Original Article

Machine Learning for Targeted Advance Care Planning in Cancer Patients: A Quality Improvement Study

Mihir N. Patel, BS, Alexandria Mara, MD, Yvonne Acker, RN, BSN, Jamie Gollon, MS, Noppon Setji, MD, Jonathan Walter, MD, Steven Wolf, MS, S. Yousuf Zafar, MD, MHS, Suresh Balu, MS, MBA, Michael Gao, MS, Mark Sendak, MD, MPP, David Casarett, MD, MA, Thomas W. LeBlanc, MD, MA, MHS, and Jessica Ma, MD, MHSc

Duke University School of Medicine, Durham, North Carolina; Atrium Health Levine Cancer Institute, Concord, North Carolina; Patient Safety and Quality, Duke University Health System, Durham, North Carolina; Business Transformation, Duke University Health System, Durham, North Carolina; Department of Medicine, Duke University Medical Center, Durham, North Carolina; Department of Biostatistics and Bioinformatics, Duke University School of Medicine, Durham, North Carolina; Duke Institute for Health Innovation, Durham, North Carolina; Geriatric Research Education and Clinical Center, Durham VA Health System, Durham, North Carolina

Abstract

Context. Prognostication challenges contribute to delays in advance care planning (ACP) for patients with cancer near the end of life (EOL).

Objectives. Examine a quality improvement mortality prediction algorithm intervention's impact on ACP documentation and EOL care.

Methods. We implemented a validated mortality risk prediction machine learning model for solid malignancy patients admitted from the emergency department (ED) to a dedicated solid malignancy unit at Duke University Hospital. Clinicians received an email when a patient was identified as high-risk. We compared ACP documentation and EOL care outcomes before and after the notification intervention. We excluded patients with intensive care unit (ICU) admission in the first 24 hours. Comparisons involved chi-square/Fisher's exact tests and Wilcoxon rank sum tests; comparisons stratified by physician specialty employ Cochran-Mantel-Haenszel tests.

Results. Preintervention and postintervention cohorts comprised 88 and 77 patients, respectively. Most were White, non-Hispanic/Latino, and married. ACP conversations were documented for 2.3% of hospitalizations preintervention vs. 80.5% postintervention ($P<0.001$), and if the attending physician notified was a palliative care specialist (4.1% vs. 84.6%) or oncologist (0% vs. 76.3%) ($P<0.001$). There were no differences between groups in length of stay (LOS), hospice referral, code status change, ICU admissions or LOS, 30-day readmissions, 30-day ED visits, and inpatient and 30-day deaths.

Conclusion. Identifying patients with cancer and high mortality risk via machine learning elicited a substantial increase in documented ACP conversations but did not impact EOL care. Our intervention showed promise in changing clinician behavior. Further integration of this model in clinical practice is ongoing. J Pain Symptom Manage 2024;000:1−9. *Published by Elsevier Inc. on behalf of American Academy of Hospice and Palliative Medicine.*

Key Words

Advance care planning, end-of-life, cancer, machine learning, quality improvement

Key Message

This quality improvement study implemented a mortality prediction machine learning model on a dedicated solid malignancy inpatient unit. Documented advance care planning conversations increased substantially thereafter, but other end-of-life care outcomes were not impacted. This intervention has potential to change clinician behavior.

Address correspondence to: Jessica Ma, MD, Department of Medicine, Duke University School of Medicine, 710 West Main, Box 104427, Durham, North Carolina, 27701, USA. E-mail: jessica.ma@duke.edu

Accepted for publication: 29 August 2024.

Published by Elsevier Inc. on behalf of American Academy of Hospice and Palliative Medicine.

0885-3924/$ - see front matter
https://doi.org/10.1016/j.jpainsymman.2024.08.036

Additional research is needed to improve end-of-life outcomes.

Introduction

Clinicians often struggle to provide care that is congruent with patients' wishes near the end of life (EOL).[1] Several analyses of bereaved caregivers demonstrate that decedents received EOL care that was inconsistent with their wishes 11%−24% of the time.[2–4] Patients are more likely to endorse goal-discordant care if they die in hospitals or nursing homes as opposed to their home, are admitted to the intensive care unit (ICU) and/or receive life-prolonging care, or have poorly controlled symptoms at the EOL.[4] Conversely, patients who delineate their care preferences via advance directives are more likely to receive goal-concordant care.[3,5] Indeed, discussions about EOL care are associated with earlier hospice enrollment, less aggressive care, and improved quality of life.[5,6]

However, several patient-, clinician-, and system-level barriers preclude timely advance care planning (ACP) conversations. These barriers include hesitancy to acknowledge death and dying, challenges with predicting complex disease trajectories, poor coordination among healthcare team members on prognostic determinations, poor communication about EOL care, and challenges with longitudinal documentation of care preferences in the electronic health record (EHR).[7–9]

In oncology, prognostication continues to pose a significant challenge. Extensive evidence suggests that physicians often overestimate life expectancy, particularly near the EOL, a tendency more pronounced in cancer cases than in other conditions.[10–13] This task has grown even more daunting in recent years due to the rapid expansion of therapeutic options for many cancers.[14] Overestimation of life expectancy is associated with hospice underutilization and more aggressive care near the EOL.[11]

Early identification of patients at high risk for mortality during a hospitalization may improve clinical decision-making and patient outcomes at the EOL.[15] A new strategy for this is leveraging machine learning to predict mortality risk using in-hospital data. Several studies have developed and validated such models for hospitalized patients, including within the Duke University Health System,[16–21] but additional data on their impact on ACP documentation and EOL care outcomes following integration into clinical practice are needed.

The Duke Institute for Health Innovation recently developed and validated a machine learning model with excellent discrimination for predicting mortality risk for hospitalized, all-comer, adult patients on the day of admission.[21] To explore the impact of machine learning risk prediction on ACP documentation and EOL care outcomes in oncology clinical practice, we implemented this validated mortality risk machine learning model on a dedicated solid malignancy inpatient unit at Duke University Hospital. The primary aim of this quality improvement (QI) initiative was to increase the number of documented ACP conversations in hospitalized patients with solid malignancies.

Methods

Objectives and Hypotheses

This study is a retrospective analysis of a QI project applying a mortality risk prediction machine learning model on an inpatient solid malignancy unit. The primary aim of this initiative was to increase the number of documented ACP conversations. We hypothesized that the number of documented ACP conversations would be greater in the postintervention cohort compared to the preintervention cohort. Secondary endpoints included several EOL care metrics. We hypothesized that length of stay (LOS), inpatient mortality, ICU admission rate, 30-day readmission rate, and 30-day emergency department (ED) return rate would decrease postintervention. We hypothesized that discharge to hospice and change in code status to do not attempt resuscitation (DNAR) would increase.

