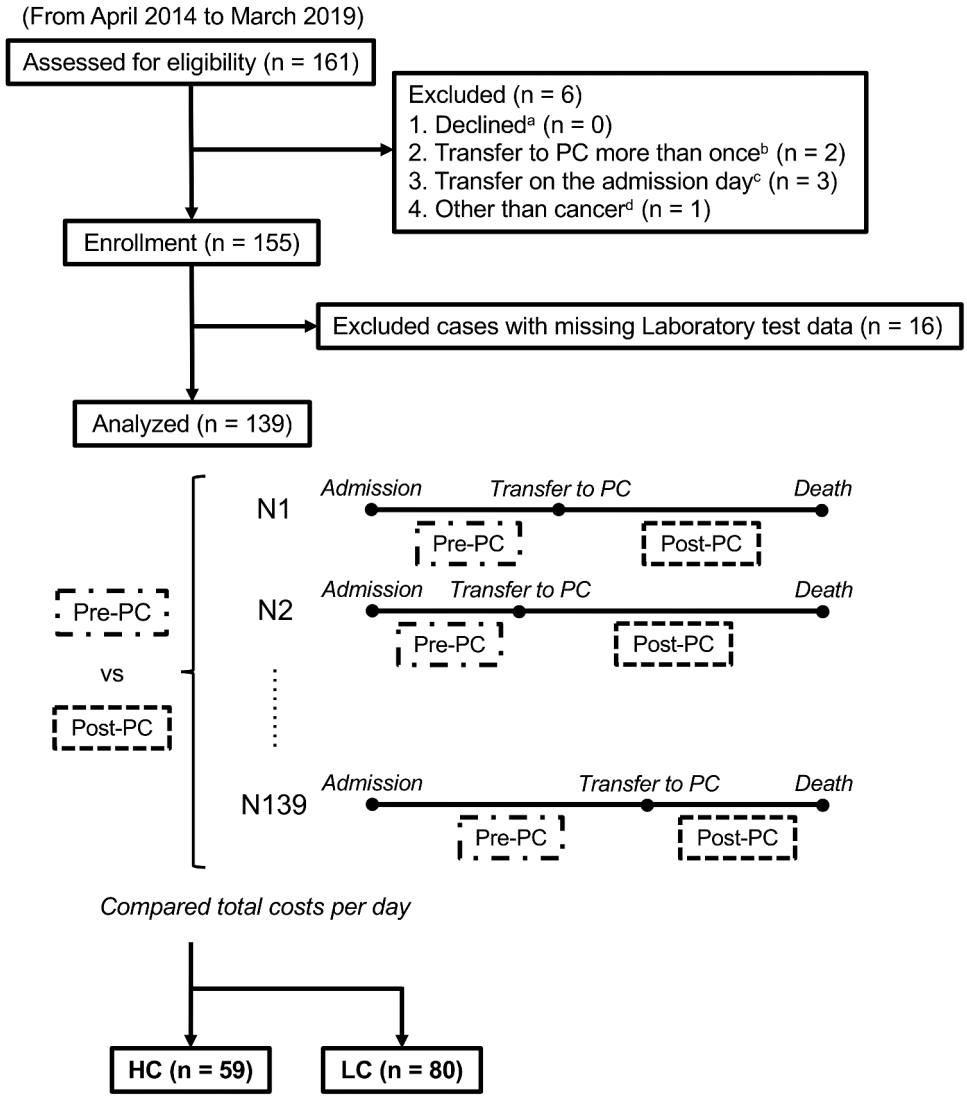

Figure 1. Flowchart of study participant enrollment.

data, 139 patients were included in the analysis (Figure 1). These patients were divided into two groups (59 HC and 80 LC) by comparing the total medical costs per day of pre-PC to those of post-PC. Based on the criterion of $p < 0.1$, nine candidate predictive factors were selected: age ≤ 74 years, presence of gastroenterological cancer, AST ≤ 206 IU/L, BUN ≥ 15.5 mg/dL, CRN ≥ 0.68 mg/dL, CRP ≥ 10.82 mg/dL, HGB ≤ 8.8 g/dL, K ≤ 3.3 mEq/L, and LDH ≤ 188 IU/L (Table 1).

