CARE DELIVERY ReCAP

original contributions

Impact of Augmented Intelligence on Utilization of Palliative Care Services in a Real-World Oncology Setting

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QUESTION ASKED: Can the use of an augmented intelligence (AI) tool to predict 30-day mortality improve rates of palliative care (PC) and hospice referrals in a community hematology-oncology practice?

SUMMARY ANSWER: Deployment of an AI tool at a hematology-oncology practice was found to be feasible for identifying patients at risk for short-term mortality. Insights generated by the tool drove clinical practice changes, resulting in significant increases in PC and hospice referrals.

WHAT WE DID: Between June 2018 and October 2019, all patients seen within a large hematology-oncology practice in the United States were scored weekly for risk of short-term mortality using the AI tool and mean monthly rates of PC and hospice referrals were calculated.

WHAT WE FOUND: Compared with 5 months before deployment of the AI tool, the mean rate of PC referrals increased from 17.3 to 29.1 per 1,000 patients per month, whereas the mean rate of hospice referrals increased from 0.2 to 1.6 per 1,000 patients per month. After 6 months of deployment, the increase in PC and hospice referrals persisted and was further accentuated.

BIAS, CONFOUNDING FACTOR(S), REAL-LIFE IMPLICATIONS: This study evaluated the deployment of a commercially available AI tool at a single practice involved in the training and validation of the algorithm, and the results may not be generalizable to all oncology practices. Timely referral to PC or hospice for patients with advanced cancer can aid in symptom management and can improve quality of life for patients at end of life. Our study found that insights into short-term mortality risk generated by the AI were effective in prompting clinical practice changes, leading to increased PC and hospice referrals for patients with cancer. Establishing a downstream workflow is critical to harness the benefits of identifying at-risk patients by the AI tool.

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ASSOCIATED CONTENT

Appendix

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abstract

PURPOSE For patients with advanced cancer, timely referral to palliative care (PC) services can ensure that end-of-life care aligns with their preferences and goals. Overestimation of life expectancy may result in underutilization of PC services, counterproductive treatment measures, and reduced quality of life for patients. We assessed the impact of a commercially available augmented intelligence (AI) tool to predict 30-day mortality risk on PC service utilization in a real-world setting.

METHODS Patients within a large hematology-oncology practice were scored weekly between June 2018 and October 2019 with an AI tool to generate insights into short-term mortality risk. Patients identified by the tool as being at high or medium risk were assessed for a supportive care visit and further referred as appropriate. Average monthly rates of PC and hospice referrals were calculated 5 months predeployment and 17 months postdeployment of the tool in the practice.

RESULTS The mean rate of PC consults increased from 17.3 to 29.1 per 1,000 patients per month (PPM) pre- and postdeployment, whereas the mean rate of hospice referrals increased from 0.2 to 1.6 per 1,000 PPM. Eliminating the first 6 months following deployment to account for user learning curve, the mean rate of PC consults nearly doubled over baseline to 33.0 and hospice referrals increased 12-fold to 2.4 PPM.

CONCLUSION Deployment of an AI tool at a hematology-oncology practice was found to be feasible for identifying patients at high or medium risk for short-term mortality. Insights generated by the tool drove clinical practice changes, resulting in significant increases in PC and hospice referrals.

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INTRODUCTION

Augmented intelligence (AI) and machine learning (ML) have found many applications in health care in recent years. For cancer care, these efforts have primarily focused on improving diagnoses: all six of the AI tools for oncology cleared by the US Food and Drug Administration are for diagnostic applications.[1] Although AI tools for other applications within oncology (such as treatment decision support[2]) are in development, few have used ML to predict mortality among patients with cancer.[3-6] Accurate prognostic data for patients with cancer have the potential to inform clinical decision making and improve timely integration of palliative care (PC) into patients' management at end of life (EOL).

