

# Computationally assisted patient finding for navigation to optimize pancreatic cancer care access

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## Abstract

**Background:** Patient navigators are increasingly utilized in cancer care but ensuring patients are properly identified and referred to navigators is a significant challenge. The primary objective was to compare time from radiographic report to biopsy, oncology visit, and treatment before versus after implementation of a computationally assisted navigation referral stream. Secondary objectives included evaluating care delivery across demographic groups and assessing survival outcomes.

**Materials and Methods:** A quality initiative at Northwell Health compared care delivery metrics between 2 cohorts of patients with suspected pancreatic cancer: those identified retrospectively using computational methods in January 2023 and those identified and navigated prospectively in June 2023. Radiology reports from a centralized health information exchange were analyzed by an ML-based natural language processing (NLP) model to detect findings suspicious of pancreatic cancer. Participants deemed eligible for navigation were contacted by a navigator to improve the likelihood and expediency of follow-up care.

**Results:** Seventy-one patients were included, with 38 patients in the retrospective cohort and 33 patients in the prospective cohort. The prospective cohort showed numeric reduction in time to biopsy (12-6 days,  $P=0.173$ ), oncology appointment (27-17 days,  $P=0.192$ ), and treatment (56-35 days,  $P=0.136$ ), though these results were not statistically significant. These metrics showed a significant reduction in standard deviation ( $P<0.001$ ), including among racial and ethnic minorities. The survival of patients in both cohorts was comparable (hazard ratio [HR]=0.82,  $P=0.66$ ).

**Conclusion:** This study provides promising evidence that an NLP-assisted identification workflow can improve care delivery and investigation in a larger study is warranted to validate these findings.

**Key words:** pancreatic cancer; natural language processing; navigation; care delivery; care disparities.

## Implications for Practice

An automated natural language processing (NLP) computational model was implemented as a navigation referral stream with the hypothesis that computationally assisted navigation would improve equitable care delivery for our institution's patients with pancreatic cancer. This quality improvement study demonstrated significant improvements in care consistency across demographic groups for patients with newly suspected pancreatic. Additionally, more patients participated in research studies. These promising results suggest that centralized, computationally assisted navigation has the potential to enhance care delivery within large healthcare systems.

## Introduction

Timely access to high quality care is a core principle of health care delivery, yet the complexity of cancer diagnosis and work-up poses substantial challenges for patients, especially for patients who face language barriers or have limited resources.<sup>1</sup> Care navigators provide personalized assistance to

patients as they transition into and through the cancer care continuum,<sup>2,3</sup> resulting in improved patient satisfaction,<sup>4</sup> decreased time to diagnosis and treatment,<sup>5,6</sup> and improved cancer care equity.<sup>7</sup>

Management of newly suspected pancreatic cancer represents an example of an operationally complex sequential

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process whereby initial signs or symptoms trigger a need for imaging, diagnostic biopsy, referral to specialists, trial review, and treatment initiation. Timely work-up of newly suspected cases is critical as disease progression and patient deterioration can limit access to curative therapies and clinical trial options. Patient navigators are increasingly utilized to assist pancreatic cancer care coordination.<sup>8,9</sup> However, proper identification and referral of patients to navigators remains a significant challenge, especially within large health care systems comprising multiple affiliated hospitals and geographically dispersed clinics. Patient care navigators and clinical trial coordinators typically rely on late, passive referral streams, which can result in missed opportunities, delays in care, and lower participation in clinical trials and biospecimen studies.

The goal of this quality improvement initiative was to improve clinical outcomes equitably through standardizing the process by which patients with suspected pancreatic cancer are identified and referred to navigators. To start, we observed that patients who underwent diagnostic biopsy for a suspected pancreatic cancer universally had pre-biopsy imaging; accompanying imaging reports contained recurrent patterns of language, such as “mass,” indicating suspected pancreatic cancer; and all radiology reports across the network are deposited in 1 centralized database. We hypothesized that a machine learning (ML) natural language processing (NLP) model could analyze imaging reports and flag those with findings suspicious of pancreatic cancer. This model could then serve as a centralized tool for patient identification and navigator referral.