Costs

Compared with HC, the LC group exhibited a significant reduction in total costs per day (92 USD [95% CI: 62, 122] vs −356 USD [95% CI: −535, −177], $p < 0.001$). Therefore, the LC group had 448 USD of cost-saving compared with HC. Moreover, compared with HC, LC significantly reduced costs for pharmacy, surgery, medical supplies, laboratory, diagnostic imaging, blood transfusion, and nursing costs per day, and tended to reduce radiation therapy, rehabilitation, and other treatment costs per day. However, there was no significant difference in the period of hospitalization between the two groups (Table 2).

Cost-saving prediction model

The forward stepwise logistic regression analysis was conducted with the nine candidate predictors (age ≤ 74 years, presence of gastroenterological cancer, AST ≤ 206 IU/L, BUN ≥ 15.5 mg/dL, CRN ≥ 0.68 mg/dL, CRP ≥ 10.82 mg/dL, HGB ≤ 8.8 g/dL, K ≤ 3.3 mEq/L, and LDH ≤ 188 IU/L). Cost-saving predictors finally selected at $p < 0.05$ were age ≤ 74 years, CRN ≥ 0.68 mg/dL, HGB ≤ 8.8 g/dL, K ≤ 3.3 mEq/L, and LDH ≤ 188 IU/L.

Based on each beta-coefficient, age ≤ 74 years, CRN ≥ 0.68 mg/dL, and LDH ≤ 188 IU/L were assigned 2 points each, HGB ≤ 8.8 g/dL was assigned 3 points, and K ≤ 3.3 mEq/L was assigned 4 points. The derived prediction model was confirmed by the bootstrap method. The predictive scores assigned to each factor were identical in both the original and bootstrapped results (Table 3).

We calculated the sum of points for each patient and drew a ROC curve (Figure 2). The AUC of this cost-saving prediction rule was 0.78 (95% CI: 0.70, 0.85). A cost-saving prediction model with a maximum score of 13 points was derived. When total scores were 0 points, 2–3 points, 4–5 points, 6–7 points, or more than 8 points, LC proportions were 0.0%, 44.4% 59.6%, 86.2%, and 100%, respectively (Figure 3).

Discussion

This study developed the first cost-saving prediction model of transfer to PC for cancer patients at end-of-life by comparing total costs per day of pre-PC with post-PC for patients who were transferred to PC and died during hospitalization. Based on objective indicators, the five predictors identified by multivariate logistic regression analysis were age ≤ 74 years, CRN ≥ 0.68 mg/dL, LDH ≤ 188 IU/L, HGB ≤ 8.8 g/dL, and K ≤ 3.3 mEq/L. Our model exhibited good predictive ability (AUC = 0.78, 95% CI: 0.70, 0.85) [26].

The predictors of our model are consistent with those suggested in other studies. Regarding age, a previous study suggested that the younger age of patients may affect PCU hospitalization costs [28]. Moreover, because the KPS score, which has been shown to be a cost predictor [12,13], is also a prognostic predictor for terminal cancer patients [29], it was reasonable to assume that LDH and HGB, known prognostic factors for such patients [21,22], would be cost predictors. In addition, the HGB factor may indicate a reduction in blood transfusion costs after transfer to PC. This is because blood transfusions that did not lead to symptom relief might have been discontinued in PC [30].

Our study is unique in that CRN (≥0.68 mg/dL) and K (≤3.3 mEq/L) were also included in the cost-saving model. Regarding CRN, an indicator of renal function, high CRN might suggest that urinary retention was caused by cancer progression. In UC, urinary retention can be treated with invasive and costly surgery, such as the placement of a retrograde ureteral stent, while in PC, considering QOL and prognosis, urinary retention is usually treated with a less invasive and less costly procedure, such as a urethral catheterization [31,32]. Hence, the CRN factor might indicate a decrease in surgery costs and a slight increase in other treatment costs after transfer to PC.