Both the National Comprehensive Care Network and ASCO guidelines recognize the importance of documenting a patient's values, preferences, and goals for EOL.[7,8] Care of patients with cancer at EOL is also reflected in quality measures endorsed by the National Quality Forum.[9] However, physician estimates of survival tend to be poor. One study showed that only 20% of physicians with terminally ill patients could accurately predict their survival; overall, the physicians overestimated patient life expectancy by a factor of more than five times.[10] As a result of this overoptimism, treatment inertia may occur and important conversations regarding the patient's wishes for EOL might not be initiated in a timely manner. For example, although studies have shown that the majority of Americans say that they prefer to die at home,[11] less than half of the patients with cancer actually do.[12] This incongruence can lead to negative ramifications, with patients with cancer dying in an acute

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care setting experiencing more physical and emotional distress and worse quality of life than patients dying at home.[13] These negative consequences also affect the patients' caregivers, who were found to be at increased risk for developing psychiatric illness when the patient died in a hospital versus at home.[13] For those patients with cancer who are referred to PC, the referral may come too late to meaningfully improve their experience: a recent study showed that the median duration of stay in PC was only 15 days for patients with malignant disease.[14] These findings point to an unmet need for a decision support tool to assist with identification of patients with cancer at risk for short-term mortality.

The objective of this study was to evaluate the impact of deploying a commercially available AI tool (developed and validated to predict 30-day mortality among patients with cancer) on PC service utilization in a real-world setting. We deployed the AI tool at a large community oncology practice in the Pacific Northwest of the United States and compared rates of PC and hospice referral before and after deployment. This retrospective cohort study measured the potential of actionable insights generated by an AI tool to change clinician behavior in a community oncology practice.

METHODS

AI Approach

The Jvion CORE uses a proprietary continuously learning eigen-based n-dimensional space environment to determine the most likely trajectory for an individual. That trajectory is used to determine an individual's risk for mortality by understanding the likelihood that the trajectory intersects with high-risk areas within the eigen space.

Data used by the CORE include clinical elements from the electronic health record (EHR) and professional billing information such as diagnosis codes, assessments, laboratories, medications, cancer staging information, vitals, and screenings. Socioeconomic data from publicly available sources including the US Census Bureau, US Department of Agriculture, and National Oceanic and Atmospheric Administration are also used by the CORE. Additionally, US Census data are fed into the tool, including poverty, income, education, household size, transportation, employment, and neighborhood characteristics. Finally, behavioral data purchased from third-party data vendors such as Acxiom (Conway, AR), Experian (Costa Mesa, CA), and TransUnion (Chicago, IL) are integrated into the model. These sources provide indices at a patient level on history of internet searches on health conditions, purchasing channels, and life stage. The CORE combines these data with clinical data to generate an n-dimensional space within which patients are mapped along vectors, resulting in thousands of relevant clusters of clinically or behaviorally similar patients. These clusters have a mathematical propensity to respond to a clinical intervention, which are updated dynamically with new data from the site.

Practice, Patients, and Clinical Workflow

Northwest Medical Specialties is a large community oncology practice with six locations in the Pacific Northwest. There are 21 providers (10 medical oncologists and 11 mid-levels) managing an average of 4,329 unique patients per month (PPM). The practice participates in the Oncology Care Model (OCM), and alongside their use of the Jvion solution, they use nonclinical patient care coordinators (PCCs) in a variety of ways to review at-risk patients and triage the information to their PC advanced practice provider (APP) and primary oncologists.

All active patients were scored each week with updated Jvion CORE insights available by 7 AM PST each Monday, regardless of whether they had a visit. The CORE ranked patients from lowest to highest risk of a mortality event in the next 30 days, with approximately the top 50 considered to be high risk and the next 100 patients to be medium risk. The risk information was displayed in a secure web portal. Additionally, the driving clinical and socioeconomic risk factors and the top five recommendations were provided for each patient at high or medium risk. The recommended interventions were individualized on the basis of specific patient factors and broadly categorized as PC, pain management, nonpain symptom management, and social support interventions (Appendix Table A1, online only). A notation was made each week of the newly added patients as compared with the previous week.

