Using machine learning for targeted advance care planning (ACP) conversations in cancer patients: a quality improvement initiative

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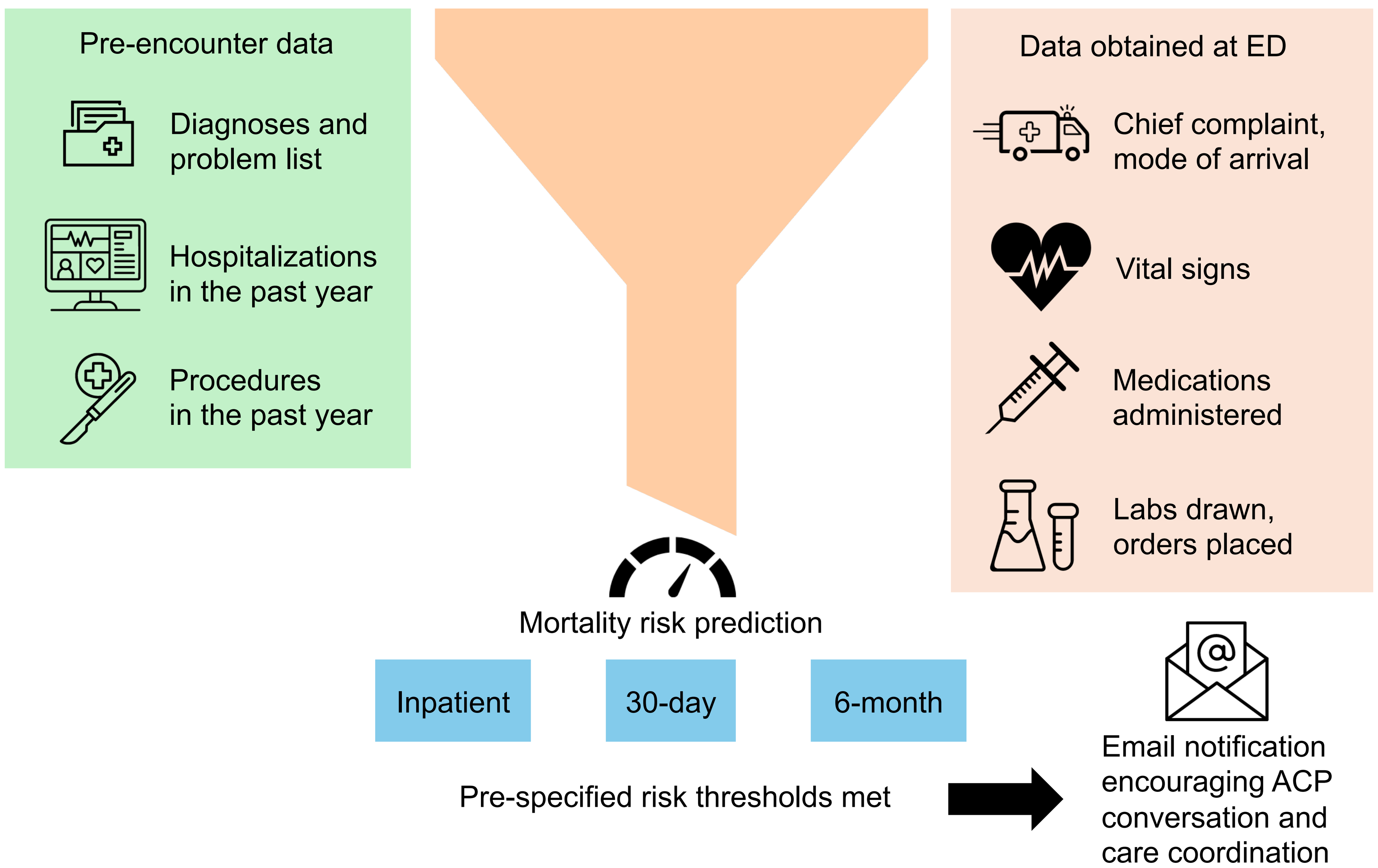
Introduction

- Despite improvements, patients with advanced cancer do not always receive end-of-life (EOL) care that is consistent with their wishes.[1] Patients who receive ACP conversations are more likely to receive goal-concordant care at the EOL.[2]
- A significant barrier toward timely ACP conversations is challenges with prognostication.[3]
- Machine learning models could help identify which patients are at high risk for near-term mortality and therefore identify patients in need of ACP conversations.[4]
- **We examined the impact of a mortality prediction model and notification strategy on ACP conversations and EOL care for hospitalized solid malignancy patients.**

Methods

Setting: Inpatient solid malignancy unit at a quaternary academic medical center.