The K factor may reflect the decrease in laboratory costs after transfer to PC. This could be because K supplementation requires frequent blood tests, as overdose can be fatal, whereas electrolyte supplementation, including K, in PC is less aggressive than in UC, and consequently, laboratory tests are less frequent than in UC.

This model demonstrated an important improvement over previous studies [12,13]. Although previous studies have included the KPS score as a predictor [12,13], the score is affected by physician and patient subjectivity and patient cognitive function. Therefore, it may not be generally applicable to all clinical settings. In addition, previous studies have not shown

Table 1. Candidate predictors of PC cost-saving.

Variable	HC (n = 59)	LC (n = 80)	P[a]
Age, mean (95% CI), years	69.0 (65.9, 72.2)	66.5 (63.9, 69.0)	0.10
Predictive factors, n (%)			
Age ≤ 74 years	34 (57.6)	61 (76.3)	0.027
Sex, female	32 (54.2)	36 (45.0)	0.31
Marital status (presently married)	29 (49.2)	46 (57.5)	0.39
Having at least one child	34 (57.6)	48 (60.0)	0.86
Cancer types			
Breast	12 (20.3)	16 (20.0)	1.00
Gastroenterological	33 (55.9)	29 (36.3)	0.025
Gynecological	1 (1.7)	2 (2.5)	1.00
Head and neck	0 (0.0)	3 (3.8)	0.26
Hematologic	1 (1.7)	1 (1.3)	1.00
Lung	7 (11.9)	13 (16.3)	0.63
Urology	5 (8.5)	12 (15.0)	0.30
Others	0 (0.0)	4 (5.0)	0.14
Medical history[b]			
Chemotherapy	45 (76.3)	61 (76.3)	1.00
Radiation therapy	16 (27.1)	26 (32.5)	0.58
Surgical intervention	28 (47.5)	32 (40.0)	0.39
Laboratory tests			
Albumin ≥ 3.2 g/dL	12 (20.3)	22 (27.5)	0.43
ALT ≤ 31 IU/L	33 (55.9)	52 (65.0)	0.30
AST ≤ 206 IU/L	53 (89.8)	78 (97.5)	0.071
BUN ≥ 15.5 mg/dL	42 (71.2)	67 (83.8)	0.096
CL ≤ 99 mEq/L	27 (45.8)	47 (58.8)	0.17
CRN ≥ 0.68 mg/dL	29 (49.2)	61 (76.3)	0.001
CRP ≥ 10.82 mg/dL	16 (27.1)	35 (43.8)	0.051
HGB ≤ 8.8 g/dL	5 (8.5)	24 (30.0)	0.003
K ≤ 3.3 mEq/L	1 (1.7)	9 (11.3)	0.044
LDH ≤ 188 IU/L	5 (8.5)	16 (20.0)	0.092
NA ≥ 130 mEq/L	47 (79.7)	71 (88.8)	0.16
Platelets ≤ 226,000/mm^3	21 (35.6)	40 (50.0)	0.12
WBC ≤ 6,800/μL	12 (20.3)	23 (28.8)	0.32

PC: palliative care, HC: patients with higher total medical costs per day after transfer to the PC department than before transfer, LC: patients with lower total medical costs per day after transfer to the PC department than before transfer, CI: confidence interval, ALT: alanine aminotransferase, AST: aspartate aminotransferase, BUN: blood urea nitrogen, CL: chlorine, CRN: creatinine, CRP: C-reactive protein, HGB: hemoglobin, K: potassium, LDH: lactate dehydrogenase, NA: sodium, WBC: white blood cell count.

[a]P values were calculated by the independent-samples t-test for continuous variables and Fisher's exact test for categorical variables.