This study was determined exempt as QI by the Duke Health Institutional Review Board (Pro00104527).

Setting

This intervention was implemented within a dedicated solid malignancy oncology unit at Duke University Hospital, a quaternary, academic hospital in North Carolina. All patients whose primary reason for inpatient admission is related to their solid malignancy are admitted to this unit. Patients are cared for by one medical oncology or one palliative care attending physician and supported by internal medicine interns, advanced practice clinicians, and nurse coordinators. Patients are assigned to one of the two teams (medical oncology or palliative care) based on their greatest need on admission, management of cancer treatment and complications or palliation of malignancy-associated symptoms. During the study, 25 total oncology attending physicians (19 during the preintervention period, 24 postintervention) and 10 total palliative care attending physicians (6 preintervention, 8 postintervention) rounded on this unit. Providers on this service do not receive any further formal training in conducting ACP conversations prior to starting.

Machine Learning Model

The machine learning model was developed by the Duke Institute for Health Innovation and was both retrospectively and prospectively validated across multiple

hospitals within Duke University Health System.[21] This model was trained on all adult inpatient admissions occurring at three major hospitals within Duke University Health System between January 1, 2015 and December 31, 2018. On inpatient services where this model has been integrated (e.g., this dedicated solid malignancy unit), it runs automatically within 24 hours of when a patient is admitted to the service from the ED (or via transfer from other hospitals within Duke University Health System). The model integrates from structured data fields in the EHR patient history (past-year diagnoses, problem list, past-year procedures, past-year hospitalizations) and preadmission features (chief complaint, mode of arrival to the ED, urgency of the encounter, vital signs, laboratory values, orders placed, and medications administered in the ED). The model determines in-hospital, 30-day, and 6-month risk of death.[21] Albeit validated on all-comer hospitalizations, this model has not been validated on patients with solid malignancies specifically.

Notification Process

While the model had previously been deployed, the notification intervention was initiated on the solid oncology unit on September 22, 2020. Risk thresholds for notification trigger were any level of risk for inpatient mortality; medium (threshold: 0.252, sensitivity: 0.501, positive predictive value: 0.288), high (0.548, 0.204, 0.499), or critical (0.940, 0.017, 0.841) risk for 30-day mortality; and critical risk (0.811, 0.021, 0.840) for 6-month mortality. These are outlined in further detail in the Supplement Appendix. Patients meeting said thresholds were reviewed by a QI specialist; if appropriate for the intervention (i.e., had not been discharged already or transferred to another unit), an e-mail was sent to key members of the multidisciplinary care team, including the current attending physician, unit nurse manager, case management staff, clinical documentation improvement (CDI) team, and pharmacist. Notifications were sent within 24−48 hours of admission. A notification was not sent if the patient was discharged or pending discharge before the notification could be sent or if the patient was transferred to another service before the notification could be sent.

An email template is outlined in the Supplement Appendix. Each email contained specific instructions for each care team member. Clinicians were encouraged to initiate an ACP conversation during the admission. They were also asked to reply to the email if an ACP conversation would be inappropriate. They were encouraged to document the conversation within the EHR, using "bookends" or templates within the EHR. These text markers allow ACP content to be pulled into a dedicated ACP tab in the EHR for easy identification by the QI team and for accessibility to other clinicians to inform care. A note template to encourage a robust conversation was also created, to allow quick and formatted documentation of detailed and dynamic patient wishes. The ACP tab, located prominently on the home screen of the EHR, can be referenced and updated if further conversations occur later in this hospitalization or at other points in the patient's care.[22,23]

The notification was also sent to multidisciplinary care team members. Pharmacy staff were encouraged to reconcile all medications prior to discharge. CDI specialists were encouraged to review all documentation to ensure the patient's complexity of condition was accurately reflected in the medical documentation. Case management staff were encouraged to facilitate appropriate referrals, assist with discharge resources, and ensure that patient wishes were accurately conveyed to any receiving facility at the time of discharge. Finally, nursing leadership were encouraged to have supportive conversations with patients after the clinicians had initiated an ACP conversation.

Variables

Measures collected include demographic data (age, race, ethnicity, and marital status), presence of ≥1 ACP note in the electronic health record (as identified via either notes located in the ACP tab in the EHR or specific text markers used to denote ACP notes [i.e., Smartlinks, Smart text, ACP bookends]) during the hospitalization, attending physician clinical division (palliative care or medical oncology), inpatient LOS, unplanned readmission rate and ED visits within 30 days of discharge (considering only those hospitalizations eligible for readmission or return ED visit per the Centers for Medicare and Medicaid Services [CMS] criteria for hospital-wide all-cause unplanned readmissions and internal health system criteria for return ED visits), discharge to hospice, code status change (from full code to DNAR), in-hospital mortality rate, and deaths within 30 days of discharge. All variables were obtained via automated abstraction from the EHR.

Patient Population

During both the pre- and postintervention periods, patients included in this analysis had a solid malignancy, were admitted to the solid oncology unit from the ED or via transfer, and were identified to meet risk thresholds by the machine learning model. Patients were excluded if they were admitted to the ICU within the first 24 hours of care or tested positive for COVID-19 (these patients were admitted to a separate hospitalist team). Patients were identified via automated abstraction from the EHR. We performed a pre-post analysis. The preintervention cohort included patients hospitalized from January 7, 2019 to October 25, 2019, and the postintervention cohort included patients hospitalized from September 19, 2020 to August 31, 2021.

We selected August 31, 2021 as our cutoff date since notifications became automated thereafter. For a couple patients admitted shortly before but discharged after model go-live, mortality risk scores were still calculated; there were no patients who remained hospitalized following automation of notifications. We manually confirmed that notifications were sent for all patients in the postintervention cohort.

Analysis

Since the model incorporates past hospitalizations in mortality risk determinations and several identified patients had multiple hospitalizations over the same time period, our primary analysis focused on index hospitalizations only. We also performed a sensitivity analysis including all hospitalizations during the pre- and postintervention time periods.

For descriptive analysis, we reported mean, standard deviation (SD), median and interquartile range (IQR) for continuous variables; we reported counts and percentages for categorical variables. To compare between preintervention and postintervention cohorts, we used chi-square or Fisher's exact tests as appropriate for categorical variables and Wilcoxon rank sum tests for continuous variables. To determine whether outcomes were associated with physician specialty in palliative care or oncology, we stratified comparisons by physician division using Cochran-Mantel-Haenszel tests for categorical variables and Kruskal-Wallis tests for continuous variables.