Operational Workflow

The lead PCC accessed the portal each Monday and reviewed the newly added patients, risk factors, and recommendations. This information was shared with the primary oncologist. The subsequent management and the option to follow the recommended interventions for a given patient were at the discretion of the primary oncologist. The PCC also reviewed the patient in OncoEMR, the practice's EHR, and determined if the patient was a qualified OCM patient. With direction or approval from the primary oncologist or the assigned APP, the lead PCC verified if the patient was in need of any additional resources such as hospice or alternative plans and the risk factors were documented in Navigating Care, a case management workflow management tool. A key factor that was considered was whether the patient was already scheduled for or had a recent supportive care visit. For Northwest Medical Specialties, a supportive care visit is synonymous with a PC visit. If the patient had been scheduled for a supportive care visit, the PCC lead ensured that the visit occurred in a timely manner and that any follow-up items from the visit such as the depression screening results were addressed. If a supportive care visit had not recently occurred for the at-risk patient, the PCC lead worked with the PCCs to coordinate the scheduling of a supportive care or PC visit.

The PCC reviewed the chart to determine if the supportive care visit scheduling required escalation in terms of timing. If not, the supportive care visit was scheduled at the next available time. If the visit did require escalation on the basis of the risk category, the PCC consulted the PC APP at the weekly huddle. During this huddle, the PCC and APP discussed the appropriateness of participation in their Palliative Outreach Program. Also, the PCC and APP discussed if this patient should be brought to the attention of the primary oncologist and if a priority supportive care visit or a hospice referral was clinically appropriate, it was determined whether the PC APP or the primary oncologist would have this discussion with the patient and family.

Outcome Metrics

Given that the intent of the Jvion CORE insights is to ensure the clinically appropriate care if or when patients' prognosis deteriorates, the process metric measured is the average monthly number of PC consults and hospice referrals in the at-risk population. The average monthly rates across high- or medium-risk patients seen in the practice and irrespective of their diagnosis (oncology or hematology) were calculated 5 months before Jvion CORE deployment (January 2018 through May 2018) to serve as a baseline and then 17 months following the integration of the Jvion CORE into the clinical workflow (June 2018 through October 2019). This analysis represents a snapshot in time of the risk characterization of the patients.

RESULTS

Between June 2018 and October 2019, a total of 28,246 unique patients were screened with the Jvion CORE. Of these, 886 were identified as being at medium or high risk for 30-day mortality within the 17-month period. The characteristics of the overall patient population and those flagged by the algorithm as being at risk for 30-day mortality are presented in Table 1. In the overall patient population (Table 1), 46.4% of patients were over age 65 years and 58.2% of the patients were female. Nearly half of the patients were White (44.3%). An oncology diagnosis was noted for 40.2% of the patients. Among the patients identified as being at medium or high risk for mortality within 30 days (Table 1), 68.0% of the patients were over age 65 years, 50.9% were female, and 52.8% were White. The most prevalent cancer diagnosis within the at-risk group was lung cancer (24.9%), followed by breast cancer (22.1%) and small intestine or colorectal cancer (11.9%).

Pre- versus postdeployment, the mean rate of PC consults per 1000 PPM increased from 17.3 to 29 (168%; Fig 1A). When the first 6 months of Jvion CORE deployment were eliminated to account for user learning curve, the mean rate of monthly PC consults per 1,000 PPM increased 191% over baseline (17.3-33). The absolute average monthly PC referrals decreased from 207.6 in the predeployment period to 136.1 in the index post-Jvion deployment period. After eliminating the first 6 months of Jvion deployment, the average monthly referrals were lower at 108.3 (Fig 1B). For high- or medium-risk patients, the monthly averages increased from 76.2 in pre-Jvion to 126.4 and 142.4 in the post-Jvion and after 6 months of Jvion deployment, respectively. The mean rate of hospice referrals increased eight-fold from pre- to postdeployment, from 0.2 to 1.6 per 1,000 PPM (Fig 2A). Eliminating the first 6 months of Jvion CORE deployment to account for user learning curve, the mean hospice referral rate rose 12-fold over baseline (0.2-2.4) per 1,000 PPM. The average monthly rates of hospice referrals for high- or medium-risk patients in the pre-Jvion, post-Jvion, and 6 months post-Jvion were 0.8, 6.94, and 10.27, respectively (Fig 2B), with corresponding monthly rates of 128, 124, and 111, respectively, in the low-risk patients.