In this study, we describe the implementation of an NLP model to enhance the efficiency and equity of patient care. As secondary objectives, we evaluated the use of NLP model identification to find patients in real-time for biospecimen-based research studies. To our knowledge, this is the first study implementing an AI-assisted navigation referral stream for pancreatic cancer.

## Methods

The primary objective of this project was to improve equitable access to timely care and research studies for pancreatic cancer patients at our institution by developing a standardized, system-wide, AI-based, identification and referral process. To develop this solution, we deployed an NLP model we previously developed, which flags radiology reports containing language suspicious for pancreatic cancer. The primary objective was evaluated using a 2-stage study design. First, we conducted a retrospective cohort study, where we cataloged the natural history of NLP-identified, manually adjudicated patients to determine our institution’s historical care delivery metrics for newly diagnosed pancreatic cancer patients. Second, we implemented a prospective cohort study, using a daily workflow, combining NLP-identification, manual adjudication, and navigation referral. We then compared care delivery metrics between the retrospective and prospective cohorts to determine the impact of the AI-assisted navigation referral stream on care efficiency.

### Identification of patient candidates using computational NLP

We previously developed an NLP classifier to analyze textual data in radiology reports for language suspicious for pancreatic

cancer.<sup>10</sup> The base model utilizes Google’s open-source NLP framework, BERT,<sup>11</sup> which was pre-trained by an engineer (A.C.) using a large corpus of 2.1 million radiology texts. This pre-training step equipped the model with the vocabulary and syntax necessary to interpret language patterns in radiology documents. In a subsequent fine-tuning step, a multidisciplinary team comprising a radiologist (M.B.), a gastrointestinal medical oncologist (D.K.), and a coordinator (C.V.) created a radiology classification training set of 1076 abdominal CT or MRI radiology reports from a racially and ethnically diverse patient population, where a consensus determination was made regarding the presence or absence of pancreatic cancer suspicion. “Suspicious” was defined by report text denoting masses, discrete lesions, cystic masses, pancreatic atrophy, or any indication by the radiologist of a potential, albeit unclear, underlying pancreatic mass (eg, a double duct sign suspicious for malignancy). Cystic lesions, especially large cysts or “cystic masses,” were included as they were felt to represent pre-neoplastic high-risk lesions that may require intervention, and because we aimed for a more permissive, sensitive model. Other abnormal findings, including inflammation, stranding, pancreatitis, pancreatic calcification, and fatty infiltration, were excluded from the “suspicious” category. In addition, findings of ductal dilatation without a lesion or without documented suspicion of a lesion were considered not suspicious. If both suspicious and not suspicious findings were present, the report was labeled as suspicious. A list of 23 phrases, including “pancreatic cancer,” were provided as a positive indicator of disease suspicion. Assessment of the model’s performance demonstrated a positive predictive value of 77% and a sensitivity of 94%.<sup>10</sup>

All radiology reports produced from any in-patient or out-patient imaging facility across our institution are published to a centralized health information exchange (HIE). The NLP model selects only abdominal CT and MRI imaging tests. The model flags suspicious reports, and deposits them in a restricted-access, PHI-secure database for manual review.

### Manual review of patient candidates

During the study period, a GI oncologist (D.K.), coordinator (J.T.), and medical student (K.M.J.) conducted a manual review of the lesions and patients from the list of NLP-flagged reports, in 2 steps: *lesion review* and *patient review*.

*Lesion review* entailed manual review of the flagged lesion for accuracy, to confirm presence of a pancreatic lesion suspicious for cancer. The lesion was further characterized using manual annotation by lesion type, including mass, cyst, abnormal but not malignant, and abnormal but not pancreatic in origin. For this project, only radiographic findings indicative of pancreatic cancer—specifically, masses or suspected occult masses with double-duct sign—were included.

*Patient review* entailed manual review of the patient’s electronic medical record (EMR) to determine navigation eligibility. Navigation-eligible patients were defined as patients needing clinical work-up for biopsy, oncology visit, or treatment. Patients were excluded from navigation eligibility if chart review revealed that their treating physicians had documented clinical deterioration and shared-decision making such that further diagnostic work-up was not clinically indicated, such as patients whose goals of care discussions had resulted in a decision to forego further workup or who had transitioned to hospice care. Patients meeting criteria for navigation eligibility

were further reviewed and categorized based on the following: demographic data (age, sex, and race), scan setting (in-patient vs out-patient), scan location (Central: Nassau County; Eastern: Suffolk County, Western: Richmond, New York, Westchester Counties); and insurance type (Federal: patients with Medicare or Medicaid, vs. Non-Federal: commercial, including Medicare with supplemental insurance) was documented as a proxy of socioeconomic class.