In the postintervention cohort, we also described ACP note authors and note co-signature requirements. We considered all ACP notes written, except for addenda to existing notes and subsequent co-signatures (i.e., signatory approvals done by attending physicians for existing notes written by medical trainees and other members of the care team [e.g., physician assistants, nurse practitioners]).

A *P*-value <0.05 was considered significant. All analyses were done in R (version 4.3.2; the R foundation, Vienna, Austria).

Results

Among 1242 hospitalizations during the preintervention period, 105 met inclusion criteria (8.5%). Hence, the preintervention cohort comprised 105 total hospitalizations, including 88 index hospitalizations (i.e., unique patients). Among 1184 hospitalizations during the postintervention period, 84 met inclusion criteria and had a notification sent (7.1%). Hence, the postintervention cohort comprised 84 hospitalizations, including 77 index hospitalizations (i.e., unique patients). The following analyses consider index hospitalizations only. As shown in Table 1, in the preintervention cohort, mean (SD) age was 64.8 (11.9) years; 60.2% were White with 33.0% Black/African American, 3.4% Hispanic/Latino, and 63.6% married. In the postintervention cohort, mean (SD) age was 66.7 (12.3) years; 50.6% were White with 42.9% Black/African American, 2.6% Hispanic/Latino, and 59.7% married. No patients in the preintervention or postintervention cohorts had an ACP note prior to their hospitalization.

An ACP note was written for 2 hospitalizations (2.3%) preintervention despite the mechanism for recording these notes already in place at our institution, whereas an ACP note was written for 62 hospitalizations (80.5%) postintervention (*P* <0.001) (Table 2). This relationship held even if the attending physician was a palliative care specialist (4.1%

Table 1
Patient Demographic Characteristics Across Index Hospitalizations

	Preintervention (n = 88 hospitalizations)	Postintervention (n = 77 hospitalizations)	*P*-Value
Age			0.640[a]
Mean (SD)	64.8 (11.9)	66.7 (12.3)	
Median (min, max)	66.0 (28.0, 92.0)	66.0 (37.0, 92.0)	
Race			0.587[b]
Caucasian	53 (60.2)	39 (50.6)	
Black or African American	29 (33.0)	33 (42.9)	
Other	3 (3.4)	3 (3.9)	
Not reported/declined	3 (3.4)	2 (2.6)	
Ethnicity			1.000[b]
Hispanic/Latino	3 (3.4)	2 (2.6)	
Not Hispanic/Latino	81 (92.0)	72 (93.5)	
Not reported/declined	4 (4.5)	3 (3.9)	
Marital status			0.677[b]
Married	56 (63.6)	46 (59.7)	
Single	21 (23.9)	17 (22.1)	
Divorced or legally separated	3 (3.4)	7 (9.1)	
Widowed	7 (8.0)	6 (7.8)	
Unknown	1 (1.1)	1 (1.3)	

Number (%) of all hospitalizations is listed unless otherwise specified.
[a]Wilcoxon rank sum test.
[b]Fisher's exact test.

Table 2
ACP Documentation and EOL Care Outcomes Among Index Hospitalizations

	Preintervention (n = 88 hospitalizations)	Postintervention (n = 77 hospitalizations)	*P*-value
ACP note written	2 (2.3)	62 (80.5)	<0.001[a]
Inpatient LOS (days): median (IQR)	3.9 (3.8)	4.7 (4.7)	0.193[b]
30-day readmission occurred[c]	12 (21.4)	11 (20.8)	0.931[a]
30-day ED visit occurred[d]	19 (24.7)	16 (22.5)	0.760[a]
In-hospital death occurred	11 (12.5)	5 (6.5)	0.193[a]
Death within 30 days of discharge occurred	36 (40.9)	37 (48.1)	0.357[a]
Discharged to hospice	26 (29.5)	29 (37.7)	0.270[a]
Code status change (full code to DNAR)			0.786[e]
Occurred	24 (27.3)	21 (27.3)	
Did not occur	64 (72.7)	55 (71.4)	
Missing	0	1 (1.3)	
ICU admission occurred after first 24 hours	3 (3.4)	3 (3.9)	1.000[e]
Total ICU LOS (days): median (IQR)	148.2 (80.1)	35.9 (32.2)	0.700[b]

Number (%) of index hospitalizations is listed unless otherwise specified.
[a]Chi-square test of independence without Yates' continuity correction.
[b]Wilcoxon rank sum test.
[c]Percents are out of the number of hospitalizations considered eligible for readmission (i.e., n = 56 hospitalizations in the preintervention cohort and n = 53 hospitalizations in the postintervention cohort).
[d]Percents are out of the number of hospitalizations considered eligible for return ED visit (i.e., n = 77 hospitalizations in the preintervention cohort and n = 71 hospitalizations in the postintervention cohort).
[e]Fisher's exact test.

preintervention vs. 84.6% postintervention) or oncologist (0% vs. 76.3%) (P <0.001) (Table 3). Findings were similar when considering all hospitalizations for patients with multiple hospitalizations (Supplement Tables 1–3). Median (IQR) number of days from inpatient admission to ACP note publication was 2.0 (2.0).

Considering patients in the postintervention cohort for whom ACP notes were documented, demographic characteristics aligned closely with the group at large: mean (SD) age was 66.7 (12.7) years, and 50.0% were White with 43.5% Black/African American, 3.2% Hispanic/Latino, and 58.1% married Supplement Table 4).

Table 3
ACP Documentation and EOL Care Outcomes Among Index Hospitalizations Stratified by Attending Physician Clinical Division