The 30-day mortality ML algorithm demonstrated predictive accuracy, with area under the receiver operator characteristic curve values of 0.93 at 30 days and 0.92 at 90 days (Figs 3A and 3B). At 30 days after being flagged as medium or high risk, 91 (10.3%) of the 886 patients had died, and at 90 days, 145 (16.4%) of the patients had died.

DISCUSSION

In this study, we found that the integration of an AI tool to predict 30-day mortality into the workflow of a large oncology practice in the United States resulted in significant increases in both PC consults and hospice referrals. This effect was even more pronounced when looking at data 6 months after the initial deployment. The findings from our study demonstrate that integrating an AI tool into clinical practice is both feasible and effective at generating data to assist decision making with respect to EOL discussions in patients with cancer.

Communication with patients regarding their prognosis is a critical component of care: this information is necessary to guide treatment discussions, to plan ahead for EOL care, and to ensure that patients have the opportunity to attend to personal matters. Referral to PC services has also been associated with less depression and longer survival for patients with cancer, while decreasing hospital costs.[15,16] However, determining the prognosis for an individual patient is a complex process that is influenced by multiple factors, which may change over time. For this reason, some oncologists put off discussions with patients regarding EOL.[17] In addition, research has shown that physicians tend to overestimate survival in their prognostic assessment of patients with advanced cancer.[18] Validated prognostic tools such as the Palliative Prognostic Score and Palliative Prognostic Indicator were created to complement a physician's clinical judgment; however, data regarding their accuracy are limited and they are not used routinely in clinical practice.[19] Similarly, geriatric assessment is recommended in older patients with cancer to better risk

TABLE 1. Patient Characteristics

Variables	Characteristics of Overall Patient Population (N = 28,246), No. (%)	Characteristics of High- or Medium-Risk Patient Population Identified by Jvion CORE (n = 886), No. (%)
Age, years		
< 51	6,573 (23.3)	53 (6.0)
51-65	8,534 (30.2)	230 (26.0)
66-80	9,367 (33.2)	437 (49.3)
> 80	3,735 (13.2)	166 (18.7)
Sex		
Female	16,446 (58.2)	451 (50.9)
Male	11,800 (41.8)	435 (49.1)
Race		
White	12,512 (44.3)	468 (52.8)
Black or African American	898 (3.2)	15 (1.7)
Asian	729 (2.6)	24 (2.7)
Unknown or Others	14,107 (49.9)	379 (42.7)
Primary diagnosis		
Oncology	11,363 (40.2)	100%
Nononcology	16,883 (59.8)	—
Top 5 diagnoses in the high- or medium-risk patients		
Lung cancer	—	221 (24.9)
Breast cancer	—	196 (22.1)
Colorectal or small intestinal cancer	—	105 (11.9)
Prostate cancer	—	82 (9.3)
Pancreatic cancer	—	56 (6.3)

stratify risk of toxicity and aid treatment decision making, but uptake has been limited.[20,21] The shortage of PC specialists and our aging population underscore the growing need for a tool to address the challenge of accurately identifying patients at risk for death in the short term.[22]

Although several studies have evaluated ML tools to predict mortality in patients with cancer,[3-6] to our knowledge, thus far, only one has been shown to influence clinical practice, by increasing the number of Serious Illness Conversations.[23] However, the intervention in this trial combined the