### Measuring care delivery impact of computationally assisted navigation referral workflow

As a primary objective, we compared key clinical metrics following implementation of this novel NLP identified assisted navigation approach (prospective cohort) versus prior to implementation (retrospective cohort). This was measured by comparing the average (mean, median) and dispersion (standard deviation) in time (days) from (1) report date to biopsy date, (2) from report date to oncology appointment date, and (3) report date to treatment date (date of surgery, chemotherapy, or radiation, whichever came first). These metrics were chosen because care efficiency requires expediency of these co-dependent steps.

As secondary objectives, we evaluated whether care delivery changes were equitably shared across demographic groups. Due to the small sample size, patients identifying as Hispanic ethnicity or African American/Black were grouped under the category of “racial/ethnic minority.” In addition, we compared the distribution of localized versus metastatic disease (staged at the time of identification), the fraction of patients managed with upfront hospice care, and the number of patients treated with definitive, curative-intent therapy between the retrospective and prospective cohorts.

The prospective cohort review was implemented using a daily workflow, consisting of a 20–45 minute virtual meeting each weekday morning, involving a coordinator, a GI oncologist, and a navigator. The team conducted *lesion review* and *patient review* together. The meeting included a navigator-led discussion on how to address the navigation needs of eligible patients. Patients referred for navigation were entered into a navigation worklist and, per institutional standard navigation practice, were contacted either by the physician who ordered the scan or directly by the navigator if the scan findings were already disclosed by a clinician. Charts were reviewed retrospectively to determine time to each key care delivery metric.

The retrospective cohort review was conducted in July 2023 on reports published from January 1 through January 31, 2023. The prospective cohort review was conducted on weekdays from June 1 through June 30, 2023, on reports published the previous day, with the exception of reports published on weekends which were reviewed the following Monday.

All statistical analyses and plots were generated in R (Version 4.2.0) using the tidyverse package. Numerical parameters were compared by Mann–Whitney *U* tests with statistical significance determined as *P*-value < 0.05. Overall survival was analyzed using the Kaplan–Meier method and the survival comparison between cohorts was measured using the log-rank test. Bar graphs were generated using Graphpad Prism (Version 8.4.3) and the workflow schematic was created using BioRender.

### Impact on clinical translational research

Biospecimen-based research is essential to improve our understanding of the molecular drivers of pancreatic cancer. A key

challenge we observed underlying low enrollment was insufficient lead time for biospecimen coordinators to identify and approach patients, which for some studies, was required prior to biopsy. This was especially apparent in the Polyethnic-100012 pancreatic substudy, focused on the elucidation of molecular determinants of worse outcomes from pancreatic cancer in African American/Black patients. Beginning on June 1, 2023, patients deemed navigation-eligible were also referred to a biospecimen coordinator for review and consideration for study enrollment. We compared enrollment between 2 groups: a historical group of patients enrolled onto studies from August 12, 2021 through May 31, 2023 (a 21-month period, overlapping with the January 2023 retrospective cohort), and a group enrolled after the computational-assisted navigation referral method was implemented from June 1, 2023, to December 1, 2023, overlapping with the prospective cohort. We compared the fraction of patients approached, consented, and enrolled between the 2 study periods.

## Results

### Patient cohort description

The number of reports identified by the retrospective and prospective cohorts and number of patients meeting the inclusion criteria of this study are presented in [Figure 1](#). In the retrospective period, 14 526 abdominal imaging reports were analyzed and 6.3% (917) were flagged as suspicious, originating from 852 unique patients. Among these there were 149 reports flagged as suspicious for a mass, and others were cysts or atypical but nonmalignant. In the prospective cohort, there were 17 685 reports analyzed, among which 1235 (7.0%) were flagged as suspicious, and ultimately, 137 patients with a mass. After accounting for previously diagnosed patients, there were 65 and 53 patients in the retrospective and prospective groups, respectively, who were potentially eligible for work-up of newly suspected disease. Both cohorts included a substantial fraction of patients with poor performance status, though this was more common in the retrospective group at 34% (22/65) compared to the 23% (12/53) in the prospective cohort, suggesting that daily prospective review may have helped patients access work-up. Ultimately, 38 patients in the retrospective cohort and 33 patients in the prospective cohort were identified with newly suspected pancreatic cancer and deemed navigation-eligible ([Table 1](#) and [Figure S1](#), see online supplementary material for a color version of this figure). Patients in both cohorts represented diverse demographic backgrounds, geographic regions, and socioeconomic classes ([Table 1](#)).