	Preintervention (n = 88 hospitalizations)		Postintervention (n = 77 hospitalizations)		*P*-Value
	Palliative care (n = 49)	Medical oncology (n = 39)	Palliative care (n = 39)	Medical oncology (n = 38)	
ACP note written	2 (4.1)	0	33 (84.6)	29 (76.3)	<0.001[a]
Inpatient LOS (days): median (IQR)	3.8 (5.0)	3.9 (2.8)	4.4 (4.7)	5.0 (4.7)	0.307[b]
30-day readmission occurred[c]	4 (13.8)	8 (29.6)	5 (20.8)	6 (20.7)	0.879[a]
30-day ED visit occurred[d]	7 (17.1)	12 (33.3)	7 (18.9)	9 (26.5)	0.744[a]
In-hospital death occurred	8 (16.3)	3 (7.7)	2 (5.1)	3 (7.9)	0.208[a]
Death within 30 days of discharge occurred	23 (46.9)	13 (33.3)	19 (48.7)	18 (47.4)	0.333[a]
Discharged to hospice	17 (34.7)	9 (23.1)	21 (53.8)	8 (21.1)	0.202[a]
Code status change (full code to DNAR)					0.828[a,e]
Occurred	18 (36.7)	6 (15.3)	14 (35.9)	7 (18.4)	
Did not occur	31 (63.2)	33 (84.6)	24 (61.5)	31 (81.6)	
Missing	0	0	1 (2.6)	0	
ICU admission occurred after first 24 hours	1 (2.0)	2 (5.1)	1 (2.6)	2 (5.3)	NA[f]
Total ICU LOS (days): median (IQR)	5.12 (0)	156.8 (8.6)	35.9 (0)	47.7 (32.2)	NA[g]

Number (%) of index hospitalizations is listed unless otherwise specified.
[a]Cochran-Mantel-Haenszel test without Yates' continuity correction.
[b]Kruskal-Wallis test.
[c]Percents are out of the number of hospitalizations considered eligible for readmission (i.e., n = 29 hospitalizations in the preintervention cohort where the attending physician was a palliative care physician, n = 27 hospitalizations in the preintervention cohort where the attending physician was a medical oncologist, n = 24 hospitalizations in the postintervention cohort where the attending physician was a palliative care physician, n = 29 hospitalizations in the postintervention cohort where the attending physician was a medical oncologist).
[d]Percents are out of the number of hospitalizations considered eligible for return ED visit (i.e., n = 41 hospitalizations in the preintervention cohort where the attending physician was a palliative care physician, n = 36 hospitalizations in the preintervention cohort where the attending physician was a medical oncologist, n = 37 hospitalizations in the postintervention cohort where the attending physician was a palliative care physician, n = 34 hospitalizations in the postintervention cohort where the attending physician was a medical oncologist).
[e]Missing values were omitted to enable expected sample size assumption for Cochran-Mantel-Haenszel test to be met.
[f]Cochran-Mantel-Haenszel test could not be done since expected sample size assumption was not met.
[g]Differences shown between cohort subsets are not interpretable due to exceedingly low sample size.

Among 121 ACP notes, 19.1% were written by attending physicians, 24.4% by residents, 26.0% by licensed clinical social workers, and 19.1% by physician assistants; 50.4% of notes had a co-signature (Supplement Table 5).

None of the secondary outcomes differed significantly between preintervention and postintervention cohorts (Table 2). Some noteworthy but statistically insignificant trends are highlighted below. There was an increase in the rate of discharge to hospice from 29.5% to 37.7% ($P = 0.270$) and a decrease in in-hospital deaths from 12.5% to 6.5% ($P = 0.193$). Death within 30 days of discharge increased from 40.9% to 48.1% ($P = 0.357$). Median (IQR) inpatient LOS was slightly longer in the postintervention cohort (4.7 [4.7] vs. 3.9 [3.8] days). As shown in Table 3, for patients cared for by palliative care physicians, the rate of discharge to hospice increased notably (34.7% to 53.8%) and in-hospital deaths decreased (16.3% to 5.1%). For patients cared for by medical oncologists, 30-day readmissions (29.6% to 20.7%) and 30-day ED visits (33.3% to 26.5%) decreased; the rate of 30-day deaths increased (33.3% to 47.4%). Median inpatient LOS slightly increased among patients cared for by palliative care physicians by 0.6 days and medical oncologists by 1.1 days.

Over the course of the study period, an ACP note was written for 100% of notifications through the first 3.5 months following model go-live. From January 2021 however, responsiveness to notifications began to gradually decline, reaching a nadir of 44.4% in August 2021 (Fig. 1).

Discussion

This QI study employed a mortality prediction algorithm and notification intervention for patients admitted to a dedicated solid malignancy inpatient unit. While there was a gradual decline in responsiveness to notifications over time, we observed a substantial increase in documented ACP conversations following implementation of the notification intervention. This trend was consistent between palliative care and oncology physicians and held regardless of whether repeat hospitalizations were considered in the analysis. While it remains unclear the degree to which this impact is attributable to targeted identification of patients at high risk for near-term mortality or to the email nudge itself, we note that this intervention was effective despite other nudges for ACP conversations, such as an ACP tab in the EHR and EHR-based notifications for patients without prior ACP, being in place already at our institution.[22] Further integration of this model in clinical practice is ongoing; it has also been used for patients admitted to the general medicine service and is being expanded to other services and other hospitals within the health system.

While we observed trends—albeit statistically insignificant—toward increased hospice referrals and decreased in-hospital mortality, especially among patients cared for by palliative care physicians, this intervention did not appreciably impact EOL care outcomes. It is plausible that our study was underpowered to detect any such differences. However, our findings also parallel other studies that have implemented