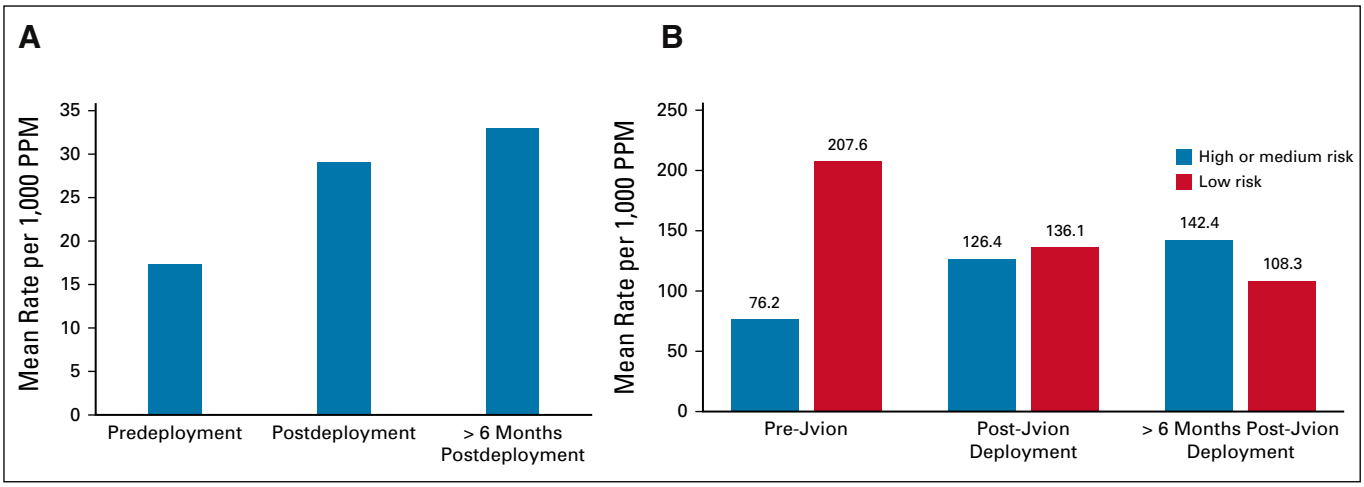

FIG 1. (A) Rate of PC consults pre- and postdeployment of the Jvion CORE (per 1,000 PPM). (B) Average total monthly PC consults by risk. PC, palliative care; PPM, patients per month.

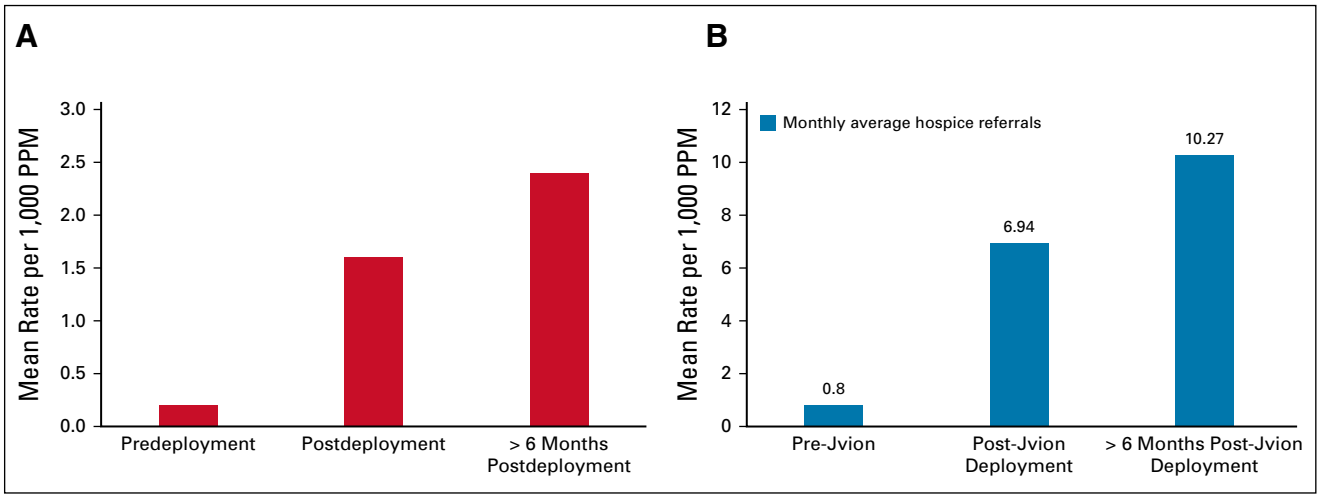

FIG 2. (A) Hospice referrals pre- and postdeployment of the Jvion CORE in high- or medium-risk patients (per 1,000 PPM). (B) Average monthly hospice referrals in high- or medium-risk patients. PPM, patients per month.