[b]'Medical history' was defined as the number of patients who received chemotherapy, radiation therapy, or surgical intervention for cancer before admission.

a prediction model for the cost-saving probability when terminal cancer patients are transferred to PC [12,13]. Our model allows the user to sum only five scores assigned to each predictor to determine the probability of cost-saving following the transfer of terminal cancer patients to PC, enabling quick and easy application in clinical settings.

There are some limitations to our study. First, although the most useful outcome measure for decision makers and the preferred dependent variable in primary analyses [33], we did not evaluate the total medical cost as an outcome measure because it was impossible to exclude the effect of variation in the period of hospitalization between pre-PC and post-PC. For example, if a patient is admitted to pre-PC (600 USD/day) for 5 days and to post-PC (400 USD/day) for 10 days, total medical costs of pre-PC (3,000 USD) are lower than those of post-PC (4,000 USD), but this result only reflects the difference in the period of hospitalization, not the effect of cost-saving. Thus, our selected outcome (cost per day) was adjusted for the period of hospitalization, to account for variability.

Second, this study was based on data from a single hospital, with a limited number of patients. Therefore, our final cost-saving prediction model may be overfitted. Although internal validation showed that this model was relatively robust, external validation is needed in future studies.

Third, some costs (e.g., the cost of equipment depreciation, food, and utilities) could not be included in the total costs because these data did not exist for each patient. Thus, the actual treatment costs might be higher than the total costs calculated from the hospital data.

Fourth, approximately 10% (16/155) of the enrolled patients were excluded owing to missing laboratory tests data. The missing data may have occurred because

Table 2. Direct costs before and after transfer to PC.

	HC (n = 59)			LC (n = 80)			P[b] (Net)
Cost, USD[a]	Pre-PC	Post-PC	Net	Pre-PC	Post-PC	Net	
Per admission, mean (95% CI)							
Total	4,744 (3,327, 6,162)	5,037 (3,747, 6,327)	292(−1,495, 2,080)	9,219(5,898, 12,540)	5,148(4,057, 6,240)	−4,071(−7,502, −641)	0.027
Pharmacy	960(522, 1,399)	890(600, 1,180)	−70(−542, 401)	1,208(890, 1,526)	1,080(762, 1,398)	−128(−541, 286)	0.86
Radiation therapy	93(−38, 225)	0(0, 0)	−93(−225, 38)	152(17, 287)	0(0, 0)	−152(−287, −17)	0.54
Surgery	0(0, 0)	0(0, 0)	0(0, 0)	942(324, 1,559)	14(−13, 40)	−928(−1,544, −312)	0.004
Medical supply	38(21, 56)	34(22, 46)	−4(−22, 13)	409(228, 590)	31(18, 43)	−378(−560, −196)	<0.001
Laboratory	530(404, 657)	134(84, 184)	−397(−522, −271)	868(697, 1,039)	122(92, 152)	−746(−916, −576)	0.001
Diagnostic imaging	272(205, 339)	63(42, 84)	−209(−279, −140)	341(284, 398)	65(44, 87)	−276(−336, −216)	0.15
Blood transfusion	292(−170, 754)	225(−91, 540)	−68(−414, 279)	2,698(172, 5,224)	0(0, 0)	−2,698(−5,224, −172)	0.043
Rehabilitation	180(43, 316)	147(74, 219)	−−33(−173, 107)	164(76, 251)	155(81, 230)	−8(−109, 93)	0.77
Nursing	2,114(1,640, 2,587)	3,067(2,249, 3,886)	953(40, 1,867)	2,142(1,639, 2,644)	3,208(2,527, 3,889)	1,067(286, 1,847)	0.85
Other treatment	264(177, 351)	478(339, 617)	214(58, 369)	296(219, 374)	473(354, 591)	176(55, 298)	0.71
Per day, mean (95% CI)							
Total	247(220, 273)	339(297, 381)	92 (62, 122)	651(473, 829)	295(284, 306)	−356 (−535, −177)	<0.001
Pharmacy	46(33, 59)	72(50, 94)	26 (14, 38)	91(64, 118)	62(53, 71)	−29 (−55, −3)	<0.001
Radiation therapy	2(−1, 5)	0(0, 0)	−2 (−5, 1)	7(0, 14)	0(0, 0)	−7 (−14, 0)	0.18
Surgery	0(0, 0)	0(0, 0)	0(0, 0)	38(16, 59)	0(0, 1)	−37 (−59, −16)	<0.001
Medical supply	2(1, 3)	4(2, 6)	1 (−1, 2)	23(12, 35)	2(2, 3)	−21 (−32, −10)	<0.001
Laboratory	33(28, 39)	10(7, 14)	−23 (−29, −17)	90(73, 108)	10(7, 13)	−80 (−97, −64)	<0.001
Diagnostic imaging	16(13, 19)	7(2, 12)	−9 (−15, −4)	35(28, 43)	4(3, 6)	−31 (−39, −23)	<0.001
Blood transfusion	7(−4, 19)	14(−6, 35)	7 (−7, 20)	194(21, 368)	0(0, 0)	−194 (−368, −21)	0.024
Rehabilitation	6(3, 9)	7(5, 9)	1 (−2, 3)	7(5, 9)	6(4, 8)	−1 (−3, 1)	0.24
Nursing	119(115, 122)	187(184, 190)	69(64, 73)	142(130, 154)	183(181, 185)	41(29, 53)	<0.001
Other treatment	15(12, 18)	37(17, 58)	22 (4, 40)	23(19, 26)	27(23, 31)	4 (1, 7)	0.050
Period, day	17.9(13.8, 22.0)	16.5(12.1, 20.9)	−1.5(−7.1, 4.2)	15.9(12.1, 19.6)	17.4(13.7, 21.2)	1.6(−3.2, 6.4)	0.42