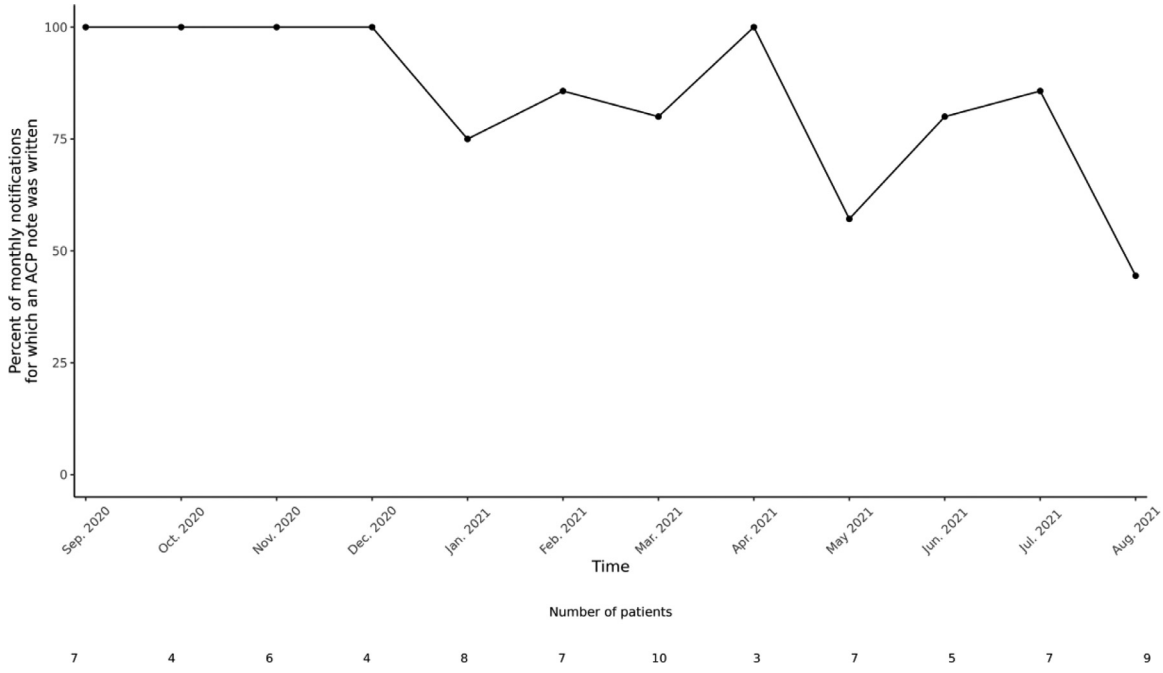

Fig. 1. Per-month percent of model notifications for which an ACP note was written in the postintervention cohort. Shown below the plot is the number of patients for which a notification was sent during each month.

mortality prediction models for hospitalized patients and in oncology. One study implementing a 30-day mortality risk prediction model for all-comer hospitalized patients also reported a substantial increase in ACP conversations; however, besides code status de-escalation, EOL care outcomes did not change, including inpatient LOS, 30-day readmissions, 30-day ED visits, and 30-day deaths.[19] A cluster randomized trial demonstrated a significant increase in ACP conversations for solid malignancy patients at community outpatient oncology practices with implementation of a 180-day mortality risk prediction model compared to usual care.[24] Long-term findings showed decreased rates of systemic therapy near the EOL, but hospice enrollment and LOS, inpatient deaths, and ICU admissions within 30 days of death did not differ between groups.[25] A secondary analysis of this study did reveal decreased mean daily spending in the last six months of life, especially for systemic therapy and outpatient care.[26] It should be considered that our intervention differs from the aforementioned outpatient oncology mortality prediction model via its restriction to the inpatient setting; as such, it is possible that ACP conversations that do occur may be occurring too late to elicit meaningful changes in decision-making regarding EOL care and may ideally need to happen prior to the hospitalization itself.

Additional work is needed to understand why increases in ACP conversations following model recommendation do not translate into improved EOL care metrics. One contributing factor may be suboptimal quality of ACP conversations and/or documentation. For instance, conversations may have been conducted poorly, too quickly, or at inopportune times. Previous work at our institution has demonstrated wide variation in the content of these ACP notes depending on whether notes were free-text or templated.[27] Heterogeneity in the efficacy and quality of ACP conversations and in ACP documentation could influence downstream adherence to patients' stated care preferences, especially when there are transitions in personnel on service or rapid deteriorations in patient condition. It is also worth mentioning that there are other EOL care metrics that could have been impacted by the intervention but were not measured during the duration of patients' hospitalizations or afterward in this study, such as patient quality of life, goal concordance of care received, or healthcare spending. Likewise, it is possible that a window longer than 30 days may be needed to detect downstream changes in ED visits, hospital readmissions, or deaths.

Nonetheless, our findings corroborate the potential for mortality prediction algorithms and clinician notification to elicit clinician behavior change. Sustaining this change however remains challenging, as responsiveness to notifications declined over one year. There were no major changes in staff that could explain this decline. However, several studies have implicated notification fatigue as an important contributor.[28–32] Further, there is considerable variation in how clinicians appraise or trust model notifications, especially when influenced by false positives or false negatives. Some clinicians remain wary of trusting model recommendations over experience or without complete knowledge of model inputs.[28,33] Trust may wane over time. Some studies have found success in personalizing model notifications to include clinicians' ACP conversation performance history in comparison to their peers.[24,25] Additional work is needed to understand which characteristics influence how clinicians appraise model recommendations and tailor notifications accordingly.

Importantly, ACP documentation for Black/African American patients was similar to White patients, relative to their respective composition of the postintervention cohort. Given disparities in ACP for racial/ethnic minorities,[34,35] this finding, which is consistent with prior literature, highlights the potential for machine learning to help bridge this gap.[19]

A unique aspect of our intervention was that other members of the care team besides attending physicians received notifications. Unfortunately, we cannot reliably measure the impact of the intervention on their work. Regarding pharmacists, tracking of medication reconciliations using a specialized pharmacy dashboard was not implemented on this unit until after the preintervention period, rendering comparison difficult. Regarding CDI specialists, we considered reporting case mix index since it reflects coding/documentation accuracy, but it is confounded by changes in patient populations and comorbidities. Additional work is needed to characterize these impacts.

This study has several limitations. It is a single-institution study, limiting its generalizability. Given the pre-post design of this QI study, changes in ACP documentation could have been influenced by changes in the structure, processes, and personnel composition of the solid malignancy unit over time. There was an 11-month gap between the pre- and postintervention periods due to interval technical issues and a focus of our research team to implement the model on other services. This gap coincides with the COVID-19 pandemic; while patients with COVID-19 were not admitted to this unit, there could have been an influence of past COVID-19 diagnosis on patients' mortality risk unaccounted for by a model trained on prepandemic data. Ultimately, to study the impact of this intervention on EOL care outcomes more thoroughly, randomized trials with larger sample size and simultaneous intervention and control arms are needed. Additionally, ACP conversations were identified using text indicators in the EHR; hence, undocumented ACP conversations were not captured. Finally, although the model did not

undergo any interval updates, we recognize the potential for this to impact which patients meet risk thresholds for inclusion over time.

Overall, this QI study highlights the potential for a mortality prediction machine learning model to change clinician behavior and improve the rate of documented ACP conversations in hospitalized patients with solid malignancies. Although this intervention did not appreciably impact EOL care outcomes, trends toward improved in-hospital mortality and discharge to hospice warrant attention, and future randomized studies with additional statistical power are needed. Expansion of this intervention to other services and other hospitals within the health system is ongoing, and this study shepherds ongoing efforts to understand how to improve model utility and downstream EOL care outcomes.