ML insights into 180-day mortality with behavioral nudges, using text message reminders, and performance reports and data on peer comparisons for Serious Illness Conversations. The combined intervention makes it difficult to tease out the specific contribution of the ML insights to driving the behavioral change. By contrast, our study provided the ML insights and recommendations within the EHR without any additional prompts directing clinicians toward specific actions, allowing for their own interpretation and decision making with respect to clinical care for the patient. A potential confounding factor is that the practice was participating in the OCM during the period of Jvion deployment. Thus, measures other than Jvion such as use of navigators, care coordination, a PC APP, and overall awareness and sensitivity to cost of care in the OCM model could have contributed to improved performance in PC at this practice. However, it is notable that Jvion CORE is one component that enhances the efficient utilization of these resources by streamlining the intake of the at-risk patient population in a quantifiable manner. Furthermore, the greater improvements in utilization of PC and hospice services after the initial 6 months of deployment suggest a potential behavior change within the practice staff and providers. A decline in the number of PC consults for low-risk patients also suggests that resources such as navigators and PC can be directed to the appropriate patients on the basis of insights generated from the AI tool.

A strength of this study is its single intervention design, which allows for the ability to attribute the change in PC or hospice referrals to the Jvion CORE insights. A second strength is the high area under the curve observed (> 0.9 at

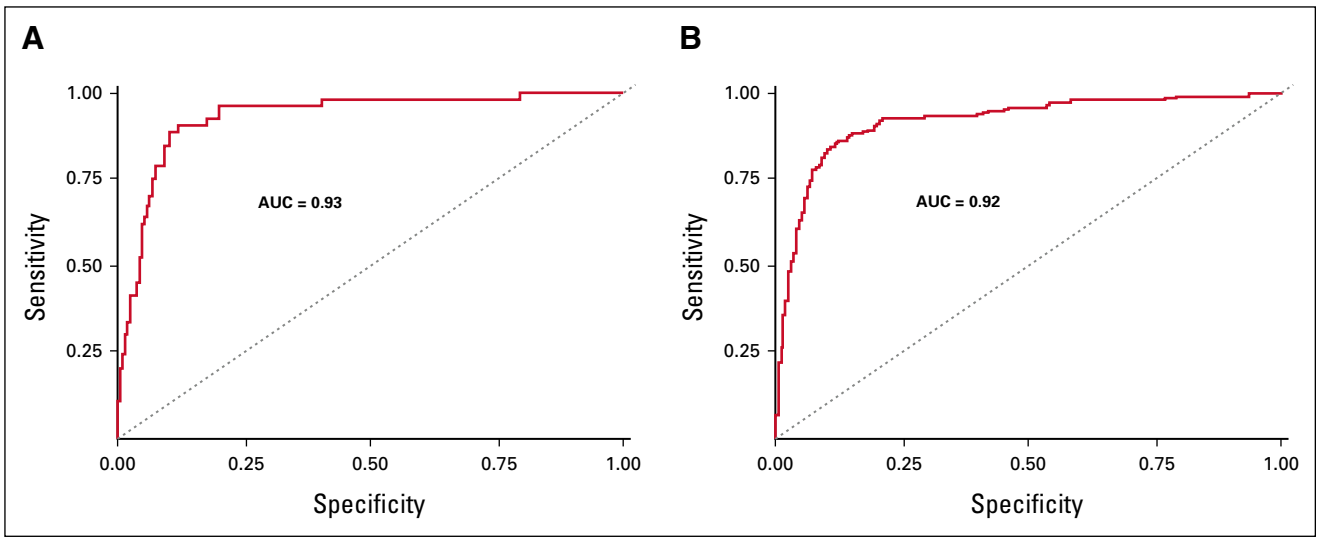

FIG 3. (A) ROC curve values for prospective predictive performance at 30 days. (B) ROC curve values for prospective predictive performance at 90 days. AUC, area under the curve; ROC, receiver operator characteristic.