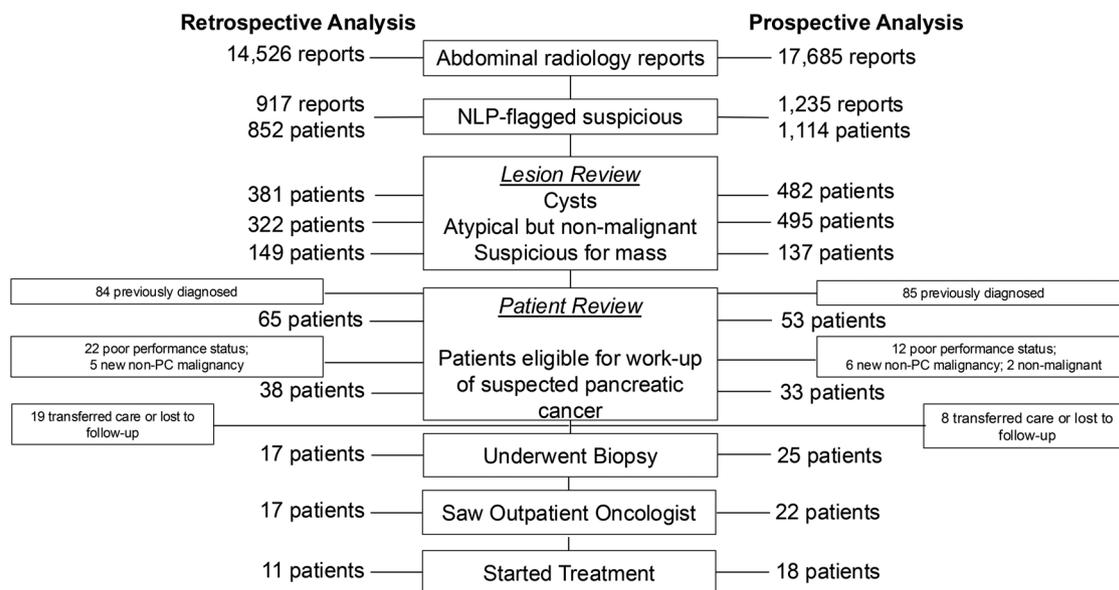
Compared to patients in the retrospective cohort, navigation eligible patients in the prospective cohort were more likely to undergo biopsy in our health care system 76% (25/33) versus 45% (17/38) and more underwent treatment in our healthcare system 55% (18/33) versus 29% (11/38) ([Figure 1](#)).

### Comparison of care delivery endpoints

The primary endpoints for measuring care delivery were the time to biopsy, oncology visit, and time to treatment from initial scan ([Figure 2A](#) and [Table 2](#)). The prospective cohort showed numeric reduction in time to biopsy from 12 to 6 days (*P*=0.173) and numeric improvement in times to oncologist visit and to treatment, with speeds 1.6–2x faster in the prospective cohort. Additionally, fewer patients experienced prolonged