Disclosures and Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Jessica Ma's effort was supported by the University of Michigan HEAL K12NS130673. The statements presented in this article are solely the responsibility of the author(s) and do not necessarily reflect the position, views, or policy of the sponsors. Mihir Patel has received royalties or licenses from Prepped Health. Steven Wolf has received grants or contracts from BMS. S. Yousuf Zafar participates on a data safety monitoring board or advisory board for Forma Health and Reimagine Care, has an unpaid leadership or fiduciary role for Family Reach, and holds stock or stock options in United Health Group. Suresh Balu has received royalties or licenses from Cohere Med, Inc. Michael Gao has received support from the National Institutes for Health and royalties or licenses from Clinetic. Mark Sendak has received grants or contracts from the National Institutes for Health, American Medical Association, Janssen/Johnson & Johnson, Gordon and Betty Moore Foundation, Roche, and Patrick J. McGovern Foundation; royalties or licenses from Cohere Med, Inc., Kela Health, Clinetic and Fullsteam Health; payments or honoraria from the American Medical Association, HIMSS, Roche, and the Office of the National Coordinator for Health IT; and support for meetings or travel from the American Medical Association, HIMSS, Roche, and the Office of the National Coordinator for Health IT. David Casarett holds equity interests in DisposeRx, Curio Wellness, The Pharm Stand, and CareYaya, and has received payments from Leafwell and Curio Wellness. Thomas W. LeBlanc has received grants or contracts from AbbVie, American Cancer Society, AstraZeneca, BMS, Deverra Therapeutics, GSK, Jazz Pharmaceuticals, The Leukemia and Lymphoma Society, and the National Institute of Nursing Research/National Institutes for Health; consulting fees from AbbVie, Agilix, Agios/Servier, Apellis, Astellas, AstraZeneca, Beigene, BlueNote, BMS/Celgene, Genentech, GSK, Lilly, Meter Health, Novartis, and Pfizer; payments or honoraria from AbbVie, Agios, Astellas, BMS/Celgene, Incyte, and Rigel; and holds stock or stock options in Dosentrx; he is also a Scholar in Clinical Research of the Leukemia and Lymphoma Society. All other authors have no relevant financial or nonfinancial interests to disclose. We gratefully acknowledge Salam Ibrahim for her contribution to obtaining the data used in this study.

References

1. Waldrop DP, McGinley JM. "I want to go home": how location at death influences caregiver well-being in bereavement. Palliat Support Care 2020;18:691–698.

2. Glass DP, Wang SE, Minardi PM, Kanter MH. Concordance of end-of-life care with end-of-life wishes in an integrated health care system. JAMA Netw Open 2021;4:e213053.

3. Haines L, Rahman OK, Sanders JJ, Johnson K, Kelley A. Factors that impact family perception of goal-concordant care at the end of life. J Palliat Med 2019;22:927–932.

4. Khandelwal N, Curtis JR, Freedman VA, et al. How often is end-of-life care in the United States inconsistent with patients' goals of care? J Palliat Med 2017;20:1400–1404.

5. Prigerson HG, Viola M, Maciejewski PK, Falzarano F. Advance care planning (ACP) to promote receipt of value-concordant care: results vary according to patient priorities. PLoS One 2023;18:e0280197.

6. Wright AA, Zhang B, Ray A, et al. Associations between end-of-life discussions, patient mental health, medical care near death, and caregiver bereavement adjustment. JAMA 2008;300:1665–1673.

7. Kim H, Flieger SP. Barriers to effective communication about advance care planning and palliative care: a qualitative study. J Hosp Palliat Care 2023;26:42–50.

8. Hagen NA, Howlett J, Sharma NC, et al. Advance care planning: identifying system-specific barriers and facilitators. Curr Oncol 2015;22:e237–e245.

9. You JJ, Downar J, Fowler RA, et al. Barriers to goals of care discussions with seriously ill hospitalized patients and their families: a multicenter survey of clinicians. JAMA Intern Med 2015;175:549–556.

10. Christakis NA, Lamont EB. Extent and determinants of error in doctors' prognoses in terminally ill patients: prospective cohort study. BMJ 2000;320:469–472.

11. Gramling R, Gajary-Coots E, Cimino J, et al. Palliative care clinician overestimation of survival in advanced cancer: disparities and association with end-of-life care. J Pain Symptom Manage 2019;57:233–240.

12. Cheon S, Agarwal A, Popovic M, et al. The accuracy of clinicians' predictions of survival in advanced cancer: a review. Ann Palliat Med 2016;5:22–29.

13. Chow E, Harth T, Hruby G, et al. How accurate are physicians' clinical predictions of survival and the available prognostic tools in estimating survival times in terminally ill

cancer patients? a systematic review. Clin Oncol (R Coll Radiol) 2001;13:209–218.

14. Patel MN, Nicolla JM, Friedman FAP, Ritz MR, Kamal AH. Hospice use among patients with cancer: trends, barriers, and future directions. JCO Oncol Pract 2020;16:803–809.

15. Bates DW, Saria S, Ohno-Machado L, Shah A, Escobar G. Big data in health care: using analytics to identify and manage high-risk and high-cost patients. Health Aff (Millwood) 2014;33:1123–1131.

16. Schwartz N, Sakhnini A, Bisharat N. Predictive modeling of inpatient mortality in departments of internal medicine. Intern Emerg Med 2018;13:205–211.

17. Escobar GJ, Gardner MN, Greene JD, Draper D, Kipnis P. Risk-adjusting hospital mortality using a comprehensive electronic record in an integrated health care delivery system. Med Care 2013;51:446–453.

18. Blanes-Selva V, Ruiz-Garcia V, Tortajada S, et al. Design of 1-year mortality forecast at hospital admission: a machine learning approach. Health Informatics J 2021;27:1460458220987580.

19. Chi S, Kim S, Reuter M, et al. Advanced care planning for hospitalized patients following clinician notification of patient mortality by a machine learning algorithm. JAMA Netw Open 2023;6:e238795.

20. Qiao EM, Qian AS, Nalawade V, et al. Evaluating high-dimensional machine learning models to predict hospital mortality among older patients with cancer. JCO Clin Cancer Inform 2022;6:e2100186.

21. Brajer N, Cozzi B, Gao M, et al. Prospective and external evaluation of a machine learning model to predict in-hospital mortality of adults at time of admission. JAMA Netw Open 2020;3:e1920733.

22. Casarett D, Lakis K, Ma JE, et al. Goal-concordant care: end-of-life planning conversations for all seriously ill patients. NEJM Catalyst 2022;3. CAT.22.0271.

23. Casarett D, Lakis K, Ma JE, Fischer J, Ibrahim S. Using design thinking to promote goals of care conversations with seriously ill patients. J Pain Symptom Manage 2023;66:e275–e281.

24. Manz CR, Parikh RB, Small DS, et al. Effect of integrating machine learning mortality estimates with behavioral nudges to clinicians on serious illness conversations among patients with cancer: a stepped-wedge cluster randomized clinical trial. JAMA Oncol 2020;6:e204759.