PC: palliative care, HC: patients with higher total medical costs per day after transfer to the PC department than before transfer, LC: patients with lower total medical costs per day after transfer to the PC department than before transfer, pre-PC: patients before being transferred to the PC department, post-PC: patients after being transferred to the PC department, CI: confidence interval.

[a]100 JPY = 1 USD.

[b]P values were calculated by the independent-samples t-test for continuous variables.

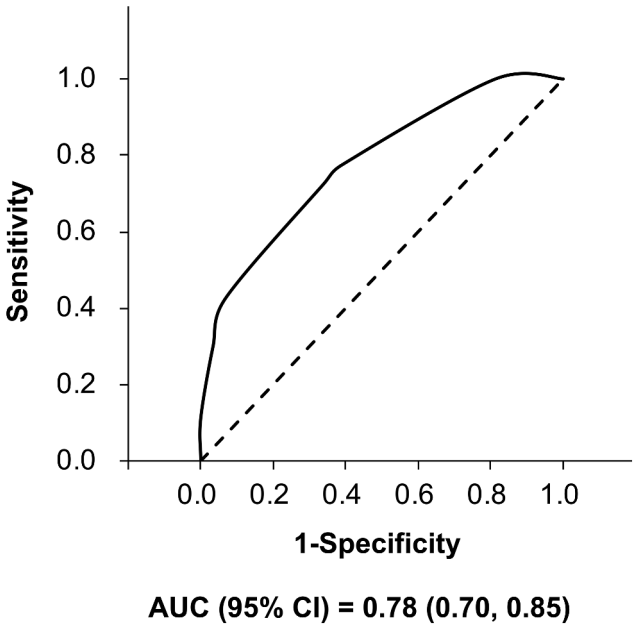

Figure 2. ROC curve of cost-saving prediction scores.