Intervention:

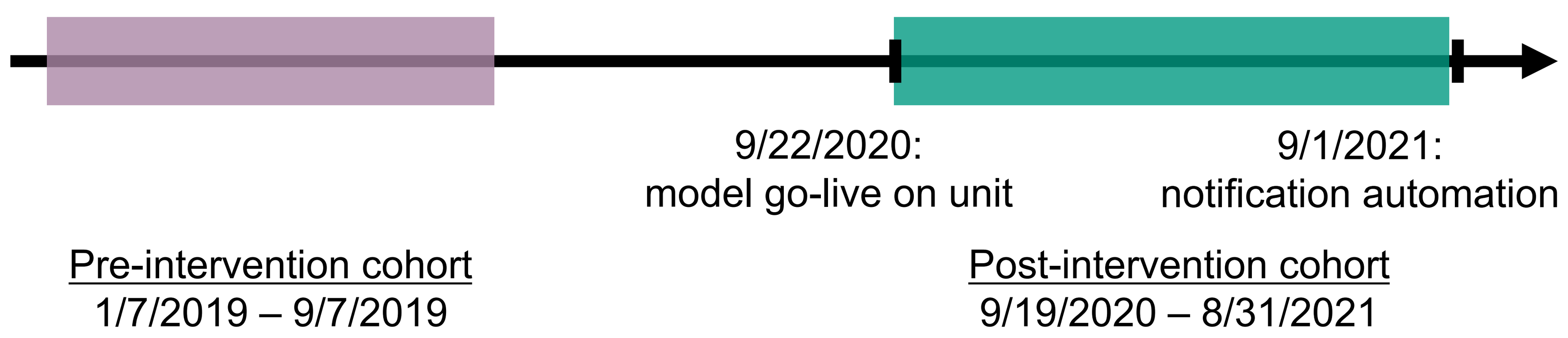


Inclusion criteria: solid malignancy, admitted to inpatient solid malignancy unit from ED
Exclusion criteria: admitted to intensive care unit (ICU) within first 24 hours

Outcomes and comparison cohorts:

- Primary: ACP documentation (whether ≥1 ACP note was written during hospitalization, as identified in EHR via specific text indicators)
- Secondary: Inpatient length of stay (LOS), discharge to hospice, code status change (full code to DNAR), ICU admission after first 24 hours, ICU LOS, inpatient deaths, 30-day deaths, 30-day readmission, 30-day ED visits

Implementing a machine learning model to predict mortality risk substantially increased documented ACP conversation rates in hospitalized patients with solid cancers but did not improve end-of-life care outcomes.



Analysis: We used chi-square or Fisher's exact tests for categorical variables and Wilcoxon rank sum tests for continuous variables; we stratified comparisons of categorical variables by physician division using Cochran-Mantel-Haenszel tests.

Scan the QR code to learn more about the mortality prediction model developed by the Duke Institute for Health Innovation (DIHI):

References:

1. Waldrop DP, McGinley JM. "I want to go home": How location at death influences caregiver well-being in bereavement. *Palliat Support Care*. Dec 2020;18(6):691-698. doi:10.1017/S1478951520000176
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Results

Table 1: Patient demographics across index hospitalizations

	Pre-intervention (n = 88 hospitalizations)	Post-intervention (n = 77 hospitalizations)
Age		
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		
Caucasian	53 (60.2)	39 (50.6)
Black or African American	29 (33.0)	33 (42.9)
Ethnicity		
Hispanic/Latino	3 (3.4)	2 (2.6)
Marital status		
Married	56 (63.6)	46 (59.7)
Single	21 (23.9)	17 (22.1)
Divorced, separated, or widowed	10 (11.4)	13 (16.9)

Table 2: ACP documentation and EOL care outcomes among index hospitalizations

	Pre-intervention (n = 88 hospitalizations)	Post-intervention (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	12 (13.6)	11 (14.3)	0.904[a]
30-day ED visit occurred	18 (20.5)	15 (19.5)	0.876[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[c]
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[c]
ICU LOS (days): median (IQR)	148.2 (80.1)	35.9 (32.2)	0.700[b]

[a] Chi-square test of independence without Yates' continuity correction.
[b] Wilcoxon rank sum test.
[c] Fisher's exact test.

Table 3: ACP documentation among index hospitalizations by attending physician specialty

	Pre-intervention (n = 88 hospitalizations)		Post-intervention (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]

[a] Cochran-Mantel-Haenszel test without Yates' continuity correction.