**Table 1.** Study patient composition.

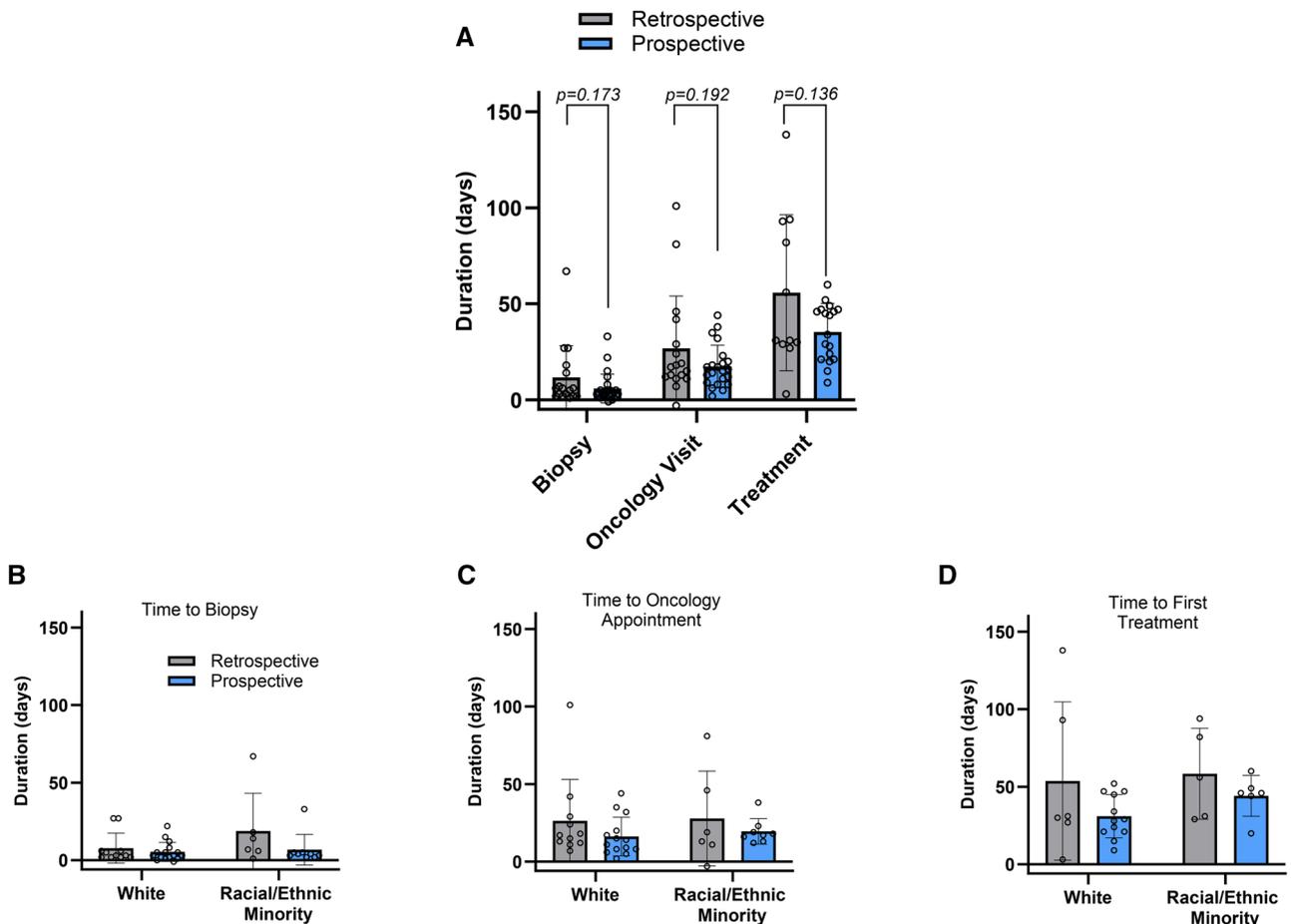
		Retrospective	Prospective	Total
<i>n</i>		38	33	71
Age		72 ± 14	68 ± 13	70 ± 14
Gender	Male	16 (42%)	19 (58%)	35 (49%)
	Female	22 (58%)	14 (42%)	36 (51%)
Race	Asian/Pacific Islander	3 (8%)	4 (12%)	7 (10%)
	African American/Black	6 (16%)	8 (24%)	14 (20%)
	Caucasian/White	18 (47%)	13 (39%)	31 (44%)
	Other/Unknown	11 (29%)	8 (24%)	19 (27%)
	Non-Hispanic/Latino	32 (84%)	30 (91%)	62 (87%)
Ethnicity	Hispanic/Latino	6 (16%)	3 (9%)	9 (13%)
	CT	37 (97%)	31 (94%)	68 (96%)
Scan type	MRI	1 (3%)	2 (6%)	3 (4%)
	Inpatient	29 (76%)	28 (85%)	57 (80%)
Scan setting	Outpatient	9 (24%)	5 (15%)	14 (20%)
	Central	19 (50%)	21 (64%)	40 (56%)
Scan location	Eastern	6 (16%)	3 (9%)	9 (13%)
	Western	13 (34%)	9 (27%)	22 (31%)
	Commercial	3 (8%)	9 (27%)	12 (17%)
Insurance	Medicaid	6 (16%)	6 (18%)	12 (17%)
	Medicare	24 (63%)	15 (45%)	39 (55%)
	Self-pay	1 (3%)	-	1 (1%)
	Unknown	4 (10%)	3 (9%)	7 (10%)

