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

Yuki Hashimoto a,b, Akitoshi Hayashi c, Takashi Tonegawa d, Lida Teng a and Ataru Igarashi c

*Department of Health Economics and Outcomes Research, Graduate School of Pharmaceutical Sciences, the University of Tokyo, Tokyo, Japan; †Department of Pharmacy, St. Luke’s International Hospital, Tokyo, Japan; ‡Palliative Care Department, St. Luke’s International Hospital, Tokyo, Japan; §Medical Affairs Department, St. Luke’s International Hospital, Tokyo, Japan

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.

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’...
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], chloride [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

![Flowchart of study participant enrollment](image-url)

**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 \( \leq 74 \) years, presence of gastroenterological cancer, AST \( \leq 206 \) IU/L, BUN \( \geq 15.5 \) mg/dL, CRN \( \geq 0.68 \) mg/dL, CRP \( \geq 10.82 \) mg/dL, HGB \( \leq 8.8 \) g/dL, K \( \leq 3.3 \) mEq/L, and LDH \( \leq 188 \) 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 \( \leq 74 \) years, presence of gastroenterological cancer, AST \( \leq 206 \) IU/L, BUN \( \geq 15.5 \) mg/dL, CRN \( \geq 0.68 \) mg/dL, CRP \( \geq 10.82 \) mg/dL, HGB \( \leq 8.8 \) g/dL, K \( \leq 3.3 \) mEq/L, and LDH \( \leq 188 \) IU/L). Cost-saving predictors finally selected at \( p < 0.05 \) were age \( \leq 74 \) years, CRN \( \geq 0.68 \) mg/dL, HGB \( \leq 8.8 \) g/dL, K \( \leq 3.3 \) mEq/L, and LDH \( \leq 188 \) IU/L.

Based on each beta-coefficient, age \( \leq 74 \) years, CRN \( \geq 0.68 \) mg/dL, and LDH \( \leq 188 \) IU/L were assigned 2 points each, HGB \( \leq 8.8 \) g/dL was assigned 3 points, and K \( \leq 3.3 \) 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 \( \leq 74 \) years, CRN \( \geq 0.68 \) mg/dL, LDH \( \leq 188 \) IU/L, HGB \( \leq 8.8 \) g/dL, and K \( \leq 3.3 \) 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 (\( \geq 0.68 \) mg/dL) and K (\( \leq 3.3 \) 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
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.

|                      | Pre-PC (n = 59) | Post-PC (n = 80) | Net (Net) | Pre-PC (n = 59) | Post-PC (n = 80) | Net (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) |
| 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) |
| Radiation therapy    | 93 (−38, 225) | 0 (0, 0) | −93 (−225, 38) | 152 (17, 287) | 0 (0, 0) | −152 (−287, −17) |
| Surgery              | 0 (0, 0) | 0 (0, 0) | −522 | 868 (697, 1,039) | 122 (92, 152) | −746 (−916, −576) |
| Medical supply       | 38 (21, 56) | 34 (22, 46) | −4 (−22, 13) | 409 (228, 590) | 311 (18, 43) | −378 (−560, −196) |
| Laboratory           | 530 (404, 657) | 134 (84, 184) | −397 (−522) | 2,868 (1,979, 3,772) | 122 (92, 152) | −746 (−916, −576) |
| Diagnostic imaging   | 272 (205, 339) | 63 (42, 84) | −29 (−279, 140) | 341 (284, 398) | 65 (44, 87) | −276 (−336, −216) |
| Blood transfusion    | 292 (−170, 754) | 225 (−91, 540) | −68 (−414, 279) | 2,698 (172, 5,224) | 0 (0, 0) | −2,698 (−5,224, −172) |
| Rehabilitation       | 180 (43, 316) | 147 (74, 219) | −33 (−173, 107) | 164 (76, 251) | 155 (81, 230) | −8 (−109, 93) |
| Nursing              | 2,114 (1,640, 2,587) | 3,067 (2,245, 3,886) | 953 (40, 1,867) | 2,142 (1,639, 2,644) | 3,208 (2,527, 3,889) | 0.001 |
| Other treatment      | 264 (177, 351) | 478 (339, 617) | 214 (58, 369) | 296 (219, 374) | 473 (354, 591) | 176 (55, 298) |
| **Per day, mean (95% CI)** |                 |                 |           |                 |                 |           |
| Total                | 2,474 (220, 273) | 339 (297, 381) | 92 (62, 122) | 651 (473, 829) | 295 (284, 306) | −356 (−535, −177) |
| Pharmacy             | 46 (33, 59) | 72 (50, 94) | 26 (14, 38) | 91 (64, 118) | 62 (53, 71) | −29 (−55, −3) |
| Radiation therapy    | 2 (−1, 5) | 0 (0, 0) | −2 (−5, 1) | 7 (0, 14) | 0 (0, 0) | −7 (−14, 0) |
| Surgery              | 0 (0, 0) | 0 (0, 0) | 0 (0, 0) | 38 (16, 59) | 0 (0, 0) | −37 (−59, −16) |
| Medical supply       | 2 (1, 3) | 42 (6, 6) | 1 (−1, 2) | 23 (12, 35) | 2 (2, 3) | −21 (−32, −10) |
| Laboratory           | 33 (28, 39) | 107 (14, 17) | −23 (−29, −17) | 90 (73, 108) | 10 (7, 13) | −80 (−97, −64) |
| Diagnostic imaging   | 16 (13, 19) | 7 (2, 12) | −9 (−15, −4) | 35 (28, 43) | 4 (3, 6) | −31 (−39, −23) |
| Blood transfusion    | 7 (−4, 19) | 14 (−6, 35) | 7 (−7, 20) | 194 (21, 368) | 0 (0, 0) | −194 (−368, −21) |
| Rehabilitation       | 6 (3, 9) | 7 (5, 9) | 1 (−2, 3) | 7 (5, 9) | 6 (4, 8) | −1 (−3, 1) |
| Nursing              | 119 (115, 122) | 187 (184, 190) | 69 (64, 73) | 142 (130, 154) | 183 (181, 185) | 41 (29, 53) |
| Other treatment      | 15 (12, 18) | 37 (17, 58) | 22 (4, 40) | 23 (19, 26) | 27 (23, 31) | 4 (1, 7) |
| **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) |