25. Manz CR, Zhang Y, Chen K, et al. Long-term effect of machine learning-triggered behavioral nudges on serious illness conversations and end-of-life outcomes among patients with cancer: a randomized clinical trial. JAMA Oncol 2023;9:414–418.

26. Patel TA, Heintz J, Chen J, et al. Spending analysis of machine learning–based communication nudges in oncology. NEJM AI 2024;1:AIoa2300228.

27. Schlichte L, Setji N, Walter J, et al. The use of templates for documenting advance care planning conversations: a descriptive analysis. J Pain Symptom Manage 2023;66:123–136.

28. Parikh RB, Manz CR, Nelson MN, et al. Clinician perspectives on machine learning prognostic algorithms in the routine care of patients with cancer: a qualitative study. Support Care Cancer 2022;30:4363–4372.

29. Emanuel EJ, Wachter RM. Artificial intelligence in health care: will the value match the hype? JAMA 2019;321:2281–2282.

30. Park H, Chae MK, Jeong W, et al. Appropriateness of alerts and physicians' responses with a medication-related clinical decision support system: retrospective observational study. JMIR Med Inform 2022;10:e40511.

31. Wong A, Berenbrok LA, Snader L, et al. Facilitators and barriers to interacting with clinical decision support in the ICU: a mixed-methods approach. Crit Care Explor 2023;5:e0967.

32. Ma JE, Lowe J, Berkowitz C, et al. Provider interaction with an electronic health record notification to identify eligible patients for a cluster randomized trial of advance care planning in primary care: secondary analysis. J Med Internet Res 2023;25:e41884.

33. Sendak MP, Gao M, Brajer N, Balu S. Presenting machine learning model information to clinical end users with model facts labels. NPJ Digit Med 2020;3:41.

34. Bazargan M, Bazargan-Hejazi S. Disparities in palliative and hospice care and completion of advance care planning and directives among non-Hispanic blacks: a scoping review of recent literature. Am J Hosp Palliat Care 2021;38:688–718.

35. Fennell G, Hoe D, Zelinski E, Enguidanos S. Factors associated with advance care planning by race. Am J Hosp Palliat Care 2023;40:164–172.

Supplementary Appendix

Model performance metrics and definitions of mortality risk thresholds for notification:

Inpatient mortality risk:

- Medium: 0.232; 22.8% of patients who die in the inpatient setting historically fall in this category; sensitivity: 0.356; positive predictive value (PPV): 0.218.
- High: 0.331; 10.8%; 0.129; 0.407.
- Critical: 0.501; 2.0%; 0.020; 0.727.

30-day mortality risk:

- Medium: 0.252; 29.6% of patients who die within 30 days of discharge from an inpatient admission historically fall in this category; sensitivity: 0.501; PPV: 0.288.
- High: 0.548; 18.7%; 0.204; 0.499.
- Critical: 0.940; 1.7%; 0.017; 0.841.

6-month mortality risk:

- Medium: 0.386; 19.5% of patients who die within 6 months of discharge from an inpatient admission historically fall in this category; sensitivity: 0.500; PPV: 0.478.
- High: 0.561; 21.8%; 0.206; 0.651.
- Critical: 0.811; 1.0%; 0.021; 0.840.

These mortality risk thresholds are not meant to be interpretable; they are only used to refer to the retrospective sensitivity and positive predictive value that result from treating the model as dichotomous at the indicated timepoint.

Template of email notification sent to multidisciplinary care team:

To: [Attending Physician Email Address]

Cc: [Physician Assistant Email Address]; ACP Team Group Email

Bcc: [Pharmacy, Case Management, Clinical Documentation Integrity Group Email]

Subject: (Send Secure) 9300 high-risk patient

Body of Email:

To: [Attending Physician Name] (CC: [Physician Assistant Name])

Bcc: Pharmacy, Case Management and CDI Teams

Your patient, [Patient Name] (MRN: XXXXX), who was admitted on [Inpatient Admission Date] has been identified as potentially benefitting from Advance Care Planning (ACP). This identification has been made as a part of the 9300 Advance Care Planning Project (details below and project education slides at [link]).

The following ACP Care Bundle should be initiated prior to discharge:

1) Treatment Team: Please consider a goals of care discussion during this admission, and document using the .acpbegin and .acpend bookends. Please do not delete the header or the blue box at the end. (Note: Completed Advance Care Planning can be billable). If you believe the patient is not appropriate for Advance Care Planning, reply to this email indicating why Advance Care Planning was not provided so we can better understand potential obstacles.
2) Pharmacy will provide medication reconciliation at discharge. Please notify the rounding 9300 pharmacist when patient is ready for discharge.
3) Case Management will be doing their usual assessment and will determine if any additional discharge resources are indicated. They are also available to participate with the provider in any Advance Care Planning discussions that are being had with the patient and/or family. For patients being discharged to our community partners and facilities (e.g. home health, skilled nursing facility or hospice), the Case Manager will include the Advance Care Planning note in the information that is sent to the organization/facility.
4) Clinical Documentation Integrity (CDI) nurse will be closely reviewing the chart to make sure documentation is accurately reflecting the patient's current medical condition and co-morbidities. Please respond to any posed queries as soon as possible or contact the CDI reviewer if documentation clarification requests are unclear.

The goal of this project is to improve the quality of care for this at-risk patient population and to ensure each patient's wishes are documented appropriately for future care.

Thank you for providing this valuable service for our patients.

Supplement Table 1

Patient Demographic Characteristics Across All Hospitalizations

	Preintervention (n = 105 hospitalizations)	Postintervention (n = 84 hospitalizations)	*P*-Value
Age			0.899[a]
Mean (SD)	64.9 (11.4)	66.0 (12.2)	
Median (min, max)	66.0 (28.0, 92.0)	65.0 (37.0, 92.0)	
Race			0.683[b]
Caucasian	63 (60.0)	44 (52.4)	
Black or African American	35 (33.3)	35 (41.7)	
Other	3 (2.9)	3 (3.6)	
Not reported/declined	4 (3.8)	4 (4.8)	
Ethnicity			0.838[c]
Hispanic/Latino	4 (3.8)	2 (2.4)	
Not Hispanic/Latino	97 (92.4)	78 (92.9)	
Not reported/declined	4 (3.8)	4 (4.8)	
Marital status			0.758[c]
Married	69 (65.7)	51 (60.7)	
Single	24 (22.9)	19 (22.6)	
Divorced or legally separated	4 (3.8)	7 (8.3)	
Widowed	7 (6.7)	6 (7.1)	
Unknown	1 (1.0)	1 (1.2)	

Number (%) of all hospitalizations is listed unless otherwise specified.
[a]Wilcoxon rank sum test.
[b]Chi-square test of independence without Yates' continuity correction.
[c]Fisher's exact test.