**Figure 1.** A CONSORT diagram describing the retrospective and prospective cohorts. NLP, natural language processing; PC, pancreatic cancer.

delays in care: in the retrospective cohort, 5 patients were not treated within 50 days of their scan, while only 2 patients in the prospective cohort faced such a delay. There was a statistically significant reduction in the standard deviation of time to each of the 3 care delivery metrics, with reductions of 53%-65% across metrics, demonstrating improved consistency in care delivery. Overall, the computationally assisted navigation intervention demonstrated promising improvements in efficiency, as reflected by these significant improvements in consistency.

As secondary endpoints, care delivery metrics were evaluated by demographic groups and geography (Figure 2B and Table S1). When stratified for race, the time between biopsy,

outpatient oncology visit, and treatment, decreased considerably across all racial groups. For racial/ethnic minorities, the mean (median; SD) number of days from scan to biopsy decreased from 19 to 7 days (11-4; 24-10), from scan to oncology visit decreased from 28 to 20 days (16-18; 31-8), and from scan to treatment decreased from 58 to 44 days (56-46; 29-13). The consistency of time to biopsy and time to oncologist were significantly improved for racial/ethnic minorities ( $P=0.026$ ,  $P=0.003$ ). These reductions indicate a substantial improvement in care delivery for racial/ethnic minorities. Time to biopsy, oncologist appointment, and treatment were all significantly expedited in the Central Region ( $P<0.001$ ), but less so in the Eastern/Western region (Table S2). Though not



**Figure 2.** (A) Care delivery metrics pre- and post-implementation of AI-guided navigation workflow were compared. Mean time (days) from radiology report to: biopsy decreased from 12 to 6 days ( $P= .173$ ), outpatient oncology visit decreased from 27 to 17 days ( $P= .192$ ), and treatment initiation decreased from 56 to 35 days ( $P= .136$ ). (B–D) Care delivery metrics pre- and post-implementation of AI-guided navigation workflow were compared by racial/ethnic groups.

**Table 2.** Clinical endpoints.

Endpoint	Cohort	N	Time to endpoint (days)			
			Range	Median	Mean	SD
Biopsy	Retrospective	17	66	6	12	17
	Prospective	25	34	3	6	8
P-value	-	-	-	.192	.173	<.001
Oncologist	Retrospective	17	104	17	27	27
	Prospective	22	42	16	17	11
P-value	-	-	-	.403	.192	<.001
Treatment	Retrospective	11	135	31	56	41
	Prospective	18	51	39	35	15
P-value	-	-	-	.225	.136	<.001

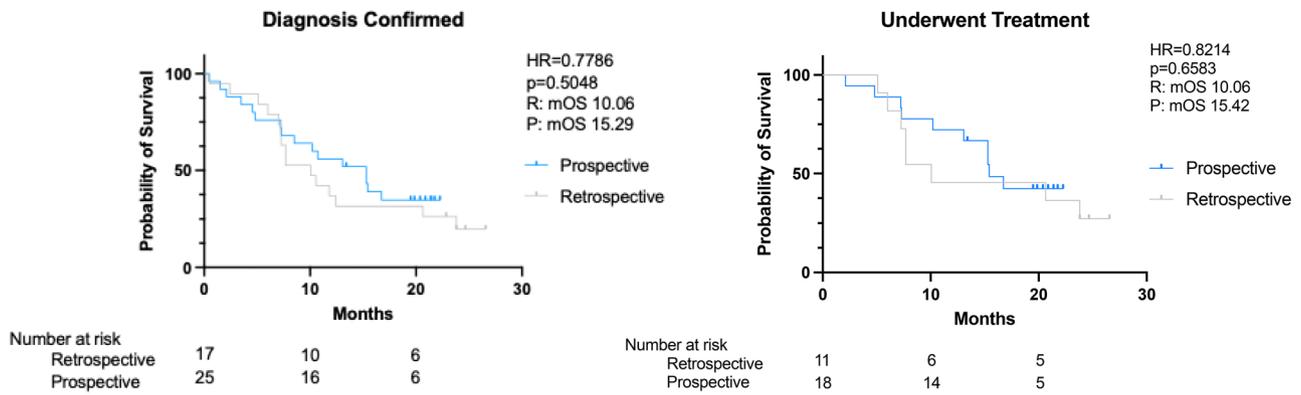
significant, there were also numeric reductions in time to these metrics for patients regardless of scan setting (Table S3). Furthermore, consistency of time to biopsy, oncologist, and treatment were significantly improved for patients who underwent scan in the inpatient setting (Table S3). Care consistency showed significant improvements across all metrics in patients