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 being transferred to the PC department; Post-PC: patients after being transferred to the PC department; CI: confidence interval.

a100 JPY = 1 USD.

bP 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
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.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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* | Original βb | Bootstrapped βc | Predictive scoresd |
|-----------|---------------------|-----|-------------|-----------------|-------------------|
| 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, 4.18) | 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.

*p values were calculated by logistic regression analysis.

bOriginal β was the logistic regression beta-coefficient calculated from the original model.

cBootstrapped β was the logistic regression beta-coefficient confirmed by the bootstrap validation.

dPredictive scores were obtained based on the beta-coefficient.

Funding

The authors have no funding to report.

ORCID

Yuki Hashimoto http://orcid.org/0000-0003-0629-0814
Ataru Igarashi http://orcid.org/0000-0001-6307-6916

References

[1] Malhotra C, Faroqui MA, Kanesvaran R, et al. Comparison of preferences for end-of-life care among patients with advanced cancer and their caregivers: a discrete choice experiment. Palliat Med. 2015;29(9):842–850.
[2] Gaertner J, Siemens W, Meerpohl JJ, et al. Effect of specialist palliative care services on quality of life in adults with advanced incurable illness in hospital, hospice, or community settings: systematic review and meta-analysis. BMJ. 2017;357:j2925.
[3] Nathaniel JD, Garrido MM, Chai EJ, et al. Cost savings associated with an inpatient palliative care unit: results from the first two years. J Pain Symptom Manage. 2015;50(2):147–154.
[4] May P, Garrido MM, Cassel JB, et al. Prospective cohort study of hospital palliative care teams for inpatients with advanced cancer: earlier consultation is associated with larger cost-saving effect. J Clin Oncol. 2015;33(25):2745.
[5] Yadav S, Heller IW, Schaefer N, et al. The health care cost of palliative care for cancer patients: a systematic review. Support Care Cancer. 2020;28:4561–4573.
[6] Hashimoto Y, Hayashi A, Teng L, et al. Real-world cost-effectiveness of palliative care for terminal cancer patients in a Japanese general hospital. J Palliat Med. 2021. DOI:10.1089/jpm.2020.0649.
[7] Finkelstein E, Malhotra C, Chay J, et al. Impact of treatment subsidies and cash payouts on treatment choices at the end of life. Value Health. 2016;19(6):788–794.
[8] Masukawa K, Miyashita M Data on palliative care in Japan. In: Kizawa Y, Takamiya Y, Shima Y, et al., editors. Hospice palliative care white paper. 1st ed. Tokyo (Japan): Seikaisha; 2020. p. 63–99. Japanese.
[9] OECD Health Statistics 2021 [Internet]. Economic references. Organisation for Economic Co-operation
and Development. 2021 [cited 2021 Aug 1]. Available from: http://www.oecd.org/health/health-data.htm
[10] Vital Statistics Japan [Internet]. Ministry of Health, Labour and Welfare. 2019 [cited 2021 Aug 3]. Available from: https://www.mhlw.go.jp/toukei/saikin/hw/jinkou/kaku_teiki18/index.html. Japanese
[11] Hopfe M, Stucki G, Marshall R, et al. Capturing patients’ needs in carminax: a systematic literature review on the value of adding functioning information in reimbursement systems. BMC Health Serv Res. 2015;16:1–17.
[12] Becker C, Leidl R, Schildmann E, et al. A pilot study on patient-related costs and factors associated with the cost of specialist palliative care in the hospital: first steps towards a patient classification system in Germany. Cost Eff Resour Alloc. 2018;16(1):1–11.