both 30 and 90 days), indicating accuracy on par with or better than other tools in development.[3-6] Third, this study examined the deployment of the AI tool in community practice, a setting where most patients with cancer in the United States receive treatment.[24] This setting, combined with our large sample size, which included patients with many different cancer types, may make the results more generalizable to the overall population. Our study is subject to several limitations. First, there was overlap in the timeframe for the validation of the Jvion CORE at this practice and this study, leading to the potential for patients included in the validation set to be included in this study. Additional studies are underway at practices not involved in the training and validation of the algorithm. Second, this study evaluated data from deployment of the AI tool in a single oncology practice in the United States and the results may not be equivalent at all practices. Integration of the AI solution into other practices with differing workstreams is underway. Third, our study did not collect data on health care utilization (eg, emergency department visits, inpatient admissions, intensive care unit admissions, radiation or chemotherapy in the last month of life, and length of stay with hospice) and it is unknown whether the increase in PC consults and hospice referrals as a result of deployment of the AI solution affected these metrics. This will be the subject of future studies. Notably, this study was performed at a site that had APP support for PC and further study is needed to demonstrate the generalizability of these results to practices without such resources. Although the downstream workflow can vary by practice, clinicians can use this information to direct patients to appropriate care in the context of their practice and resources. Finally, this study was limited to the impact of the AI solution on patients at risk for short-term mortality. Although the 30-day mortality predictions by the algorithm were supported by a high receiver operator characteristic of 0.93, the actual deaths at 30 and 90 days among the high- or medium-risk patients were lower. Possible hypotheses for lower true mortality could include the prevention or delay in short-term mortality because of an actionable insight such as treating occult infection and limiting mortality from toxicity of cytotoxic therapy in individuals with poor physiologic reserve. Future directions for research include evaluating the effect of the AI solution to identify other subsets of at-risk patients (eg, patients with depression or those requiring pain management) to generate actionable output with the goal of improving care of patients with cancer.

In conclusion, timely referral to PC or hospice in patients with advanced cancer can aid in symptom management and can improve QOL for patients at EOL. Our retrospective cohort study found that incorporation of a novel AI solution into the workflow at a large oncology practice in the United States was feasible. The 30-day mortality insights generated by the AI were effective in prompting clinical practice changes, resulting in increases in both PC consults and hospice referrals. This study provides early evidence that AI can assist with and improve decision making in the management of patients with cancer at EOL identified as high or medium risk for short-term mortality.

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AUTHORS' DISCLOSURES OF POTENTIAL CONFLICTS OF INTEREST

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AUTHORS' DISCLOSURES OF POTENTIAL CONFLICTS OF INTEREST

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Open Payments is a public database containing information reported by companies about payments made to US-licensed physicians (Open Payments).

No potential conflicts of interest were reported.

APPENDIX

TABLE A1. List of Interventions Recommended for High- or Medium-Risk Patients

Summary Intervention List
Category: PC
Evaluate the benefits of palliative or hospice care
Consider referral to appropriate health care professionals
Consider mobilizing community support
Consider re-evaluating care plan
Encourage advance care planning, if not already accomplished
Category: pain
Assess patient for pain and treat according to guidelines
Consider nonpharmacologic therapies for pain
Category: symptom management
Focus on symptom management and comfort: dyspnea
Focus on symptom management and comfort: anorexia and cachexia
Focus on symptom management and comfort: nausea and vomiting
Focus on symptom management and comfort: constipation
Focus on symptom management and comfort: diarrhea
Focus on symptom management and comfort: delirium and terminal restlessness
Focus on symptom management and comfort: cough
Focus on symptom management and comfort: fatigue
Focus on symptom management and comfort: dysphagia
Consider antimicrobial, antifungal, and antiviral prophylaxis according to guidelines[a]
Category: social support
Evaluate and provide social support and/or consider resource management
Prepare patients/families/caregivers

Abbreviation: PC, palliative care.

[a]National Comprehensive Cancer Network. NCCN clinical practice guidelines in oncology: Prevention and treatment of cancer related infections. Version 1.2020. https://www.nccn.org/professionals/physician_gls/pdf/infections.pdf