with federal insurance types, suggesting benefits to patients of lower income levels (Table S4).

The proportion of patients with localized disease was similar in the prospective cohort 60% (15/25) compared to the retrospective cohort 53% (10/19) (Figure S2, see online supplementary material for a color version of this figure). Definitive multimodal therapy for localized disease with curative intent (surgical resection with or without peri-operative chemotherapy) was more common in the prospective cohort, 44% (8/18) of patients, compared to the retrospective cohort, 27% (3/11) of patients (Figure S3, see online supplementary material for a color version of this figure). Patients in both cohorts had comparable survival, among diagnosed patients (hazard ratio [HR]=0.78,  $P=0.50$ ), and among treated patients (HR=0.82,  $P=0.66$ ) (Figure 3).

### Impact of prospective intervention on biospecimen study enrollment

The prospective daily workflow of direct referral of patients before diagnostic biopsy to a biospecimen coordinator was implemented to study the impact on the number of patients who were approached, consented, and enrolled on at least one of the 2 biospecimen studies available at our institution. Compared to historical monthly average, there was a significant



**Figure 3.** Survival pre- and post-implementation of AI-guided navigation workflow was compared for patients who underwent diagnostic confirmation and patients who underwent treatment of their pancreatic cancer.

increase in the monthly rate of patients approached (4.0 vs. 1.8), consented (4.0 vs. 1.5), and enrolled (3.2 vs. 0.9). Furthermore, the declination rate was reduced from 30% to 17%.

## Discussion

This work describes a quality improvement initiative to enhance timely access to care for our patients with suspected pancreatic cancer. The initiative involved implementing an NLP model to screen radiology reports for suspected pancreatic cancer, which enabled creation of a centralized referral pathway to cancer care navigators. We hypothesized that early identification and prompt referral to navigators and research coordinators would improve efficiency, consistency, and equity of care delivery.

Our findings showed that patients identified through NLP and navigated by care teams experienced encouraging improvements in the timeliness and consistency of care as demonstrated through nonstatistically significant numeric improvements in average expediency and significant improvements in the consistency of core care efficiency metrics. Notably, navigation services were available during both study periods. However, in the retrospective study, patients were referred to navigators through traditional, passive referral pathways following tissue diagnosis, while in the prospective study, the NLP model created a new referral stream that ensured eligible patients were consistently connected to navigators earlier in the diagnostic timeline. Additionally, computationally identified and navigated patients were less likely to require upfront hospice management, more likely to undergo biopsy and treatment, and more likely to be referred for potentially curative surgical management. Notably, the improvements were particularly pronounced in patients from racial and ethnic minority groups, a critical observation given that these populations often face increased health-related social needs and have fewer resources, resulting in barriers to care.

Our approach also uncovered intriguing epidemiologic findings. For example, a substantial proportion of patients with radiologically suspected, but never diagnosed, pancreatic cancer was immediately eligible for hospice care due to clinical deterioration, highlighting the unmet need of earlier identification and management. Furthermore, most navigation-eligible patients had their imaging performed at an in-patient setting, suggesting that most new patients have symptoms and signs for pancreatic cancer. Computational assistance improved cohort discovery of patients prior to their diagnostic biopsy,

leading to more patients being approached and enrolled in biospecimen-based research studies (Figure S4, see online supplementary material for a color version of this figure).