[13] Rozman LM, Campolina AG, Patiño EG, et al. Factors associated with the costs of palliative care: a retrospective cost analysis at a university cancer hospital in Brazil. J Palliat Med. 2021;24(11):1481–1488.
[14] Ministry of Education, Culture, Sports, Science and Technology, Ministry of Health, Labour and Welfare. Ethical guidelines for medical and health research involving human subjects. [cited 2022 Mar 15]. Available from: https://www.lifescience.mext.go.jp/files/pdf/n2181_01.pdf.
[15] Hamel MB, Teno JM, Goldman L, et al. Patient age and decisions to withhold life-sustaining treatments from seriously ill, hospitalized adults. Ann Intern Med. 1999;130(2):116–125.
[16] Hamel MB, Davis RB, Teno JM, et al. Older age, aggressiveness of care, and survival for seriously ill, hospitalized adults. Ann Intern Med. 1999;131(10):721–728.
[17] Potosky AL, Saxman S, Wallace RB, et al. Population variations in the initial treatment of non–small-cell lung cancer. J Clin Oncol. 2004;22(16):3261–3268.
[18] Dobie SA, Baldwin LM, Dominitz JA, et al. Completion of therapy by medicare patients with stage III colon cancer. J Natl Cancer Inst. 2006;98(9):610–619.
[19] Yellen SB, Cella DF. Someone to live for: social well-being, parenthood status, and decision-making in oncology. J Clin Oncol. 1995;13(5):1255–1264.
[20] Kikuchi N, Ohmori K, Kuriyama S, et al. Survival prediction of patients with advanced cancer: the predictive accuracy of the model based on biological markers. J Pain Symptom Manage. 2007;34(6):600–606.
[21] Kao YH, Chen CN, Chiang JK, et al. Predicting factors in the last week of survival in elderly patients with terminal cancer: a prospective study in southern Taiwan. J Formos Med Assoc. 2009;108(3):231–239.
[22] Suh SY, Choi YS, Shim JY, et al. Construction of a new, objective prognostic score for terminally ill cancer patients: a multicenter study. Support Care Cancer. 2010;18(2):151–157.
[23] Ohde S, Hayashi A, Takahashi O, et al. A 2-week prognostic prediction model for terminal cancer patients in a palliative care unit at a Japanese general hospital. Palliat Med. 2011;25(2):170–176.
[24] Youden W. Index for rating diagnostic tests. Cancer. 1950;3:32–35.
[25] Sullivan LM, Massaro JM, RB D Sr. Presentation of multivariate data for clinical use: the Framingham Study risk score functions. Stat Med. 2004;23(10):1631–166y0.
[26] Fischer JE, Bachmann LM, Jaeschke R. A readers’ guide to the interpretation of diagnostic test properties: clinical example of sepsis. Intensive Care Med. 2003;29(7):1043–1051.
[27] Steyerberg EW, Harrell FE Jr, Borsboom GJ, et al. Internal validation of predictive models: efficiency of some procedures for logistic regression analysis. J Clin Epidemiol. 2001;54(8):774–781.
[28] Tibi-Lévy Y, Le Vaillant M, de Pouvourville G. Determinants of resource utilization in four palliative care units. Palliat Med. 2006;20(2):95–106.
[29] Pirovano M, Maltoni M, Nanni Q, et al. A new palliative prognostic score: a first step for the staging of terminally ill cancer patients. J Pain Symptom Manage. 1999;17(4):231–239.
[30] To TH, To LB, Currow DC. Can we detect transfusion benefits in palliative care patients? Palliat Med. 2016;19(10):1110–1113.
[31] Lapitan MC, Buckley BS. Impact of palliative urinary diversion by percutaneous nephrostomy drainage and ureteral stenting among patients with advanced cervical cancer and obstructive uropathy: a prospective cohort. J Obstet Gynaecol Res. 2011;37(8):1061–1070.
[32] Spencer BA, Insel BJ, Hershman DL, et al. Racial disparities in the use of palliative therapy for ureteral obstruction among elderly patients with advanced prostate cancer. Support Care Cancer. 2013;21(5):1303–1311.
[33] May P, Normand C. Analyzing the impact of palliative care interventions on cost of hospitalization: practical guidance for choice of dependent variable. J Pain Symptom Manage. 2016;52(1):100–106.