Supplement Table 2

ACP Documentation and EOL Care Outcomes Among All Hospitalizations

	Preintervention (n = 105 hospitalizations)	Postintervention (n = 84 hospitalizations)	*P*-Value
ACP note written	3 (2.9)	68 (81.0)	<0.001[a]
Inpatient LOS (days): median (IQR)	4.6 (4.38)	4.7 (4.9)	0.836[b]
30-day readmission occurred[c]	16 (22.9)	13 (22.4)	0.952[a]
30-day ED visit occurred[d]	24 (25.5)	18 (23.4)	0.745[a]
In-hospital death occurred	11 (10.5)	6 (7.1)	0.426[a]
Death within 30 days of discharge occurred	44 (41.9)	40 (47.6)	0.432[a]
Discharged to hospice	34 (32.4)	33 (39.3)	0.324[a]
Code status change (full code to DNAR)			0.315[e]
Occurred	28 (26.7)	24 (28.6)	
Did not occur	77 (73.3)	58 (69.0)	
Missing	0	2 (2.4)	
ICU admission occurred after first 24 hours	3 (2.9)	3 (3.6)	1.000[e]
Total ICU LOS (days): median (IQR)	148.2 (80.1)	35.9 (32.2)	0.700[b]

Number (%) of all hospitalizations is listed unless otherwise specified.
[a]Chi-square test of independence without Yates' continuity correction.
[b]Wilcoxon rank sum test.
[c]Percents are out of the number of hospitalizations considered eligible for readmission (i.e., n = 70 hospitalizations in the preintervention cohort and n = 58 hospitalizations in the postintervention cohort).
[d]Percents are out of the number of hospitalizations considered eligible for return ED visit (i.e., n = 94 hospitalizations in the preintervention cohort and n = 77 hospitalizations in the postintervention cohort).
[e]Fisher's exact test.

Supplement Table 3

ACP Documentation and EOL Care Outcomes Among All Hospitalizations Stratified by Attending Physician Clinical Division

	Preintervention (n = 105 hospitalizations)		Postintervention (n = 84 hospitalizations)		*P*-Value
	Palliative care (n = 58)	Medical oncology (n = 47)	Palliative care (n = 46)	Medical oncology (n = 38)	
ACP note written	3 (5.2)	0	39 (84.8)	29 (76.3)	<0.001[a]
Inpatient LOS (days): median (IQR)	4.6 (5.9)	4.1 (3.2)	4.0 (4.2)	5.0 (4.7)	0.360[b]
30-day readmission occurred[c]	5 (13.9)	11 (32.4)	7 (24.1)	6 (20.7)	0.940[a]
30-day ED visit occurred[d]	9 (18.0)	15 (34.1)	9 (20.9)	9 (26.5)	0.779[a]
In-hospital death occurred	8 (13.8)	3 (6.4)	3 (6.5)	3 (7.9)	0.430[a]
Death within 30 days of discharge occurred	29 (50.0)	15 (31.9)	22 (47.8)	18 (47.4)	0.428[a]
Discharged to hospice	22 (37.9)	12 (25.5)	25 (54.3)	8 (21.1)	0.3068[a]
Code status change (full code to DNAR)					0.650[a,e]
Occurred	21 (36.2)	7 (14.9)	17 (37.0)	7 (18.4)	
Did not occur	37 (63.8)	40 (85.1)	27 (58.7)	31 (81.6)	
Missing	0	0	2 (4.3)	0	
ICU admission occurred after first 24 hours	1 (1.7)	2 (4.3)	1 (2.2)	2 (5.3)	NA[f]
Total ICU LOS (days): median (IQR)	5.12 (0)	156.8 (8.6)	35.9 (0)	47.7 (32.2)	NA[g]

Number (%) of all hospitalizations is listed unless otherwise specified.
[a]Cochran-Mantel-Haenszel test without Yates' continuity correction.
[b]Kruskal-Wallis test.
[c]Percents are out of the number of hospitalizations considered eligible for readmission (i.e., n = 36 hospitalizations in the preintervention cohort where the attending physician was a palliative care physician, n = 34 hospitalizations in the preintervention cohort where the attending physician was a medical oncologist, n = 29 hospitalizations in the postintervention cohort where the attending physician was a palliative care physician, n = 29 hospitalizations in the postintervention cohort where the attending physician was a medical oncologist).
[d]Percents are out of the number of hospitalizations considered eligible for return ED visit (i.e., n = 50 hospitalizations in the preintervention cohort where the attending physician was a palliative care physician, n = 44 hospitalizations in the preintervention cohort where the attending physician was a medical oncologist, n = 43 hospitalizations in the postintervention cohort where the attending physician was a palliative care physician, n = 34 hospitalizations in the postintervention cohort where the attending physician was a medical oncologist).
[e]Missing values were omitted to enable expected sample size assumption for Cochran-Mantel-Haenszel test to be met.
[f]Cochran-Mantel-Haenszel test could not be done since expected sample size assumption was not met.
[g]Differences shown between cohort subsets are not interpretable due to exceedingly low sample size.

Supplement Table 4

Patient Demographic Characteristics for Hospitalizations in the Postintervention Cohort for Which an ACP Note Was Written

	Postintervention, ACP Note Written (n = 62 Hospitalizations)
Age	
Mean (SD)	66.7 (12.7)
Median (min, max)	66.0 (37.0, 92.0)
Race	
Caucasian	31 (50.0)
Black or African American	27 (43.5)
Other	3 (4.8)
Not reported/declined	1 (1.6)
Ethnicity	
Hispanic/Latino	2 (3.2)
Not Hispanic/Latino	58 (93.5)
Not reported/declined	2 (3.2)
Marital status	
Married	36 (58.1)
Single	15 (24.2)
Divorced or legally separated	5 (8.1)
Widowed	5 (8.1)
Unknown	1 (1.6)

Supplement Table 5

Characteristics of All ACP Notes Written in the Postintervention Cohort

	ACP Notes (n = 131)
Author type	
Attending physician	25 (19.1)
Resident	32 (24.4)
Licensed clinical social worker	34 (26.0)
Nurse practitioner	12 (9.2)
Physician assistant	25 (19.1)
Physician assistant student	2 (1.5)
Pharmacist	1 (0.8)
Co-signature requirement	
Needed	66 (50.4)
Not needed	65 (49.6)