Although our results show promising trends, there are limitations to the current study including small sample size, limiting statistical comparisons. The experimental design compared outcomes in a prospective, experimental group, to a retrospective, control group, assembled ~6 months prior; a disadvantage of this design is the potential for other care delivery improvements to confound the attribution of our intervention as the source of care efficiency improvement. However, we are not aware of any other major care delivery changes implemented in our institution at this time. Nevertheless, to address these limitations, we are planning a larger, prospective, randomized design. Also, we observed that the time to treatment was improved variably based on location in our network, which reflects an opportunity to understand inter-regional differences and distribute resources accordingly to improve care delivery. Additionally, the NLP model occasionally misclassifies certain nonmalignant pancreatic abnormalities as suspicious, which reduced the positive predictive value of “suspicious” lesions, increasing lesion review time. Lastly, due to limitations of the NLP model’s technical capabilities, manual patient review is currently required to determine eligibility for navigation, which has limited sample size due to feasibility. To this end, we are exploring the use of large language models to more comprehensively synthesize data from multiple domains of the EMR to further automate the process of determining patient eligibility and improve scalability of this approach.

Nevertheless, our findings offer hope that proactive, expedited work-up may be associated with improved care delivery. AI offers a significant opportunity to shift the traditional cancer care paradigm toward proactive healthcare by utilizing EMR data (Figure S5, see online supplementary material for a color version of this figure). In our own health system, we are using such tools to create referral streams for aneurysm detection, triggering referral to vascular surgery; elevated PSA levels in at risk patients, triggering referral to urology; and pancreatic cysts, triggering referral to gastroenterology. Clearly, the mining of electronic health record data using artificial intelligence has great potential to improve health care delivery. Advanced AI tools, including large language models capable of summarizing patient notes and synthesizing data, could help streamline or even replace the validation and triage tasks currently needed. In future work, we aim to leverage these AI tools to

further refine the pre-filtering process for patients considered for navigation. By integrating these advancements, we aim to enhance the precision and efficiency of patient identification, ultimately improving outcomes for those with pancreatic cancer.

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## Author contributions

Daniel A. King (Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing—original draft, Writing—review & editing), Kristen M. John (Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing—original draft, Writing—review & editing), Joseph Tenner (Conceptualization, Data curation, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing—original draft, Writing—review & editing), Sandeep Nadella (Conceptualization), Tiffany Zavadsky (Conceptualization), Anthony Carvino (Conceptualization, Software), Shama Khan (Conceptualization, Software), Rolando Croocks (Methodology, Resources, Supervision), Tara McEvoy (Methodology, Resources, Supervision), Kristen Beyer (Methodology, Resources, Supervision), Rita Mercieca (Methodology, Resources, Supervision), Cristina Valente (Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision), Bernadette Bingham (Methodology, Supervision), Elizabeth G. Cohn (Conceptualization, Formal analysis, Investigation, Methodology, Resources, Writing—original draft, Writing—review & editing), Amber N. Habowski (Data curation, Formal analysis, Methodology, Validation, Visualization, Writing—original draft, Writing—review & editing), David A. Tuveson (Conceptualization, Formal analysis, Methodology, Supervision, Writing—original draft, Writing—review & editing), Matthew A. Barish (Conceptualization, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Writing—original draft, Writing—review & editing), and Richard Carvajal (Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing—original draft, Writing—review & editing)

## Supplementary material

Supplementary material is available at *The Oncologist* online.

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## Conflicts of interest

D.A.T. is a member of the Scientific Advisory Board and receives stock options from Leap Therapeutics, Surface Oncology, and Cygnal Therapeutics and Mestag Therapeutics outside the submitted work. D.A.T. is scientific co-founder of Mestag Therapeutics. D.A.T. has received research grant support from Fibrogen, Mestag, and ONO Therapeutics. D.A.T. receives grant funding from the Lustgarten Foundation, the NIH, and the Thompson Foundation. Dr. King received honoraria from ClearView, Ipsen, The Kineticx Group, Omni Health Media, Prestige Biopharma, and Histosonics for participation on advisory boards or consultation services. None of this work is related to the publication. No other disclosures were reported.

## Data availability

Pertinent data are contained within the article. For further questions, please contact the corresponding author.

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