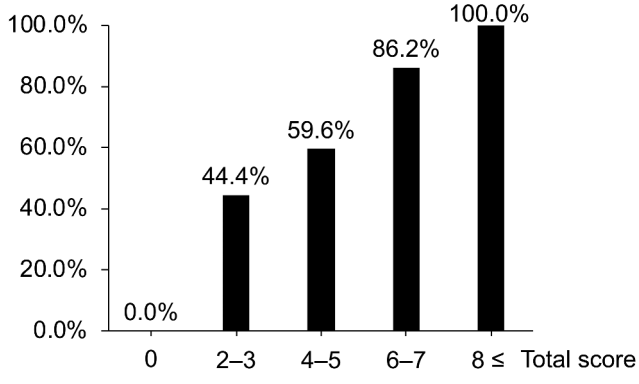

Figure 3. Proportion of terminal cancer patients with daily medical cost reduction after transfer to the PC department based on cost-saving prediction scores.

these patients were so sick that a blood draw could not be conducted. Our results may only apply to terminal cancer patients sick enough to be considered for transfer to PC but well enough to withstand blood draw.

Fifth, comorbidities were not included as candidate predictors during the development of this pilot

Table 3. Results of stepwise logistic regression: determinants of patients with lower medical costs after transfer to PC than before transfer.

Predictor	Odds ratio (95% CI)	P[a]	Original β[b] (95% CI)	Bootstrapped β[c] (95% CI)	Predictive scores[d]
Age ≤ 74 years	2.7 (1.2, 6.2)	0.021	0.50 (0.08, 0.93)	0.50 (0.04, 1.00)	2
CRN ≥ 0.68 mg/dL	3.2 (1.4, 7.0)	0.005	0.57 (0.18, 0.98)	0.62 (0.23, 1.09)	2
HGB ≤ 8.8 g/dL	4.8 (1.6, 14.6)	0.005	0.79 (0.27, 1.39)	0.82 (0.28, 1.66)	3
K ≤ 3.3 mEq/L	9.9 (1.2, 85.2)	0.036	1.15 (0.25, 2.63)	1.21 (0.31, 9.18)	4
LDH ≤ 188 IU/L	3.7 (1.1, 12.3)	0.036	0.65 (0.07, 1.30)	0.67 (0.06, 1.44)	2

PC: palliative care, CI: confidence interval, CRN: creatinine, HGB: hemoglobin, K: potassium, LDH: lactate dehydrogenase.
[a]P values were calculated by logistic regression analysis.
[b]'Original β' was the logistic regression beta-coefficient calculated from the original model.
[c]'Bootstrapped β' was the logistic regression beta-coefficient confirmed by the bootstrap validation.
[d]'Predictive scores' were obtained based on the beta-coefficient.

model for the following two reasons: (1) the data on comorbidities were unreliable because it was difficult to identify any such missing data as this was a retrospective cohort study; (2) the type of disease, much less the type of comorbidity, had a lower priority as a candidate factor than factors such as the age and the family structure because the end-of-life care generally focuses on improving QOL of patients and their families [1]. However, a comorbidity requiring high medical costs may affect the outcome. Thus, comorbidities may need to be included as candidate predictors to improve the prediction model in future studies.

Finally, this model applies solely to terminal cancer patients with approximately one month of life expectancy and may not be applicable to terminal patients with longer life expectancy or with non-cancer diagnoses. This was because the patients in this study were terminal cancer patients and died on average approximately one month after admission for both HC (17.9 + 16.5 = 34.4 days) and LC (15.9 + 17.4 = 33.3 days) groups, based on the period in Table 2. Further research is needed to develop the use of the model with other populations.

Conclusions

Our study demonstrated the first cost-saving prediction model consisting of five predictors: age ≤ 74 years, CRN ≥ 0.68 mg/dL, HGB ≤ 8.8 g/dL, K ≤ 3.3 mEq/L, and LDH ≤ 188 IU/L. This prediction model exhibited good predictive ability, and the formula is easy to calculate in a clinical setting. This model may help provide a cost-saving prediction rule for healthcare providers who need to consider the economic aspects of the transfer to PC for terminal cancer patients.

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